DOCTORAL DISSERTATION

DEVELOPMENT OF INTERRELATED MULTI-CRITERIA APPROACH TO DISTRIBUTION OF FUNDS

Study program: Economy and Management
Field of study: Business Administration and Management
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Ostrava, 2019
STATEMENT

I hereby declare that I have developed the entire doctoral thesis including annexes myself. All sources of information have been indicated in the bibliography and were quoted appropriately throughout the doctoral thesis.

Ostrava, ................................
Signature ...................................
WORDS OF THANKS

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ABSTRACT

The Cohesion Policy is an essential and powerful tool designed to provide a basis for the prosperity and wellbeing of people in a vulnerable position due to providing considerable financial support to the lagging regions. Around 33% of the EU budget needs an effective redistribution amongst correctly identified lagging regions satisfying their social and economic needs. However, at the present days, the rules of a redistribution game are not transparent, have some methodological and theoretical unsoundness and on the final step of decision-making are the subject to political negotiations. In particular, the decision-making process, underlying the Structural funds' distribution, is still in its infancy phase and requires improvements regarding the measurement of regional performance, its classification, and optimisation of funds' distribution.

The research objective is to develop the interrelated multi-criteria approach to the solution of the real-life problem of Structural funds' distribution. The proper solution to this problem heavily depends on such considered aspects as measurement, selection and optimisation. Application of this approach will improve an existent set of rules and procedures employing deliberately developed, selected and logically interconnected MCDM methods, optimisation models and approaches providing an objective, rigorous and verified measurement of regional performance and fair distribution of Structural funds.

The novelty of results steams from the identified gaps in the literature related to the measurement, classification and selection aspects of MCDM methods' application. The main contribution is that all methodological suggestions are gathered into the interconnected multi-criteria approach allowing the solution of the main practical problem of funds' distribution.

Implementation of the developed interrelated multi-criteria approach, which is based on selected MCDM methods, optimisation models and comprehensive measurement approaches, will minimise the need for the political negotiating and eliminate subjective influence on the decision-making process underlying the distribution of Structural funds.

The application part used the cross-sectional 2013, 2015 years data from official statistical web sites describing the socio-economic performance of Ukrainian and EU regions.

Keywords: regional performance, multi-criteria decision-making methods, measurement, interaction, classification, clustering, selection, optimisation, Structural funds’ distribution

JEL Classification: C44, R15
Politika soudržnosti je důležitým a výkonným nástrojem navrženým tak, aby poskytoval základ pro prosperitu a dobré životní podmínky lidí ve zranitelném postavení v důsledku poskytování značné finanční podpory zaostávajícím regionům. Přibližně 33 % rozpočtu EU potřebuje účinné přerozdělení mezi řádně identifikované zaostávající regiony, čímž budou uspokojeny jejich sociální a ekonomické potřeby. V současné době však pravidla redistribuční hry nejsou transparentní, mají určitou metodologickou a teoretickou neopodstatněnost a v posledním kroku rozhodování jsou předmětem politických jednání. Zejména rozhodovací proces, který je základem distribuce Strukturálních fondů je stále v počáteční fázi a pokud jde o měření výkonnosti regionů, jejich klasifikaci a přerozdělování prostředků, vyžaduje zlepšení.

Cílem výzkumu je vyvinout vzájemně propojený vícekriteriální přístup k řešení problému rozdělení Strukturálních fondů. Správné řešení tohoto problému do značné míry závisí na zvažovaných aspektech jako je měření, výběr a optimalizace. Uplatnění tohoto přístupu zlepší existující soubor pravidel a postupů prostřednictvím záměrně vyvinutých, vybraných a logicky propojených MCDM metod, optimalizačních modelů a přístupů, poskytujících objektivní, důsledné a transparentní měření regionální výkonnosti a spravedlivé rozdělení Strukturálních fondů.

Nově jsou výsledky určeny zjištěnými mezerami v literatuře, které jsou spojené s takovými aspekty použití MCDM metod jako je měření, klasifikace a výběr. Hlavním přínosem je, že všechny metodické návrhy jsou shromážděny do vzájemně propojeného vícekritériálního přístupu, který umožňuje řešení hlavního problému rozdělení fondů.

Implementace rozvinutého, vzájemně propojeného vícekriteriálního přístupu, založeného na vybraných MCDM metodách, optimalizačních modelech a komplexních přístupech k měření, minimalizuje potřebu politického vyjednávání a eliminuje subjektivní vliv na rozhodovací proces, který je podkladem pro distribuci strukturálních fondů.

Aplikační část je založena na průřezových datech z roku 2013 a 2015, získaných z oficiálních statistických webových stránek, popisujících socioekonomickou výkonnost ukrajinských a evropských regionů.

**Klíčová slova:** regionální výkon, vícekriteriální rozhodovací metody, měření, klasifikace, shlukování, interakce, výběr, optimalizace, distribuce Strukturálních fondů

**Klasifikace JEL:** C44, R15
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INTRODUCTION

The Cohesion policy is the primary tool providing financial and regulatory support for the effective functioning of the EU. The performance of many EU NUTS 2 regions (about 2/3) depends on the redistributed share of Structural Funds. The latest is the leading financial tool of Cohesion policy consisting of roughly 20% of the EU budget. This essential amount of money needs to be redistributed effectively, satisfying the social and economic needs of correctly identified lagging regions. Here the very pressing issue comes alive, as the question “why did this or that region appear to be a recipient getting a certain amount of financial resources?”, which cannot be answered subjectively without the verified use of the sound methodology. Such obvious importance of the stated question implies the distribution of Structural funds to be based on the fair, objective, methodologically sound, mathematically rigorous and transparent decision-making process.

An extensive recent research (Booysen, 2002; Saltelli, Munda, Nardo 2006; OECD-JRC, 2008; Goletsis, Chletsos, 2011; Meyer, Jongh, 2016; Stamenković, Savić, 2017; Mazziotta, Pareto, 2013; Melecký, 2017; Gibari, Gómez, 2018) provides evidence of the high importance of MCDM methods within the regional policy practice. The first motivation for the application of MCDM methods implying the multi-dimensional aggregating power is the omnipresent critique of single GDP criterion lying as the foundation for the Cohesion Policy. The GDP per capita is insufficient to characterise the regions benefiting from European Regional Policy funds (Martín et al., 2012). The regions differ not only in terms of their average income but also in terms of other indicators in line with the concerns raised by Soares et al. (2003), Cuadrado and Marcos (2005) and Del Campo et al. (2008). It is common awareness that many socioeconomic phenomena cannot be measured by a single descriptive indicator and that, instead, they should be represented with multiple dimensions (Mazziotta, Pareto, p. 1, 2013).

In this aspect, some authors claim that MCDM techniques are highly suitable in multi-dimensional frameworks when aggregating single indicators into a composite one (Saisana and Tarantola 2002; Freudenberg, 2003; Jacobs et al., 2004; Nardo et al., 2005, 2008; Gibari et al., 2018). In particular, composite indicators are increasingly recognised as a useful tool in policy analysis and public communication (Gibari et al., 2018).
However so far, the rules of redistribution game about Structural funds are complicated enough, partly biased, subjectively influenced by political negotiations and have some methodological and theoretical unsoundness. In all this, nowadays in the literature, there are no suggested improvements related to the decision-making process addressing the distribution of Structural funds.

Being in such a predicament Cohesion policy requires specific improvements on the solutions to such sub-problems as measurement and classification of regional performance, optimisation of Structural funds distribution and selection of the most suitable MCDM method. Only the integrated approach is capable of providing a complex solution for the multi-problem situation. Therefore, the proper solution to the real-life problem of SF distribution can be obtained by the application of developed and existent MCDM methods, optimisation models and selective approaches on the systemic basis and in the spirit of methodological pluralism.

**The object of the research** is the decision-making process underlying the problem of Structural funds’ distribution including multi-criteria decision-making methods and approaches applicable to the problems of regional performance measurement, regional classification, methods selection and optimisation of funds’ distribution.

**The main research question** is what the possible ways of elimination of the main sources of imperfections are, such as subjectivity, incompleteness, and unfairness, methodological and socio-economic unsoundness of decision-making process related to the distribution of Structural funds.

**The research objective** is to develop the interrelated multi-criteria approach to the distribution of Structural funds considering measurement, selection and optimisation aspects of the problem. This approach implies the application of developed, existent and logically interconnected MCDM methods, selective approaches and optimisation models to the multi-problem situation, which allows the objective, rigorous and verified solution to the practical problem of Structural funds’ distribution.

It is expected that achievement of the goal will improve the status quo of Cohesion policy in terms of Structural funds distribution, in particular, to minimise negotiating component during the distribution of Structural funds, eliminate bias and subjective influences, make it mathematically based and methodologically sound. Besides, there is hope, that this research will
change look at the discussed problem and initiate a similar search for effective alternative solutions to mentioned sub-problems.

In the practical plane of Structural funds distribution, two main questions can be highlighted: “who is who (donors or recipients)?” and “how much money to give and take way?”. Having transformed them into a scientific domain, they look like the following investigative questions: 1. “how to measure regional performance? (measurement aspect)”, 2. “what regions are considered to be lagging and ineffective? (classification aspect)”, 3. “which MCDM method is the most suitable for the problem at hand, such as optimisation of Structural funds distribution or regional performance classification? (selection aspect)”, 4. “what is the optimal Structural Funds distribution? (optimisation aspect)”.

The data for the application of all methodological suggestions was retrieved from the EU and Ukrainian official statistical web sites. Thus, all methods, approaches and models have been applied to the real cross-sectional data describing the socio-economic performance of the 276 EU and 26 Ukrainian regions at the NUTS 2 level in 2013 and 2015 years.

The dissertation consists of three chapters successively addressing theoretical, methodological and practical aspects of the topic.

The first chapter provides general conceptual and theoretical elements necessary for the understanding of the funds’ distribution real-life problem. Besides, it outlines the principles and assumptions of suggested interrelated multi-criteria approach to Structural funds’ distribution.

The second chapter presents the existent MCDM methods applicable to the regional policy problems as well as the developed measurement methods, selective approaches and optimisation models together responsible for the solution of a range of sub-problems being in the canter of practical funds’ distribution problem.

The third chapter describes the results of the application of the proposed methodology to the Ukrainian and EU regions.

The following tasks relying on investigating questions and knowledge gaps were defined as potential solutions for a highlighted range of sub-problems allowing achievement of the main research objective:

1. to assemble all the propositions and recommendations presented in the form of methods, models and approaches into the sequential interrelated multi-criteria approach on the logically coherent and systematic basis (sub-chapter 1.3);
2. to search for the new combinations of selected MCDM methods for a more comprehensive measurement of regional performance considering different aspects which are subject to a managerial interest (sec. 2.2.4, 3.1.3);

3. to investigate and measure new aspects of regional performance which of high interest from a managerial point of view (sec. 2.1.1-2.1.4, sub-chapter 3.1);

4. to select the most suitable MCDM method for the measurement of regional performance with subsequent use of ranking in the optimisation of funds distribution (sec. 2.3.2, 2.3.3, 3.2.2, 3.2.3);

5. to obtain the genuine classification of regions based on the best clustering structure produced by selected the most suitable clustering and compromise distance-based MCDM methods (sec. 2.3.1, 3.2.1);

6. to analyse and improve the current Berlin formula of Structural funds distribution offering alternative solutions of the Structural funds’ allocation (sub-chapters 1.1, 3.3, sec. 2.4.1, 2.4.2, 2.4.3).

The logical and coherent structure of the dissertation based on the discovered knowledge gaps, defined tasks and obtained knowledge contribution is presented in Appendix A (fig. A.9).

The essential original results of the research representing the methodological contribution are the following:

1. all MCDM methods, selective approaches, optimisation models and measurement approaches were successively combined into the one interrelated multi-criteria approach to Structural funds distribution (sub-chapter 1.3, chapter 2);

2. the compromised distance-based MCDM methods (VIKOR, TOPSIS, Hellwig’s) to eliminate their disadvantages were hybridised by the adoption of elements from not typical for regional studies outranking MCDM methods (ELECTRE, PROMETHE) and then compared concerning risk attitude degree (sec. 2.2.1, 2.3.1, 3.1.1, 3.2.1);

3. not typical for the regional studies but very insightful Choquet method was applied and developed as for the part of the identification of fuzzy measures necessary for the measurement of a criteria interaction effect based on the correlation instead of subjective decision-maker considerations (sec. 2.2.2);
4. a new ratio additive weighting method was developed to measure effectiveness as the missing in regional studies unorthodox aspect of regional performance based on the principle of “doing right things” (sec. 2.2.3);

5. the resonance approach based on the combination of distance-based Hellwig’s and DEA methods was developed to measure intensive and extensive aspects of regional performance considering different NUTS regional levels (sec. 2.2.4);

6. the complex verification approach to a clustering structure based on a set of validating criteria was proposed to obtain a genuine classification and select the most suitable clustering and MCDM methods (sec. 2.3.1);

7. the selective robustness approach based on error minimisation within the “Robin Hood” distribution principle was proposed to choose the most suitable MCDM method for the ranking of regions and further optimisation of funds distribution (sec. 2.3.2);

8. the approach to construct the profile of MCDM method was suggested for the comparison of methods and more profound understanding of their nature (sec. 2.3.3);

9. as an improvement of the current Berlin formula of Structural funds distribution the single and multi-variable optimisation models based on variance minimisation were developed and applied to define the best distribution strategy (sec. 2.4.1, 2.4.2);

10. as an improvement of the current Berlin formula of Structural funds distribution the multi-variable optimisation model based on Markowitz mean-variance theory was suggested to avoid the free-rider problem of lagging regions and consider the fairness of distribution based on regional effectiveness (sec. 2.4.3).

Besides, apart from the considered application in the field of EU Cohesion policy, the developed IMC approach, to varying degrees, can be applied at national and enterprise levels. In particular, at the national level, it can be used by policy-makers and government concerning the development and implementation of subsidy policies for small and medium business, non-profit organisations and different sectors of the economy (knowledge, agricultural, etc.). At the enterprise level, this approach can be partly used for the development of investment, motivation, marketing and advertising strategies.

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1. CONCEPTUAL FUNDAMENTALS OF THE INTERRELATED MULTI-CRITERIA APPROACH

The first sub-chapter 1.1 gives a general description of the current situation underlying the real-life problem of Structural funds’ distribution. The extensive state of the art presented in sub-chapter 1.2 relates to the application of MCDM and clustering methods in the regional analysis field in connection to the distribution of Structural funds. The knowledge gaps discovered in section 1.2.4 formed the basis for the research tasks and predetermined the corresponding knowledge contributions, based on which the IMC approach was developed. The final sub-chapter 1.3 introduces the general operational principles, prerequisites and assumptions of the proposed IMC approach to the distribution of funds.

1.1 Cohesion Policy basics and economic rationale of the distribution of Structural and Investment funds

This sub-chapter provides the basics of application field, where the introduced in sub-chapter 1.3 IMC approach is going to be applied. The socio-economic system of the EU does not always produce outcomes that are in line with political preferences and can lead to considerable differences in wealth and access to employment. In other words, it may lead to significant problems in terms of economic, social and territorial cohesion. Disparities in these scores are often considered as morally unjust and economically inefficient. In order to counteract the negative tendencies and to make a better distribution of wealth, necessary policies are pursued.

These three overarching policy objectives are distinguished commonly in the literature on policy interventions, such as (1) the efficiency improvement; (2) stable conditions creation; (3) reasonable levels of equity safeguarding (Musgrave and Musgrave, 1989; Sapir et al., 2004).

The EU choices of policies have been determined by the two fundamental ideologies (fig. 1.1). The first ideology comes from a liberal view to markets leading to objective 1 (allocation efficiency) and objective 2 (macroeconomic stability). The set of policies based on this ideology is focused on the improvement of the EU market functioning with the sub-goals to enhance competition, to boost productivity, international competitiveness and to create stable macroeconomic conditions for the smooth functioning of the economy.
The other ideological component comes from an interventionist view of social justice (objective 3). The redistribution (cohesion policies) which assumes taking away or cushioning the potential adverse side effects originating from two previous objectives. After all, total welfare would increase if the inequalities between groups and regions were removed. Still, the national governments are not capable of providing a cohesion policy at the EU level in an efficient way. Therefore, the EU has taken responsibility for it and made it a constitutional obligation. The objective of this social justice set of policies is to promote harmonious development that is reflected in the ultimate goal of the EU. In line with the Treaty objective (article 174 of the Treaty on the Functioning of the European Union – TFEU), Cohesion policy is designed to close the gap between poor and rich European regions. Consistent with this policy, the allocation of principles is underpinned by the main principle that resources are directed from wealthy towards the poorest countries and regions. Such transfer of resources works out as a structural policy or more concretely as regional socio-economic policy. The main instruments to realise the objectives of the EU cohesion policy also fall into two categories, namely SF (finances) and coordination of national policies (regulations). The principal instrument the EU has put in place to foster cohesion is financial redistribution, the current mechanism of which is discussed below.
Over time, the description of Cohesion policy objectives depends on the corresponding diversity of problem situations. The main objectives of Cohesion Policy before the multiannual-financial period 2014-2020 were the following: 1. convergence and 2. competitiveness and employment. Starting from 2014, two objectives were reduced and combined into one objective called “Investment for growth and jobs”. The following fig. 1.2 shows that objectives are formed based on problems identified and how they are reached due to the corresponding attacking points.

fig. 1.2: Problems, objectives and attacking points of Cohesion policy

<table>
<thead>
<tr>
<th>Problems</th>
<th>Objectives</th>
<th>Attacking points</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lagging positions of regions:</td>
<td>1. Convergence:</td>
<td>Investment in physical capital:</td>
</tr>
<tr>
<td>• agriculture orientation</td>
<td>1.1 to support structural improvement</td>
<td>• administrative efficiency</td>
</tr>
<tr>
<td>• peripheral situation</td>
<td>1.2 to speed up convergence</td>
<td>• socio-economic adaptability</td>
</tr>
<tr>
<td>• deficient infrastructure</td>
<td></td>
<td>• improvement of human capital quality</td>
</tr>
<tr>
<td>• lack of skilled labor</td>
<td></td>
<td>• development of innovation and the knowledge of society</td>
</tr>
<tr>
<td>Changed production conditions:</td>
<td>2. Competitiveness and employment:</td>
<td>Improvement of accessibility:</td>
</tr>
<tr>
<td>• inadequate infrastructure</td>
<td>2.1 strength competitiveness</td>
<td>• adaptability of workers</td>
</tr>
<tr>
<td>• old industrial areas</td>
<td>2.2 employment</td>
<td>• adaptability of entrepreneurship</td>
</tr>
</tbody>
</table>

Source: author and Molle (2007)

The EU has set concentration as a leading policy principle dealing with regional disparities. The principle allows the concentration of support on the essential problematic regions, which score the worst on various indicators of regional welfare. In addition, the EU also wants to avoid other regions falling back into that position.

To reach these Cohesion Policy goals in all EU regions, almost a third of the total EU budget (UR 351.8 billion) has been allocated for the 2014-2020 Cohesion Policy. During the 2014-2020 and 2020-2027 years 5 Structural and Investment Funds (ESI) have been operating, in particular: European Regional Development Funds (ERDF); European Social Funds (ESF);
Cohesion Funds (national level); European Agricultural Funds for Rural Development (EAFRD); European Maritime and Fisheries Fund (EMFF).

Concerning Cohesion Policy itself, it is delivered through the first three main funds (Structural and Cohesion Funds) called together as cohesion policy funds (CPF) (fig. 1.3).

fig. 1.3: Categories of funds

The Structural Funds (ERDF and ESF) provide the investment for growth and jobs goal in all NUTS 2 regions according to the standard classification of territorial units established by Regulation (EC) No 1059/2003. The amount of SF consists of around 20 % of the EU budget. ERDF targets to strengthen regional social and economic cohesion by investing in growth-enhancing sectors for jobs creation and improvement of competitiveness. The ERDF also finances cross-border cooperation projects. ESF invests in people, focusing on improving employment and education opportunities. In addition, it aims to help deprived people at risk of poverty or social exclusion. Cohesion Fund invests in green growth and sustainable development and improves connectivity in the Member States with a GDP below 90 % of the EU-27 average.

CPF consist of a redistribution of the EU’s budget, made from contributions from all Member States according to their wealth (economic status), to the poorest regions of the EU; they come with a 7-year operational budget for the Member States. In the next program period (2021-2027), the European Commission has proposed that the EU spends €373 billion, on cohesion policy (ECA, 2019). The CPF contribute to developing and pursuing the actions of the Union, leading to the strengthening of its economic, social and territorial cohesion under Article 174 of TFEU.

While the overall missions of the ESI Funds are defined clearly in the Treaties, the Europe 2020 strategy initiated policy reforms for the period 2014-2020 and 2020-2027 and resulted in the establishment of two key goals (table 1.1) such as 1. Investment for growth and jobs to be supported by the ERDF, ESF and Cohesion Fund; 2. European territorial cooperation (ETC).
table 1.1: Changes in Cohesion Policy goals for the last two periods

<table>
<thead>
<tr>
<th></th>
<th>2007-2013</th>
<th>2014-2020</th>
<th>2020-2027</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Convergence</td>
<td></td>
<td>1. Investment for growth and jobs</td>
<td></td>
</tr>
<tr>
<td>2. Regional competitiveness and employment</td>
<td></td>
<td></td>
<td>2. European territorial cooperation</td>
</tr>
<tr>
<td>3. European territorial cooperation</td>
<td></td>
<td></td>
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</tr>
</tbody>
</table>

Source: author

All types of regions, according to the Europe 2020 strategy, have a standard policy goal – investment for growth and jobs. Concerning this goal, all regions can take advantage of the same scope of intervention. The classification of regions under one of the three categories of regions shall be determined on the basis of GDP per capita (PPS) and calculated on the basis of 2007 – 2009 period of the average GDP of the EU-27 for 2014-2020 Multiannual Financial Framework (article 90, No 1303/2013) and on the basis of the period 2014-2016 correspondingly for planning period 2020-2027 (COM, 2018, article 102). The resources for the Investment for growth and jobs goal are allocated by economic status among the following three categories of NUTS level 2 regions (article 90, No 1303/2013):

– less developed regions (LDR), whose GDP per capita is less than 75 % of the average GDP of the EU-27;
– transition regions (TR), whose GDP per capita is between 75 % and 90 % of the average GDP of the EU-27;
– more developed regions (MDR), whose GDP per capita is above 90 % of the average GDP of the EU-27.

Every type of region is served by the following set of funds (table 1.2); however, the allocation mechanism is different for everyone.

table 1.2: Correspondence of funds to regions category

<table>
<thead>
<tr>
<th>Category of regions</th>
<th>ESI Funds</th>
</tr>
</thead>
<tbody>
<tr>
<td>Member State level</td>
<td>Cohesion Fund</td>
</tr>
<tr>
<td>Less developed regions (LDR)</td>
<td>ERDF, ESF, EARD</td>
</tr>
<tr>
<td>Transitions regions (TR)</td>
<td>ERDF, ESF, EARD</td>
</tr>
<tr>
<td>More developed regions (MDR)</td>
<td>ERDF, ESF, EARD</td>
</tr>
</tbody>
</table>

Source: author and Blue guide for ESI funds (2015)

Around half (52.45 % of the resources for the Investment for growth and jobs goal or EUR 164 billion) of all resources for the investment for growth and jobs goal have been allocated to less developed regions. To transition regions for the investment for growth and jobs goal, 10.24%
of the resources (or EUR 32 billion) is allocated. This is compared to the 2007-2013 period, a newly created regional category. Just 15.67 % (or € 49 billion) of the resources is allocated to more developed regions for the Investment for growth and jobs goal, i.e. those regions with GDP per capita is above 90 % of the average GDP of the EU-27.

The cornerstone of all further research propositions is the significant proportion of funds, which are dependent on the wealth criterion. Form the fig. 1.4 we can see, that LDR and TR together account for a lien share – around 60 % of all funds (351.8 bn).

**fig. 1.4:** Thematic concentration of total EU allocations of Cohesion Policy 2014-2020, mill. Euro (current prices)

![Thematic concentration of total EU allocations of Cohesion Policy 2014-2020, mill. Euro (current prices)](image)

*Source: Blue guide for ESI funds (2015) and https://ec.europa.eu*

As will be shown below in 1.3.3 (fig. 1.21), the Cohesion policy allocations to these two types of regions depend on the GDP per capita criterion. With this regard, the mentioned GDP based categories of regions and corresponding funds (with their specific allocation rules for the CPF, including ERDF and ESF) are the objects for the following analysis and improvements.

For the 2021-2027 period, the Commission for the first time has included a detailed description of the allocation methodology in the CPR proposal (COM, 2018). The extensive overview of the Commission’s proposal for translating the total EU resources into allocations in the light of different policies is given in fig. 1.5. The proposal also includes the amounts allocated to the Member States. This displays several aspects of Multiannual Financial Framework (MFF) allocations, even though some specifying elements and details are missing and therefore forthcoming fig. 1.21, fig. A.5 (Appendix A) are given.
fig. 1.5: Division of EU budget with respect to policies

The mechanism of SF distribution will be discussed in 1.3.3, where the disadvantages and alternative mathematically based way of the distribution will be outlined.

1.2 State of the art in the field of multi-dimensional analysis of regional performance

This sub-chapter is going to present an extended state of the art on the topic of application of quantitative multi-criteria methods in the regional studies field. In particular, it will be shown what is already done in the literature, what problems are still present, what questions are not discussed, and where to go for the necessary improvements. The prior attention is paid to the application of MCDM and multivariate statistical methods, such as clustering methods, in EU Cohesion policy as a particular case or specific regional policy manifestation.
1.2.1 Practical use of composite indices in the context of Structural funds’ distribution

It may be concluded, that apart of only communication function, there is also another one, even more crucial, pragmatic one, transcending the semantic area and dealing directly with a pragmatic aspect of indicators as mathematically constructed social symbols. Pragmatic aspect is being revealed in the area of regional policy. In particular, the existence of Cohesion Policy makes the usage of composite indicators and consequently MCDM methods much more critical and decisive creating the driver for the following more systemic application and selection of MCDM methods in this area.

Indeed, EU Regional Policy is a highly relevant field for the most practical application of MCDM methods. In this field, a synthetic indicator plays a decisive role in the distribution of SF, which can substantially influence the performance of lagging regions and consequently increase the life quality of millions of people populating them. Revealed interconnectedness between regional policy cycle and application of multi-criteria methodological problems underlying the funds’ distribution is presented in fig. A.2 (Appendix A). We can see that MCDM methods can be implemented exceptionally in two steps of the cycle (Molle, 2007), in particular at the stages of measurement and distribution.

The 2014 Sixth Cohesion Report (COM, 2014) mentions the intention to explore using additional indicators in cohesion policy: the application of the SF, including the Cohesion Fund, should open up to include measures to complement GDP in the next multiannual financial period as far as they are politically acceptable at all levels of governance. This was also stated in the 2008 Green Paper on Territorial Cohesion (COM, 2008) and the European Commission's 2010 communication (COM, 2010) on the future of cohesion policy. The use of “Beyond GDP” indicators has also been supported by the Committee of the Regions and debate on introducing changes in this regard in the post-2020 cohesion policy framework is continuing (COM, 2014, P. 5). Furthermore, speaking at the Committee of the Regions plenary session on 11 February 2016, Commissioner Creţu (2016) supported to that the idea of including new indicators in Cohesion Policy (Margaras, 2017), in addition of GDP, mentioning the Europe 2020 index, the OECD indicators on well-being, those on regional competitiveness, as well as the Human Development Index (HDI).

Indeed, it seems undisputed to state that exclusively looking at economic indicators allows only a limited understanding of regional performance or any complex socio-economic concept
and that considering additional indicators describing other dimensions (social, environmental, etc.) may enhance the understanding considerably.

It is less clear to what extent providing additional indicators to policy-makers will lead to changes in actual policy-making (Döpke et al., 2017). The point of view expressed by Jochimsen, Raffer (2014) and Huschka, Wagner (2010) sounds quite promising and draws the perspective clearly: “only if alternative indicators have the potential to change policy-making, they will attract persistent attention from policy-makers and the general public”. On the other hand, the chances that incoming new indices will have such changing potential are not very high. Such doubts are supported by BooySEN (2002) noting that indices are often criticised for being unable to reveal anything that a single variable (and particularly per capita income) alone cannot reveal (p. 140). From recent publications, Kassenböhmer and Schmidt (2011) argue that most variation in social indicators proposed by the Stiglitz, Sen and Fitoussi (2009) coincides with that of GDP and the unemployment rate such that there is only little additional information on these indicators. However, Jones and Klenow (2016) argue that while a welfare measure beyond GDP is highly correlated with GDP per capita, deviations between both figures are often sizeable.

Booysen F. (2002) having analyzed research made in 90-s (Diener and Suh, 1997, pp. 192–200; Ogwang, 1994; Stewart, 1985; McGillivray, 1991; Srinivasan, 1994; Felipe and Resende, 1996, pp. 187–190) came to conclusion that composite social indicators, such as HDI, Physical Quality of Life Index (PQLI) are often highly correlated with economic indicators of development and reveal anything that a single variable (and particularly per capita income) alone cannot reveal. Along with this a study done by Stewart K. (2005) confirms that GDP is a good proxy for measuring well-being encompassing five different social spheres (material well-being, productive activity, education, health, and social interaction); also, author gives his approval to the practice of EU regional policy using GDP as a proxy for regional well-being to allocate SF.

Recent research on international differences among European countries (Fahey and Smyth, 2004) has changed that picture; it shows that there is a positive relation between on the one hand the mean life satisfaction and on the other hand the level and growth of wealth (as measured by GDP per head and the recent growth of GDP per head). In other words, populations in the wealthy parts of Europe have high and relatively equal life satisfaction, while those in the poorer parts of Europe have low and unequal life satisfaction. Given these results and given the fact that the level of GDP per head is also highly correlated with a number of other aspects of cohesion, it
seems justified to take GDP/P as the main indicator of cohesion (Molle, 2007, p.17). Annoni, P., L. Dijkstra and T. Hellman (2016) in their research have found as well the presence of high correlation, but only for poor regions, where Basic Human Needs improve the most with each additional unit of GDP per capita (the relation is clear and steep), but for rich regions each extra euro of GDP per capita buys less and less social progress.

Therefore, very solid theoretical bases of GDP (Mazziotta, Pareto, 2013) and its high correlation with other popular composite indices makes the current practice of EU regional policy heavily dependent on it. In practical terms, it has become the most widely recognised indicator for wealth, well-being and progress (CoR, 2015). Thus, the allocation of funding has followed a complex methodology entirely based on GDP criterion complemented by unemployment and other coefficients variable to the status of the region. The origin of allocation methodology is a so-called “Berlin formula” (Wishlade, 1999) agreed in the Agenda 2000 in March 1999 in Berlin. So far this distribution formula has been applied for all periods (2000-2006, 2007-2013, 2014-2020) and was not essentially reconsidered except some marginal changes in parameters (Bachtler, Wishlade, 2013) without any modifications in basic principles. Of course, there is no ideal allocation methodology, especially when the allocation methodology’s main purpose is to justify politically acceptable outcomes in terms of the distribution of funds (CPMR, 2015a). However, it is indeed possible, given the number of statistical data available, to increase the number and range of indicators used, as is already the case for the calculation of theoretical regional allocations for the more developed regions (General assembly, 2014).

Not saying that this methodology is perceived as a largely unpredictable and opaque mix of political and technical ingredients (Bachtler, Wishlade, 2004), the allocation methodology of Structural Funds is criticised on several fronts (General Assembly, 2014). European Commission (p. 14, p. 85, 2007) affirms that monolithic approach criteria for eligibility need to be reconsidered and adapted as they essentially political constructs. For less developed regions in most Member States, the allocation is not based on an objective formula but is fixed to economic growth projections at the national level (capping rate). The idea behind capping runs counter to the very rationale of Cohesion Policy, as the more optimistic the economic growth is in a given Member State, the more funding will be allocated to that Member State from the Cohesion Policy budget (CPMR, 2015b). The present scaling of the national prosperity coefficients is the main cause for a (politically desirable) unequal treatment of regions with a comparable prosperity
level: regions in poorer Member States thus get higher transfers than regions with an identical GDP per capita in PPS which are located in richer Member States (Osterloh, 2009). Even though the precise choice of GNI coefficient has a potentially significant impact on outcomes, it is not specified whether national prosperity is measured in purchasing power parities or Euros; and it is also not clear whether the latest data should be used, or the same period for which regional GDP data is available (Bachtler, Wishlade, 2004). Overall, the question arises as to whether equally lagging LDR should be treated differently if they belong to different Member States with dissimilar prosperity.

The analysis revealed two components relevant to explain the different levels of funds allocated to the Member States: first, the ceiling due to limited absorption capacity and second, the modified “Berlin formula”. Since the level of transfers to the poorest member states is exclusively determined by the level of the absorption ceiling, as shown above, the calculation based on the modified, so-called Berlin formula will only affect the richer member states (Osterloh, 2009). Bachtler and Wishlade (2004) state that precisely the capping rate determines the allocation of the new EU Member States containing many of less developed regions. The application of the bottom-up Berlin methodology turns out to be the functioning limit for more developed Member States containing fewer less developed regions. Uniformity of ceilings or capping rates reached by the same calculating method as well could simplify Berlin methodology principles and ensure the equal treatment of both richer and poorer Member States.

A general reflection on it brings us to the following conclusion by pointing out the main drawbacks. First, it is appeared to be a drawback in an essential degree of subjectivity in the determination of GNI weights. Secondly, weights play the same role as the capping rate does; thus, they are used interchangeably and replicate each other to some extent. Thirdly, calculation methods for the less developed regions and transition regions seem to have the same base as GDP per capita, but they are different due to the min and max limits defined basing on the less developed regions and more developed regions calculating methods.

In the literature, there are two common ways how the topic of funds’ distribution is being investigated. The first one is related to the measurement of the efficiency of SF. Much research is devoted to this aspect. All researchers have been applying the econometric modelling (Mohl, Hagen, 2009; Bodenstein, Achim, 2011; Ferry, 2013), while some of them deal with specific Hermin-based models (Gakova, Grigonyte, Monfort, 2009; Bradley, Untiedt, Mitze, 2007), using
advanced methodology based on spatial interdependency. This direction of the analysis is focused on the ex-post analysis; meanwhile, the ex-ante aspect is left without due respect behind the scholar’s attention.

The second angle of the research devoted indirectly to the Funds distribution is the developing of the composite indices as an alternative to the predominant GDP indicator, revealing a more comprehensive range of regional features to avoid exclusively economic productivity foundation. This kind of research to some extent is connected to the question of distribution fairness but only in the sense of multi-dimension determination of lagging regions, and surely it is not focused directly on the way of funds’ allocation. Such measurement gives a more comprehensive ground for the further distribution of funds. Also, there are many analogous to GDP indicators, more than a hundred alternative indices, adopted by government organisations (and others), academia and business press (Bandura, 2008). They are Regional Competitiveness Index (Annoni, Dijsktra, 2013; Aiginger, Vogel, 2015), Genuine Progress Indicator (Anielski, 1999), Human Development Index (UN Development Program 2015) etc., which can take into account the social, environmental and other dimensions. Despite the fact that GDP indicator has been frequently criticized because of its limited economic nature it seems that the popularity of GDP has not been minimally scratched (Mazziotta, Pareto, p.2, 2013) and it remains the central reference point in the regional policy.

Its main advantage is timely availability at national and statistical levels. Still, the potential to improve the indicator, so that it provides more comprehensive information on wealth and progress, is limited, so either than opting for a substantial change of the GDP indicator (which seems very unlikely to be effectuated in practice) COR (2015) advocate to complement GDP by additional indicators and draw on the wealth of material provided by European Spatial Planning Observation Network (ESPON).

Considering all points of view, it seems necessary to conduct research showing that perhaps even a high correlation between GDP and composite measures provided by different aggregation techniques produces essential (quite significant to be investigated) differences in funds’ allocation. Such differences can be crucial for the development perspectives of lagging regions with the status of SF recipients; considering essential differences in measurement, even the status of a region can be changed to the opposite. This is still an empirically unresolved question.
General use of composite indices is well presented by Bell and Morse, who proposing the alternative regional performance index regarded two related purposes (2003, p. 49): a useful SF allocation tool in contrast with a single criterion approach based on the GDP per capita; and a communication tool to raise EU population awareness of the importance of the European Cohesion Policy. European Commission has put forward the question in the Second Report on Economic and Social Cohesion (European Commission, 2001) related to the right choice of methods applied to allocate SF among states and regions; also recognising that growing pressure will bring to discussion new allocation methods for the SF. Many other further mentioned authors referred to composite indicators as possible tools for the SF allocation. Drawing on the recent trends in well-being, the revision of the current allocation mechanism of EU SF and its complementing with information on other dimensions relative to people’s quality of life, such as inequality in income and gender, education, health, poverty and employment is mentioned by the group of authors (Bell and Morse 2003; Sánchez-Dominguez, Ruiz-Martos, 2014). European Committee of the Regions affirms (COM, 2016) that for the sake of a fairer allocation of the funds it is crucial that decisive shortcomings of GDP, such as the territorial bias caused by commuting over NUTS borders, need to be counterbalanced. To do this, the social and environmental situation (to complement GDP) in the regions has to be taken into account.

Despite an explicit mention of the need to change the allocation methodology (Berlin formula) drastically for the post-2020 period made by former Regional Policy Commissioner Johannes Hahn and a reference in the 6th Cohesion Report (COM, 2014, p. 198-200) on that point, there is seemingly no appetite within the European Commission to do so (CPMR, 2015a). Nevertheless, Martín, Molina & Fernández (2012) believe that the future priorities of EU Regional Policy should not be based solely on the GDP per capita of the regions. They should also incorporate other indicators that are not strictly monetary, such as the ones we have included in our study. They complement GDP per capita as a criterion for deciding which regions will benefit from the aid of the Cohesion Policy in the period 2014–2020.

In the draft opinion on “The future of cohesion policy beyond 2020”, the CoR (2015) suggests including additional criteria when distributing funds while retaining GDP as the main indicator for classifying regions (Widuto, 2016, p. 11). In particular, from the 2016 draft opinion on “The future of cohesion policy beyond 2020” (COM, 2016) it is pointed out that eligibility decisions are basically blind to social and environmental and territorial aspects across European
regions. The logical step would be to base future instruments on a more comprehensive, uniform method, making increased use of social, environmental and territorial indicators, which would, in particular, reveal the specific regional features set out in the Treaty, which have to be considered in the regions' eligibility.

The essential question of whether and how the SF should be allocated was discussed in depth at the CPMR. The weight of GDP as an indicator to distribute funding and the lack of coherence between Cohesion Policy objectives and indicators used to allocate funding are some of the points of criticism put forward by the CPMR (General Secretariat, 2015a).

Meanwhile even having observed such tendency to incorporate other aspects into the measurement of regional (disparities, development, well-being, etc.), there are still examples of some leading indices, like SPI, which are recognised by the authors as not capable of replacing the GDP and being the basis for the SF distribution. For instance, some authors as Annoni, P., L. Dijkstra and T. Hellman (2016) even warn that proposed Social Progress Index shall not be used for Cohesion Policy funding allocation and does not bind the European Commission, as it derived from different sources, with different margins of error and a complex aggregation structure. We can see that because of difficult synthesizing structure and reliability of composing indicators the issue of aggregating indicators into a single, composite index is certainly controversial topic in socioeconomics, especially when it comes measuring social aspects like poverty and quality of life (Wagle, 2008; Lustig, 2011; Ravallion, 2011; Decancq and Lugo, 2013).

An increasing number of recent studies show the growing tendency to replace the single GDP rationale to multidimensional synthetic index acting now just as an alternative base for the Structural funds' distribution. Cziraky D. et al. (2005) are of the opinion that accurate assessment of the level of development of territorial units is crucial for regional planning and development policy and is a crucial criterion for the allocation of various structural funds and national subsidies. Del Campo, C., Monteiro, C.M.F. and Soares, J. O., (2008) are positive that the adoption of a European regional policy where financial resources would be allocated according to a multivariate classification as the one developed in this research would certainly bring several benefits. It is considered by Martin, J. A. R., Molina et al. (2012) as the necessity to adopt a Regional Policy for the next programming period 2014–2020 in which financial resources are allocated according to a set of indicators that complement the evolution of GDP per capita and serve as an eligibility criterion for the cohesion territories. Sánchez-Domínguez Á. and Ruiz-
Martos (2014) claimed that RDI could be the allocation mechanism of the Structural Funds. For example, Döpke et al. (2017) have analysed possible changes from switching to the alternative indicator, saying that it would drive the other half out of the beneficiary group (eastern and south-eastern Europe, southern Italy, central Spain).

Despite the fact of numerous papers, where composite indices have been regarded as the alternative base for the funds' allocation, not all the authors suggested the way to incorporate indices into the optimisation problem. According to our knowledge, there is just one in its kind methodological proposal presented by Gil, Pedro, Rapún (2002), which is focused on all aspects of funds distribution mechanism, in particular, composite indices, evaluation the impact of funds and their distribution among the beneficiaries of EU regional policy. However, as authors notice the model cannot be copied verbatim and transposed into real-world situations because of a lack of comprehensive and homogeneous statistical data that would provide a clearer picture of the economic context and the potentiality factors present in the beneficiary countries (Gil, Pedro, Rapún, 2002). It is understood, that there is no genuine debate at the European Commission on whether the allocation of Structural funds should be based on alternative criteria. Besides, the fact that the EU Budget is based on national contributions from the Member States makes it politically impossible for the Commission to propose a radically new methodology going beyond GDP (General Secretariat, 2015). That is why we tend to think that the methodology will remain mostly GDP oriented, especially concerning the allocation of funds to the less-developed regions.

Therefore, according to what we have found in the literature so far, there is no research focused on the improvement of the current working mechanism (Berlin formula) based on GDP indicator. In our opinion, even though the eventual distribution of SF is politically sensitive, the Berlin Formula is a suitable tool to decrease controversy in the determination of allocations size and it looks appealing to proceed with the idea of distribution mechanism improvement and to explore new alternative ways of regional funds distribution free of present drawbacks.

Over the past decades, the complexity of economic decisions has increased rapidly, thus highlighting the importance of development and implementation of sophisticated and efficient quantitative analysis techniques for supporting and aiding economic decision-making (Zavadskas, Turskis, 2011). Up to now, over 70 MCDM methods have been proposed (Roman et al., 2004), and each method has a different analysis model intending to solve some class of problems. The number of MCDM techniques is rapidly increasing (Bouyssou et al., 2006), and researchers
almost never provide good reasons for selecting a particular one (Danesh et al., 2017). This begs the question raised by Guitouni et al. (2000): “Are all these tools making sense and can be used without any distinction?”. The question is a complex one and cannot be answered as quickly as one might think.

Indeed, from said above, and under favourable conditions, the MCDM methods perhaps could play the role of the alternative basis for the SF distribution. However, such, not always of high quality, the proliferation of studies with composite indicators has no pragmatic realisation, but the public communication function (information profit).

To put it differently, there is no practical follow-up use of it in the area of decision-making. This attitude is joined by Booysen F. (2002) saying that composite indices represent no real contribution to the literature on indicators research and are often considered to be ideological statements rather than practically functional indicators. The only alternative that has been successful, globally, is the Human Development Index or HDI (UNDP, 2010); it is published annually by the United Nations, and it considers 3 individual indicators: “Life expectancy at birth”, “Education” and “GDP per capita” (Mazziotta, Pareto, 2013). Saltelli, A., Munda, G., Nardo, M. (2006) completely share this position summarising that controversy on the use of statistical indices unfolds along with an analytic versus pragmatic axis: all models are wrong (in their full descriptive meaning), but some of them are useful. Surely, they could be beneficial if they were applied in practice, but not just discussed in theory without further implications. The sceptical attitude has been expressed even since in 80-s, when Wilson and Woods (1982, p. 11) and Sainz (1989, pp. 156–160) expressed their belief that no single yardstick exists to measure development just as no single set of objectives can adequately describe the diversity of development conditions in the world. There is not a composite index, and consequently, MCDM approach universally valid for all areas of application, and, therefore, its validity depends on the strategic objectives of the research (Mazziotta and Pareto, 2013). De Muro, Mazziotto and Pareto (2009, p. 4) emphasise that subjectivity in indicator decisions, although advantageous in some ways, might also result in loss of transparency and crucial information if choices are not based on the relevant dimensions. Henig and Buchanan (1996) called for efforts to increase objectivity in multiple criteria analyses. In particular, Mazziotta M. and Pareto A. (2013) say that the attention is focused on the search of the most suitable method depending on the following factors: type of indicators (substitutable/non-substitutable), type of aggregation (simple/complex), type of
comparisons to be made (relative/absolute), type of weights of the indicators (subjective/objective).

It should be noticed that these factors are just important ones for the pre-selection the group of suitable MCDM methods for the aggregation, but the final selection of the most suitable method lies beyond this circle. However, there is no “best”, “correct” or perfect, universal MCDM method (methodology) to address all decision problems; however, there may be appropriate or suitable approaches for a particular problem at hand (Ozernoy, 1992; Tamiz et al., 1998). It means the situation of the problematic area is a decisive one and determines the final choice of the most suitable composite index or MCDM method. Even though many researchers have attempted to identify the best technique for a decision situation and different MCDM ones have been compared with each other, there is no commonly agreed structure or procedures that enable the most suitable one(s) (Danesh et al., 2017).

The need for comparing MCDM methods and the importance of the selection problem were first recognised by MacCrimmon (1968), who suggested a taxonomy of MCDM methods. Henig and Buchanan (1996) called for efforts to increase objectivity in multiple criteria analyses. So far, there are not so many comparative studies targeted on the selection of MCDM methods. However, several comparative studies (Zanakis et al., 1998; Chastang, P., 2003; Podvezko and Podviezko 2010) and critical reviews (Barzilai, 1998; Hazelrigg, 2003; Pedersen et al., 2000; Olewnik, Lewis, 2003) give the evidence that different MCDM methods quite often produce different results being applied for the same problem.

Furthermore, the variety of suggested aggregating tools brings uncertainty and hinders more sophisticated and grounded research. Whereas some aggregation schemes would make only a little change in the SF allocation, other methods would have substantial effects. The increase over the past 20 years is exponential, and the number of yearly publications shows no sign of a decline (Greco et al., 2018). Moreover, their widespread adoption by global institutions (e.g. the OECD, World Bank, EU, etc.) has gradually captured the attention of the media and policy-makers around the globe (Saltelli, 2007), while their simplicity has further strengthened the case for their adoption in several practices. Therefore, for us it seems correct to apply the research logic expressed by Slottje, D. J. (pp. 684–685, 1991): “the best one can do is to continue searching for a composite index that balances the need for conceptual clarity and methodological simplicity”.

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1.2.2 MCDM methods as the way to “move beyond GDP”

Some extensive reviews (Mardani, Zavadskas, 2016; Mardani, Jusoh, Nor, 2015) show that multiple-criteria decision making methods (MCDM) lately have been applied in different areas of business management and administration, such as supply chain, waste, forest and planning, material, quality management, construction and project, safety and risk, manufacturing systems, technology and information, strategic management, production management, tourism, logistics and transportation, information. MCDM methods, being an effective tool allowing managers to formalise, decompose and simplify the decision-making process, also enable the DM to deliver a message reflecting the result of processing the information. Referring to the following works (Dyer et al., 1992; Behzadian et al., 2012; Zmeškal, 2012, 2014; Mardani et al., 2015; Mardani, Jusoh, Zavadskas, 2015; Mardani et al., 2016; Gibari et al., 2018), it is clear that MCDM methods commonly provide a DM with the classification, ranking or utility values of alternatives – results of multidimensional aggregation by the reduction way of thinking.

The analysis of degree of development of different groups of countries and / or territorial units in their composition, using various combinations of indicators of one or several dimensions of development, and, accordingly, an appropriate classification of observed territories into relatively homogeneous groups, in order to identify the presence and / or the extent of regional disparities, represents an attractive research niche for both scientists and professionals, as evidenced by a significant number of published works, and conducted empirical studies (Stamenković, Savić, 2017). An extensive recent research (Booysen, 2002; Saltelli, Munda, Nardo 2006; OECD-JRC, 2008; Goletsis, Chletsos, 2011; Meyer, Jongh, 2016; Stamenković, Savić, 2017; Mazziotta, Pareto, 2013; Melecký, 2017; Gibari, Gómez, 2018) indicates the high importance of multi-criteria decision-making (MCDM) methods in the regional studies.

The primary virtue of the composite (synthetic) index is their usefulness for policy analysis in that they can summarise complex and sometimes elusive issues in wide-ranging fields. Mazziotta M. and Pareto A. (2013, p. 1) state that phenomena such as development, progress, poverty, social inequality, well-being, quality of life, provision of infrastructures, etc., require, to be measured, the ‘combination’ of different dimensions, to be considered together as the proxy of the phenomenon and it requires applying methodologies known as composite indices (Salzman, 2003; Mazziotta and Pareto, 2011).
During the last decades, there are as well many remarks amongst scholars, practitioners and politicians related to the growing demand that Cohesion Policy should also “move beyond GDP” (COM, 2008; COM, 2009; Stiglitz, Sen and Fitoussi, 2009) and pay attention to other indicators aggregated by MCDM methods. However, it is worth noticing, that the discussion of GDP limitations started in 70-s (Atkinson, 1970) and in the context of regional inequality analysis actively lasted in 80-s (Atkinson and Bourguignon, 1982; Maasoumi and Jeong, 1985; Maasoumi, 1986; Maasoumi and Nickelsburg, 1988; Bradfield, 1988; Folmer, 1986; Nijkamp, 1988) and 90-s (Maasoumi and Zandvakily, 1990; Zandvakily, 1992, 1999; Davezies, 1992). Consequently, dissatisfaction with per capita GDP as an index of economic well-being (Caminada et al., 2010; Garcia and Martin, 2010, Pissourios, 2013; Cameron et al., 2013) led to a search for a better metric (Banting et al., 2001, Mizobuchi, 2014).

Therefore, the primary motivation for the application of MCDM methods implying the multi-dimensional aggregating power is the omnipresent critique of single GDP criterion lying as the foundation for the Cohesion Policy. GDP per capita is insufficient to characterise the regions benefiting from European Regional Policy funds (Martin et al., 2012). Regions differ not only in terms of their average income but also in terms of other indicators what is in line with the concerns raised by Soares et al. (2003), Cuadrado and Marcos (2005) and Del Campo et al. (2008). It is common awareness that a number of socio-economic phenomena cannot be measured by a single descriptive indicator and that, instead, they should be represented with multiple dimensions (Mazziotta, Pareto, p. 1, 2013).

Concerning the quantitative methods measuring different aspects of regional and countries’ performance, much research has been devoted to the elaboration of indices in the frame of different methodologies able to pack in main features of the performance in one multidimensional index. Some group of authors (Madonia et. al. 2013; Czirákya, Sambtb et. al. 2006; Soares, Marquês et. al. 2003; Campo, Monteiro et. al. 2008, Polednikova, 2014b; Stamenković, Savić, 2017) prefer to be armed by multivariate statistical methods (Principal Component Analysis of Hotelling, 1933, methods of Cluster Analysis, structural equation modelling – combination of two previous ones).

Others, such as Hellwig (1968), Mahmad, Yusop (2010), Dai, Zhang (2011), Polednikova (2014a,c), Önay & Yildirim (2016), Savić, Bogetić, Dobra, Petrović (2016), Marković, et al. (2016) are in favour of MCDM methods coming mostly from American school based on the
multi-attribute value functions and multi-attribute utility theory (MAUT) (Keeney, Raiffa, 1976). Within this group the simplest type of MCDM methods, occurring to be the most applicable and acceptable is the simple linear way of criteria aggregation (Annoni, Dijsktra, 2013; Annoni, Dijsktra, Kozovska, 2011; Annoni, Kozovska, 2010; Gábor, Ottaviano, 2015; Hollanders, Tarantola, Loschky, 2009; Huggins, 2003; Huggins, Thompson, 2010; Huovari, Kangasharju, Alanen, 2001; Snieška, Bruneckienė, 2009; UNDP, 2008). Much fewer scholars applied the AHP method (Nevima, Ramík, 2009; Kiszová, Nevima, 2012), which can be explained by the prominent subjectivity inheriting to this method.


A few attitudes (Mahmad, Yusop, 2010; Dai, Zhang, 2011; Polednikova, 2014a,c; Önay & Yıldırım, 2016) in regional studies are given to MCDM methods providing a compromise solution (VIKOR, TOPSIS). These two methods aggregate criteria similar to Hellwig’s method, however, they are able at the same time to process separately measured strengths and weaknesses in a specific attributed to each method way. By this characteristic, they deserve special attention.

Along with that, some authors (Charnes et al., 1978; Karkazis and Thanassoulis, 1998; Byrnes and Storbeck, 2000; Zhu, 2001; Melecký, Staníčková, 2011; Ramík, Hančlová, 2012; Charles, Zegarra, 2014) investigates another aspect such as the efficiency of performance. It is measured by the use of an entirely distinct type of space reduction methodology named as Data Envelopment Analysis (DEA), a non-parametric method introduced by Charnes and Cooper in 1978.

This majority of mentioned above research suffers from important criticisms: i) compensatory nature; ii) mutual preference independence and constant compensation ratio are necessary conditions for model's validity; iii) the model cannot handle ordinal and qualitative information, and iv) impossibility of imprecise information handling.

According to our knowledge, only the least part of the authors was armed by outranking methods (Oliva, Miguel, 2005; Fernandez, Navarro, 2011; Fernandez, Navarro, et al. 2013) able
to overcome mentioned above weaknesses. As regards Oliva and Miguel (2005), they applied the ELECTRE III method to get a partial pre-ranking or, in other way saying best to worst ranking enabling “incomparability”. In contrast to mentioned pure application of ELECTRE, Fernandez, Navarro (2011), Fernandez, Navarro, Duarte & Ibarra (2013) developed a new THESEUS multi-criteria evaluation method, in which framework they introduced ELECTRE-based preference model mainly relying on studies from Almeida-Dias, Figueira (2012) and Zopounidis, Doumpos (2000).

Thus, although the outranking methods can be applied in different fields of study, still, the very few applications have been made to the regional analysis context. The main advantage of the outranking methods and the reason for application in the regional analysis is that the comparison of the alternatives can be achieved even if there is not a clear preference for one of those (Jasemi, Ahmadi, 2018). Therefore, compared to other methods sensitive to the decision maker’s beliefs, it is more reliable. Additionally, it can process both quantitative and qualitative judgments being especially convenient with a few criteria but a large number of alternatives (e.g. regions).

The 34 journal and conference scientific papers (Table A.1, Appendix A) related to the application of quantitative multi-criteria methods in the regional studies field have been found and analysed. The papers have been divided concerning the applied methods (fig. 1.6).

fig. 1.6: Appearance of the MCDM methods in the papers devoted to regional analysis

Source: author
From the meta-analysis presenting the papers’ distribution, we can conclude that the most popular MCDM method is SAW method providing linear aggregation of criteria. That method mostly applied to the measurement of regional competitiveness. Other methods from MAUT (DP-2, VIKOR, TOPSIS, Helwig’s) and outranking groups are less frequently used. The main reason is the level of complexity of these methods, which hinders their exploitation and interpretation of results. The primary attention in the thesis will be given precisely to these methods.

Besides, the most striking is the negligibly low number of papers where the panel of MCDM methods was applied and compared (Table A.3, Appendix A). During the last 20 years, we managed to find only three papers (Önay & Yıldırım, 2016; Polednikova, 2014a,c), where several MCDM methods were compared. However, authors formed the panel of methods eclectically without any uniting criterion. Therefore, the comparison of rationally (i.e. compromise methods) or even eclectically grouped MCDM methods is of particular interest.

All the above-mentioned studies have their own specific focuses, which makes them unique. It is evident that MCDM methods still meet barriers on the way to be implemented in practice or at least to reach some agreement among scholars, meaning that much work to be done to reach connectional convergence. Nevertheless, many authors claim that MCDM techniques are highly suitable in multidimensional frameworks when aggregating single indicators into a composite one (Saisana and Tarantola 2002; Freudenberg 2003; Jacobs et al. 2004; Nardo et al., 2005, 2008; Gibari et al., 2018). In particular, composite indicators are increasingly recognised as a useful tool in policy analysis and public communication (Gibari et al., 2018).

Composites often seem easier to interpret than finding a common trend in many separate indicators and have proven useful for benchmarking a country’s performance (Marković et al., 2016, p. 2). Booysen (2002) concludes that indices remain invaluable in terms of their ability to simplify complex measurement constructs, to focus attention and to catch the eye, thus enhancing their political appeal. Speaking of general MCDM methods use, their current popularity in policy analysis and regional studies as mentioned in comparative studies (predominantly on meso- or macro level) is first and foremost unfold by at delivering the message decoded by the aggregated value of composite indicator to its receivers (people, potential investors or policy-makers). To sum up this section, the main conclusion is that MCDM methods with produced composite indices are good at delivering a message and perform the communication function. It is worth
noticing that mentioned virtue is entirely illusory unless it gets real practical value and essential influence. The last one comes alive in the case when MCDM methods can be used or at least considered in scientific papers as the alternative basis for the regional policies or SF distribution.

1.2.3 Lack of verification of clustering methods and regional classification

In the analysis of regional performance, the application of clustering methods very often goes along with MCDM methods to solve the problem of classification. The last ones can be used to provide input data for the former ones. In line with the concerns raised by Lipshitz and Raveh (1998), the EU NUTS 2 regional classification based on GDP per capita can be quite different from the classification obtained on the basis revealed clustering structure produced by the multidimensional clustering methods. Speaking of an alternative more inclusive basis for the EU regional classification, it strongly depends on the clustering structure identified and consequently on how it was formed and verified. In the case of alternative classification acceptance, the SF distribution is as well heavily depended on properly defined clustering structure. That is why this sub-topic of the current research is one of the main directions where the elaborated decision-making logic can contribute for the sake of more justified and rationalised functioning of Cohesion Policy.

Research related to the application of clustering techniques in regional studies during the two last decades has been collected and analysed. We have selected 32 scientific works (fig. 1.7, Table A.2, Appendix A) consisting mainly of journal articles and conference papers.

fig. 1.7: Distribution of papers on the topic of clustering in regional studies

Source: author
Clustering techniques in all the papers are applied to regions of different levels predominantly belonging to the EU. The most popular clustering technique, which has been met in almost half of cases (12 papers, 37.5 %) appeared to be a combination of two methods belonging to hierarchical and partitioning groups. The use of cluster analysis involves predominantly two main methods, either hierarchical or non-hierarchical. As usual, the Word’s method (hierarchical) is complemented by the k-means method partitioning or non-hierarchical. Sometimes within the hierarchical group, the average linkage method is used providing good results compared to other ones (Seifoddini, 1989). It is used when there is no specific reason for selecting some other strategy (McGarigal et al., 2000; Kaufman, Rousseeuw, 1990). Besides, this method guarantees monotonicity eliminates group size dependency and reversals, in general, producing clusters with similar variance and less influenced by extreme values than other methods.


Since in hierarchical techniques, the optimal number of clusters depends on the data, it is not necessary to define subjectively a priori the number of clusters. Nevertheless, some authors resort to a subjective or practical way of clusters determination. In this research, this way is not favoured. In our opinion, the hierarchical procedure run before is the premise for the more objective clustering structure that is sought.
As the solution based on hierarchical procedures depends on the distance measurement and the algorithm used (Leisch, 2006), another advanced strategy to find an optimal objective clustering structure was made by Cruz-Jesus, F., Oliveira, T., Bacao, F., (2012). In particular, the authors used Single, Centroid, Complet, and Ward’s methods; moreover, different distances were used. Euclidean distance, squared Euclidean distance, the city-block approach, and the Minkowsky distance were taken into consideration. After all, the best combination of hierarchical procedures defined by R-square and dendogram was used to generate the initial seeds of the non-hierarchical algorithm – k-means.

Other group of authors (Lukovics, 2009; Bakaric, 2005; Jaba, Ionescu, Iatu, Corneliu and Balan, 2009; Munandar, Azhari, 2015; Serra, Vera, Tulla, 2013; Brauksa, 2013; Panayotis, Economakis, Lagos, 2006) made up 28 % (9 papers) and preferred using exclusively non-hierarchical methods, in particular portioning medoid algorithm and most cases k-means method. Typically, the results of this method are backed up by ANOVA significance test examining between and within-group variability when testing the hypothesis that means differ between groups. Though the argument underlying the choice in favour of this clustering method is not presented at most times, what makes such kind of research not enough verifiable.

To decide the appropriate number of clusters and figure out how to differentiate a bad clustering structure from a better one are the two most challenging tasks in cluster analysis. Below we will discuss four papers (12.5 %) following the more advanced approach in obtaining a more objective clustering structure. Kaufman and Rousseeuw (1990) define a set of values called silhouettes (s) that provide the critical information about both of these tasks and measures how well an object has been classified by comparing its dissimilarity within its cluster to its dissimilarity with its nearest neighbour. In one-of-a-kind work among 32 selected and analysed papers Stamenković M. and Savić M. (2017) in addition to the k-means method, applied the additional verifying silhouette coefficient. This coefficient is considered as a comprehensive indicator of internal homogeneity and external heterogeneity of the formed clusters (Rousseeuw, 1987; Tan, Steinbach & Kumar, 2006). As well, this coefficient was used by Spicka, J. (2013) but for the verification of partitioning medoid algorithm.

Apart from that, it was found another single usage (Goletsis, Chletsos, 2011) of verification tool, namely cophenetic correlation coefficient measuring the correlation between distance values calculated during dendrogram building and the observed distance. In other words, this coefficient
helps identify the best linkage method. The results obtained by Y. Goletsis and M. Chletsos (2011) showed a small sensitivity to the clustering method used. However, in our opinion, such a conclusion does not belittle the value and necessity of this coefficient in terms of methods selection.

To conclude the part of the literature analysis related to the application of clustering methods, just a few (4 or 13 %) papers have been found with the using of verification tools, such as the cophenetic correlation coefficient and silhouette coefficient. The other minority tried to select the most qualitative and objective clustering structure due to the application of different linkage and distance measures. At the same time, a less advanced approach in terms of verification is based on a pair of partitioning methods complemented by hierarchical ones selected by orientation on a simple criterion as dendogram or scree-plot. We do not give much credit to such simplified approaches to clustering structure verification and will try to follow more complex verification approach.

1.2.4 Identified knowledge gaps and originality placement

In addition, having studied recent reviewing articles (Booysen, 2002; Gibari, Gómez, 2018; Stamenković, Savić, 2017; Meyer, Jongh, 2016; Saltelli, 2006; OECD-JRC, 2008; Mazziotta, Pareto, 2013; Goletsis, Chletsos, 2011; Melecký, 2017) devoted to a use of aggregated indicators in the field of regional studies, we identified several theoretical and methodological gaps in the field of MCDM methods application.

Search for knowledge gaps was incited by the inquisitive mind map (Appendix A, fig. A.3), where white highlights the newly stated questions. All the gaps are graphically presented in fig. 1.8, where the sectors (cubes) are formed depending on the aspects related to the already done (present in the literature) research or to be done (missing currently, new and original direction). The original directions expressed by white cubes are included in the research targets of the current dissertation.

The white cubes in fig. 1.8 are marking the expected originality in a more structured way. The originality is located on the opposite edge zone to the already explored area. It tells visually about significant differences between what has been already researched and what is going to be.
In general, we can see that novelty, for the most part, possesses such distinctive features as:

1. Methodological pluralism (M4) in the application of MCDM methods which is complemented by the selection of proper methods and development of new methods allowing to analyse different aspects of regional performance;

2. Methodological pluralism (C4) in the application of verified clustering methods to obtain the most optimal clustering structure and genuine regional classification;

3. Development of optimisation models (O1–O4) based on the improvement of the current Berlin formula (O1) using GDP criterion (O2), based on MCDM results (O3) and based on other more complex and realistic aspects of distribution as fairness, equality, equity (O4).

All the mentioned directions are going to be considered in the development of the multi-criteria approach to SF distribution. Moreover, all contributions of the research are based on the identified knowledge gaps in the previous sections. One should notice that identified gaps formed the basis for the research objective and research tasks.

First, we found a complete gap in regional studies related to the multi-dimensional measurement of regional effectiveness. In managerial literature, this term is always coupled with efficiency, making the analysis more comprehensive. Effectiveness (“doing the right things”), as
a complementing aspect of regional performance, is totally missing as well as the methodology for its measurement. This aspect is being sometimes replaced by the technical efficiency measured by DEA, competitiveness, etc. However, efficiency and effectiveness are performance domains that have been clearly distinguished (Ostroff and Schmitt, 1993). Effectiveness complementing efficiency or any other aspect of regional performance seems to add essential weight to the multi-criteria approach extending the range of managerial decisions. Regional policy is considered reliable when it solves problems efficiently and effectively. Based on this defined gap, the way of looking at how to measure effectiveness and integrate it into the problem of SF distribution seems to be promising and complementing the existing practice of lagging regions identification.

Second, another notorious characteristic of the research mentioned in reviewing papers is that application of MCDM methods in regional studies is not targeted by any means on the analysis of the criteria dependency or interaction; this aspect is merely avoided. However, there is one methodology called the Pena Distance method (DP-2) able to count the substitutability of the criteria. The DP2 solves the problems of aggregation of variables expressed in different measures and avoids redundant information through counting the determination coefficient from linear regressions. This useful feature of the method motivated to include it in the panel of applied MCDM methods.

According to the literature studied, all other methods applied in regional studies assume that there is an independency of criteria and they can be treated as just additive sum. Therefore, the fuzzy measures (accompanied by the Choquet method) (Sugeno, 1974; Grabisch, 1996; Roubens, 1996; Grabisch, 1997; Murofushi, Sugeno, 2000) allowing consideration of the interaction between criteria, have not penetrated regional studies. Their incorporation would permit higher headroom in the variables selection and aggregation making measurement more robust than done by traditional approaches (Montero, Chasco, 2010).

Thirdly, having covered much research, we have all reasons to state that in none of them an advantage was not taken from the combination of different methodologies in order to add weight to the decision-making approach extending the range of managerial decisions. It seems promising in the spirit of methodological pluralism to combine such methods as distance-based ones with the DEA methodology targeted at an efficiency (“doing the things right”). The combination of efficiency and effectiveness also pretends to be very enriching and to allow reaching more
complex and systemic measurement, providing a more realistic picture of reality. Especially such an approach is appropriate to be applied for the analysis of developing countries occurring in the transitive state heading to the fast way of development. In this case, an extensive (by distance-based methods) and intensive (by DEA methodology) aspects can be explicitly measured.

Fourthly, the application of MCDM methods from outranking family, such as ELECTRE (ELimination and Choice Expressing the Reality) (Roy, 1968; Roy, Bouyssou 1993) or PROMETHEE (Preference Ranking Organisation Method for Enrichment Evaluations) (Brans, 1982; Brans et al., 1984) is almost absent in the regional research. Besides, contrary to the outranking methods, traditional ones based on the MAUT suffer from the criticism aimed at the compensatory nature of the methods, which makes their main disadvantage. In this course, it seems beneficial to incorporate elements from outranking methods into the structure of compromise MAUT based methods for improved identification of lagging regions.

Fifthly, no matter which aggregating technique or the combination are being used, academic literature has not shown us the fact of consideration of spatial and hierarchical specifics in regional measurement by MCDM methods. MCDM methods are applied to pay no attention 1. to usually significant spatial correlation between neighbouring NUTS 2 regions and 2. to the influence of the corresponding NUTS 1 regions. Paying attention to the hierarchical interconnectedness of NUTS 1 and included NUTS 2 regions while establishing the target could lead to critical synergetic effects and deserve to be one of the sub-focuses of our attention.

Sixthly, the studied literature gives clear evidence of the absence of comparative studies analysing different MCDM methods in the context of regional policy. It is true that particular research is focused on the application of several MCDM methods; however, all the methods are combined on the eclectic basis either being from different groups and having nothing in common or being from one group but without highlighted essential difference. It could be interesting to compare methods belonging to a compromise group, for example to distance-based methods, such as Hellwig’s method, VIKOR and TOPSIS in terms of the degree of risk attitude (risk lover, cautious decision maker and risk avoider) incorporated into their aggregating function. The last two MCDM methods as it has been found did not find their application in the regional policy despite their high popularity in management literature. Such an application of a panel of MCDM methods complemented by the determination which method is more appropriate for the lagging regions’ identification could justify whether the choice of one MCDM method would preclude
the use of the other. Such pre-phase as a proper selection and justification of MCDM methods should be present in regional studies.

Seventh, the review of the literature on the topic of MCDM methods selection has shown that this aspect is quite rarely studied in the broad scope of application, all the more so in the specific regional policy field. Such pre-phase as a proper selection of MCDM methods should be present in a decision-making process of Cohesion Policy. MCDM methods being able to rank the alternatives (regions) have nothing to do with grounded classification because any of the methods do not provide some measures to define or extract the clusters and precisely classify the alternatives. Of course, outranking methods are acknowledged as good in clustering. However, these methods in their full form are excluded from the application in the current research because of the necessity to subjectively define thresholds what cannot be allowed in Cohesion Policy requiring a maximum of objectivity. Having observed such a wide variety of MCDM methods applied, the question arises whether final utility values produced by the specific MCDM method can reflect in the best way the genuine clustering structure of the alternatives being evaluated. In other words, it is unclear which methods are more prone to cluster alternatives (to combine homogeneous into one group and heterogeneous into the others) and which – to rank keeping the most substantial possible difference between ranked alternatives. Saying more, proper selection of the most suitable MCDM methods is influenced to a full extent by the after-phase (optimisation of funds’ distribution or classification) and the philosophy of the method is not in a contradiction with the context of Cohesion policy. To the extent of our knowledge in the economic and management literature, there is no research shedding light on this question of proper and objective selection of the most suitable MCDM methods to apply for the specific problem at hand. Therefore, highlighted the absence of research targeted at the proper selection of MCDM methods for the specific needs (clustering or ranking, optimisation of SF distribution) in Cohesion policy is crucial and requires its completion.

Eighthly, having analysed the applications of clustering methods for the regional performance classification, we have found that only the minority endeavoured to apply advanced tools to verify the obtained clustering cluster. However, even then it is not enough for the sufficient objectification of the clustering method applied and obtainment of genuine regional classification. Meantime the classic approach to regional classification is based on the subjectively established GDP threshold. Such a revealed situation in the area of clustering and
classification in regional studies allows us to consider the present state as immature and lacking a complex approach to verification of clustering structure as it is a basement for the realisation of SF distribution.

Ninth, we have found no suggestion on improvement of current Cohesion policy distribution mechanism while it suffers from an enormous criticism coming from scholars and representatives of the European Commission. The last ones only keep promising to take measures on the way of improving. The Berlin formula based on a single monetary GDP indicator seems to be rigidly entrenched in the current practice despite many shortcomings and oppressive critic. Therefore, we consider it entirely appropriate to search not only for the alternative mathematically based transparent distribution models based on MCDM composite indices but also for the improvement of the Berlin formula. The identity of MCDM methods is more formal and purely scientific, having no practical implications in the Cohesion policy. Application of MCDM methods should be tightened up with other functions of Cohesion Policy, such as the distribution of SF.

The last but not least gap is logically rising based on all previously mentioned gaps. As we have confirmed above, all steps underlying the distribution of SF, such as MCDM based measurement of regional performance, its classification and optimisation are sequentially dependent and interconnected into one decision-making process. Thus, consideration of those on a systematic basis could contribute to a whole Cohesion policy cycle. Therefore, we can assert that the application of MCDM methods has been still found in an embryo status and requires further development oriented on more integral and functional implementation within the Cohesion policy. The more effective employment of MCDM methods into the problem of SF distribution can be reached by the extension of the research through the integration not only MCDM methods but also clustering methods, optimisation models and selective approaches under the one multi-criteria perspective. Having studied the application aspect of MCDM methods within the SF distribution problem, we can state the following. Unfortunately, it is difficult to get a consistent and systemic picture of the MCDM methods application, which would have the form of any comprehensive and logically organised study. The quality and appearance of the grounded and objective decision-making process in the Cohesion policy depend on the development of the IMC approach and its integration into the Cohesion policy cycle.
1.3 General principles of development and application of the interrelated multi-criteria approach

1.3.1 Practical, methodological and operational aspects of the approach

Before we start discussing the assumptions and prerequisites of the IMC approach, let us briefly present the key points composing its practical plane. The first ingredient, being more as a tool, is a decision-making process. No need to prove that any average person is familiar with it to some extent. As human beings, people are always involved in a daily-life decision-making activity trying to be rational, to use some routines, rules, heuristic methods, etc. However, if daily life decisions are predominantly simple one-time solutions imposed on our emotions or subjective bias; scientific decision-making, conversely, is about deliberately prepared comprehensive, systemic and strategic decisions that lie beyond cognitive abilities and have to be with a minimum subjectivity.

Simply saying decision-making is a process of identification and evaluation of alternatives, which eventually results in an optimal or satisfactory choice (Roy, 1993; Henig, Buchanan, 1996; Larichev, 2000) (fig. 1.9).

fig. 1.9: Main steps of the decision-making process

![Diagram of decision-making process]

*Source: author*

When it comes to Cohesion Policy, according to a definition (Molle, 2007; Commission COM, 2010) it is aimed at reducing disparities, improving well-being and life quality by supporting and investing in job creation, business competitiveness, etc. (fig. 1.10).

However, the question may remain “how might multi-criteria decision-making and Cohesion policy look together?”. An excellent analogy connecting two puzzles would be the pyramid-like visualisation (fig. A.1, Appendix A), where the greater foundational area is a general policy concept including a set of ideas, principles, plans, actions, procedures. Then a more general concept is being reduced to a more specific one - Cohesion policy that served as a basis for a decision-making process guiding and fostering the realisation of Cohesion Policy aims.
fig. 1.10: The essence and aims of Cohesion policy

Source: author

This all gives a slightly vague and preliminary understanding of the topic unless the practical dimension of the topic is shown (fig. 1.11) what helps get the gist of the research and reveals its primary motivation.

fig. 1.11: Practical dimension of the research

Source: author

In the presented figure, the two main gearing questions are put into a practical dimension of the topic. Three main sub-problems presented below create the fulcrum of the solution to the SF
distribution problem. Therefore, the following sub-problems, accompanied by another methodological problem of methods’ selection, are the focus of further attention. First of all, regions as central players are expected to be measured concerning their selected attributes answering the first question “who is who?”. To answer this question, a conception of the measurement has to be defined by the DM. In current practice, the measurement problem is solved quickly enough following the classic monetary approach, which assumes the usage of a single GDP criterion. However, such simplicity in measurement suffers from the subjectivity brought by arbitrarily defined threshold dividing regions into recipients and donors. Referring to the regulation EU (No 1303/2013, article 90), the principal recipients are defined as regions having GDP per capita less than 75 and 90 % of the average GDP of the EU-27. Besides, there is no economic rationale provided for these thresholds. Meantime according to the mainstream or unorthodox multi-dimensional approaches, the status of region can be defined based on measurement of different aspects of regional performance (see sec. 1.2.2), such as competitiveness, efficiency, etc. Having conducted the meta-analysis of 34 papers devoted to the application of multi-criteria quantitative methods in the regional studies it was concluded the following. Based on Table A.3 (Appendix A), the frequency of measurement conception is displayed in fig. 1.12. The most notable aspect of the regional analysis is the “regional competitiveness” appearing in 41 % of the analysed papers. The second place is taken by the “regional development”, while the third – by “regional performance”.

fig. 1.12: The distribution of papers in the light of measurement conceptions

Source: author
The distribution of SF could be straightforwardly based on any measurement conception amongst the top three mentioned above. All of them create the alternative multi-dimensional measurement basis, which can be used instead of a single GDP criterion. The concept of “regional development is the most authentic and attributed to regional studies. The etalon definition of “regional development” can be one suggested by Stimson, Stough and Roberts (2006): “Regional economic development is the application of economic processes and resources available to a region that results in the sustainable development of, and desired economic outcomes for a region and that meet the values and expectations of business, of residents and of visitors”. The multi-dimensional aspect of regional economic development is reflected by the qualitative and quantitative variables (fig. A.6). According to the authors, the economic development also has a product and process dimension; the product is concerned with meeting stated outputs, which might be both qualitative and quantitative. One should notice that this definition is oriented mostly on the planning and strategy development, which is too specific for the main problem discussed in this thesis.

Speaking of regional studies’ authenticity, the more specific concept of competitiveness, oppositely, is adopted from management science one and introduced by Porter (Porter, Ketels, 2003) from the business level. Similar is referred to as the concept of performance. However, it is quite apparent that the term “performance is the most generic one, and measurement of regional performance aspects includes all other measurement aspects, such as development, competitiveness, innovativeness, efficiency, effectiveness, etc. Therefore, in the context of funds’ distribution and necessity to find a multi-dimensional alternative to GDP, it was decided to stick to the concept of “regional performance” as the most general. This concept seems to be, from a logical point of view, encompassing all other mentioned above aspects of measurement. Thus, from now on the regional performance is used synonymously to regional development.

Then according to the results of regional performance measurement (first problem), regions are classified and divided (second problem) into donors (more developed) and recipients (lagging or less developed). After all, one-third of the EU budget or 352 billion euro (varies slightly depending on the seven years programming period) has to be redistributed among certainly defined players, and this underlines the optimisation problem (third problem). Unfortunately, three highlighted problems have not been solved on the interrelated, systemic, verified, conceptually sound, and objective basis. Therefore, the destiny of many regions in need, the economic well-being of citizens, their life quality, colossal money, responsibility, justice and
tremendous aiding power of the decision-making tools are the main drivers of the current research. From now on, some methodological aspects will be touched as well as their level of elaboration will be presented. It is necessary to notice that all aspects are discussed within the three stated above problems, which are going to be solved due to the application of the multi-criteria approach.

The application of methods for the solution of three problems is logically and methodologically interconnected what will be explained in detail below. The solution to one problem is predetermined by the other problem’s solution. Moreover, one crucial problem of the proper methods’ selection is missing in the presented figure and will be introduced further in sub-chapters 1.3 (fig. 1.14) and 2.3.

Before the methodological part of the IMC approach comes into play, the prerequisites of its conceptual and methodological integrity have to be introduced. The methodological platform of the research is based on the MCDM methods and optimisation models directed on the solution of practical sub-problems eventually converging to the primal problem of SF distribution. However, the mentioned two methodological players do not make a sufficient pair when it comes to applying them in the arena of great veracity of homogeneous with slight differences in methods and models.

The number of methods and models pre-selected in the current research is already big enough (fig. 1.13) not saying about other existent similar methods that have not been considered on purpose or because of the limited size of the dissertation. Each sub-problem underlying the SF distribution needs a specific set of tools presented in detail in chapter 2. In particular, the measurement problem is solved by MCDM methods (sec. 2.1, 2.2), classification problem by clustering methods (sec. 2.3.1) and optimisation problem - by optimisation models (sec. 2.4 ). However, there is much more to say about methodology, than to present the set of methods and models capable of providing the solution for that or other mentioned problems. Thus, the essential thing here is not just a linear sequential representation of methods models, but an in-depth look at their interlacement. The application of methods is interconnected, and the solution to one problem is predetermined by the solution of the other problem. Regarding this fact and considering the vast number of solutions made by existent or developed in the future methods, another methodological problem comes onto the scene, in particular, the problem of the selection of the proper methods (sec. 2.3).
fig. 1.13: Methodological diamond of applied methods and models

The selection problem is presented further in fig. 1.14 as the fourth problem. We can clearly see that the interconnectedness of problems predetermines the choice of method. For example, the selection of the MCDM method depends on how the coming after classification and optimisation problems are solved.

fig. 1.14: Modelling dimension of the set of problems

Source: author
Based on said above the way to augment and enrich the MCDM measurement of regional performance with the deliberation of the objectivity continuum is going to be described and proposed below. It is done in the spirit of such prevailing conception of science as the elimination of the personal and subjective, and the attainment of the objective (Olson, David, 2009). Based on this conception, the area of MCDM application, in particular, the Cohesion Policy context cannot tolerate any inherent subjectivity. Thus, subjectivity as the core of the methods’ selection problem will be considered below.

The choice of a particular method and therefore, the final solution of practical funds’ distribution problem depend on how the methodological problem of methods’ selection is solved. Each MCDM method is just a subjective measurement perspective within some philosophical point of view going through the lenses of data. Therefore, the choice of MCDM method has to be appropriately verified and justified, and that will increase the application value of a specific MCDM method. At the modelling dimension, we can see how inputs, presented by the methods and models, are transformed into outputs, which are appropriately selected by the influence of the problem’s solution coming after (fig. 1.14). At each step of the underlying problems, the following questions are answered. At the step of the measurement problem: “How to measure regional performance?”, “What philosophy stands behind the MCDM method?”, “What are the most appropriate methods?”, “Which method is the most suitable for the further step?”. The classification problem requires answers for the questions: “How to classify regions?”, “What are the appropriate clustering methods?”, “Which method produces the best clustering structure?”. Optimisation problem raises such questions as “How to improve the current distributional model?”, “What are other possible approaches to the optimisation?”, “What distribution is the most optimal and fair?”. By this, the whole range of problems is seen in connection with the question guiding the current research and making investigative directions.

The selection problem stands aside from the mentioned problems and determines how the following clustering and optimisation problems are solved. Eventually, such interdependence of modelling blocks requires a formation of one IMC approach to the SF distribution, which follows necessary prerequisites, such as:

- context relevancy when each method is considered to be the best or the most suitable for the problem’s solution according to a practical criterion or a set of criteria;
- unsupervised objectivity when a solution to the problem is driven and influenced just by the data and problem, not by a decision maker’s view, so the subjectivity is reduced to a minimum;

- sequential consistency when the solution of the problem is influenced by the following problem at hand or when the latter problem predetermines the solution of the former.

Because all proposed approaches, methods, algorithms and models are targeted on the improvement of decision-making process underlying the distribution of SF, it is appropriate to organise all proposition into a one logically and conceptually interconnected approach (fig. 5.1). The structure of the IMC approach is based on the main interconnected problems identified within the regional policy cycle (fig. A.2, Appendix A).

The suggested IMC approach follows the principles of objectivity and methodological pluralism that do not restrict a DM to a particular and perhaps subjectively defined solution but on the contrary motivate to investigate and thoroughly rethink all spectrum of possible solutions.

From the fig. 1.15, we see that the operational structure of IMC approach embraces four blocks.

fig. 1.15: Operational structure of the IMC approach
The first block predetermines all further steps of the approach as it defines the primary vector of the decision-making, whether it will be based on a single GDP criterion or the complemented GDP approach or fully substituted by the other composite indicators. As well this block determines the initial set of MCDM methods, whether it will be eclectic one (inclusive panel), including all possible methods, or rationally collected (exclusive panel) according to a specific criterion. For instance, compromise distance-based MCDM methods can form a set based on the attitude to risk (risk lover, avoider or just cautious DM) attitude to the theory standing behind. Meanwhile, the second block is a set of steps typical for the majority of all MCDM methods. Thus, this block is applied for any selected MCDM method.

The third block solves the selection problem. A DM has to make a choice, which is not only based on the single scientifically proved method, but also objectively rational. It means that comparative research has to be done in the direction of the determination of the most suitable methods for the specific problem at hand. The absence of this block makes decision-making random, subjective and possible lobbying someone’s interests.

As it is seen from the fourth block, the final problem at hand is the optimisation of SF distribution. The implementation of this step needs the input data such as ranking, utility values and set clustering structure thoroughly prepared in the previous blocks. Besides, this block the distribution requires the selection of proper classification of regions produced by properly selected clustering methods.

All these steps together being subsequently combined and based on a consistent theoretical foundation indeed become a transparent, mathematically based and justified approach allowing politicians to come more accessible and more objectively to a grounded and verified compromise solutions with a minimum of subjective influence.

Another essential feature of the IMC approach, which still has not been mentioned, is its scenario nature allowing consideration and comparison of outcomes triggered by different theoretical conceptions underpinning the implementation of the suggested approach. The best way to present the methodological flexibility and scenario nature of the presented IMC approach is to show its conceptual and methodological dependency by the variation of a flow chart representing the steps of the decision-making process (fig. 1.17). This scenario structure will play the role of navigating map connecting the suggested methodological improvements with the general conception of the offered IMC approach. The dependency of the approach from a
conception triggering the particular exploitation (scenario) of methodologies derived determined its scenario nature. So for instance, if we agree to follow the classic monetary single GDP conception (block 1.1), the IMC approach gives us the highlighted path or scenario (blocks 1.1, 3.1, 4.1) to go through and the main problem here would be how to redistribute finds appropriately, so the improved distribution model (block 4.1, sec. 3.3.1) has to be applied. For this purpose, the imperfections and weak points of the current Berlin formula have been analysed in sec. 1.1.

The second scenario (blocks 1.2, 2.2, 3.2, 4.2) more possible scenario of the IMC approach realisation is to apply synthetic multi-dimensional view within the mainstream conception (for example, competitiveness). Application of multi-dimensional, as well as unorthodox measurement approaches, requires the formation of indicators structure according to which the composite indicator will be measured. Having analysed papers with the applied multi-dimensional approach, we identified four possible hierarchical criteria structures depending on methods and pillars applied (fig. 1.16).

fig. 1.16: Hierarchical criteria structures for the composite index aggregation

<table>
<thead>
<tr>
<th>Mixed criteria</th>
<th>Single method</th>
<th>Multiple methods</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. mixed / single method</td>
<td></td>
<td>2. mixed / multiple methods</td>
</tr>
<tr>
<td>3. multi-pillar / single method</td>
<td></td>
<td>4. multi-pillar / multiple methods</td>
</tr>
</tbody>
</table>

Graphical representation of each aggregating strategy is given in fig. A.7 (Appendix A).

After the formation of the multi-dimension basis and determination of a hierarchical criteria structure (block 1.2), the panel of MCDM methods has to be implied (block 2.2, fig. 1.17). The next problem to be solved is the problem of method’s selection and verification of clustering cluster (block 3.2). This problem is solved depending on the practical criteria either it is the quality of the clustering structure or robustness of method for the optimisation problem.

Another third option to be chosen is the unorthodox scenario (blocks 1.3, 2.3, 4.3) of funds’ distribution based on, for example, the effectiveness measurement further combined with the
Markowitz mean-variance portfolio optimisation model (block 4.3, sec. 3.3.3). Within this scenario, the optimisation allows stimulation and penalising of regions considering such aspects of distribution as equity, equitability, and effectiveness. According to the given scenario structure of IMC approach, we can see that the problems of verified classification and selection are relevant only in the context of multi-dimensional measurement scenario (blocks 1.2-4.2).

fig. 1.17: Scenario structure of the IMC approach

The scenario of unorthodox measurement also may include these problems. However, concerning the given design of the IMC approach, these problems are not stressed as the unorthodox scenario is presented as specifically tailored for the effectiveness aspect of performance. Instead of this aspect, any other could be incorporated and as well compared.

1.3.2 Pseudo-objective benchmarking as the solution of the selection problem

The existence of the various decision-making methods implies that different methods have their advantages and disadvantages and there is not a general, universal method capable of
handling all types of problems (Bazzazi et al., 2011). This abundance of quantitative methods, in particular, MCDM methods do not leave indifferent the researcher’s interest and motivates them to explore some ways how to narrow the choice of methods and choose the most reliable one.

In the current research, we keep the point of view that the current trend in the MCDM application field and the exceptional (uniqueness) popularity of some MCDM methods (fig. 1.6) should not influence and rule the choice of the method for the solution of practical problems, such as the distribution of funds. In this relation, we try to avoid the affection to a specific MCDM method with the help of additional analysis, objectively allowing the choice of the most suitable method for the measurement, classification and optimisation problem.

The hard-hitting selection problem comes to life when several plausible MCDM methods are capable of processing the input data. Each MCDM is based on a particular philosophy, and multiple methods application is often the case in complex social issues. In particular, the philosophy underpinning the method is the second source of subjectivity. When the DM does not give priority to a specific philosophy, the selection decision-making process should be repeatedly applied. In other words, the main question “which philosophy deserves to be trusted more if the preference is not a priori defined by the decision problem or DM?”.

Such a situation gives a spur to the parallel trend of approaches developed for the selection of the most suitably MCDM method amongst the massive variety of existent ones. Roy (1996) also indicated that the selection of the MCDA method is a vital element of solving a decision problem. Available wide range of MCDM methods, their assumptions and requirements confuse potential users. Each method has its weaknesses, strengths and conditions to follow. It causes phenomena known as the inconsistent ranking problem and can be caused by different MCDM methods (Zavadskas, Turskis, 2011). A foremost criticism of MCDM methods is that due to the dissimilarities among different techniques, diverse results are attained when applied to the same problem. The primary source of differences is in the different selection of the best solution. In other words, it is the methodological core stemmed from the underpinning philosophy. De Muro, Mazziotto and Pareto (2009, p. 4) emphasise that subjectivity in indicator decisions, although advantageous in some ways, might also result in loss of transparency and crucial information if choices are not based on the relevant dimensions. As for preferences being incorporated by some MCDM methods, most, if not all, people will agree that preferences are inherently subjective (Buchanan et al., 1998). Thus, other potential sources, such as weights determination, preference
functions and thresholds, are mitigated in this research. The stress is made on the selection of the MCDM method in terms of its aggregation function.

An application of MCDM methods in the context of Cohesion Policy may lead to many significant consequences for the social and economic life of lagging regions if practitioners use the results of the measurement. Therefore, this process should be as objective as possible. What is not objective is a temptation to various kinds of measurement biases. Bias takes many forms, and MCDM bias does not go around the researcher or practitioner unless the method is thoroughly selected and justified conceptually by the comparison with the rest of the competing methods. The application of even verified methods needs to be sceptical and cautious about its congruence with the practical problem. The choice of the MCDM method should be as free as possible form the influence of human nature.

Every single MCDM is the collection of choices made subjectively, starting from the data selection and finishing the methodology construction. Therefore, every MCDM is biased, and there is no method pretending to be the one that is objective or unbiased. It is possible only to choose the method that satisfies the most established criteria for the MCDM selection, while the last ones are as well are not free from subjectivity. Applicability of any method can be called into a question unless it is justified and proved the best (the most satisfying) amongst the others. The only question remains how to bring subjectivity to the minimum, considering all essential sources of it (fig. 1.18).

fig. 1.18: Sources of subjectivity considered for the process of MCDM method’s selection

Source: author

Form the picture, we pick up the following sources of subjectivity:
1. method (perspective) itself with its specificity embodied into aggregation function;
2. group of methods with a distinctive group philosophy;
3. inputs presented by data, parameters, thresholds, preference function, etc.;
4. benchmarking criteria applied for the selection problem.

Consideration of all subjectivity sources makes the problem too complicated, so sources related to inputs for the methods have not been taken into account and assumed equal. Such a decision influences the choice of groups of methods applicable in the current research. Outranking methods and AHP (ANP) are not addressed because of their methodological features processing the subjective attitude of the DM. As well for the sake of simplicity, just one selecting criterion is used. As a result, subjectivity is tolerated at the level of method, group, and benchmarking criterion.

There is an accepted inclination in the field of operations research for as much objectivity as possible. However, there is a tendency to think that objectivity concerning MCDM methods is a very difficult thing to reach, if not impossible at all. We claim that the MCDM basis for the distribution mechanism must be justified in order to be exposed to critical assessment and consideration of participants involved.

In particular, Mazziotta M. and Pareto A. (2013) say that the attention is focused on the search of the most suitable method depending on the following factors: type of indicators (substitutable/non-substitutable), type of aggregation (simple/complex), type of comparisons to be made (relative/absolute), type of weights of the indicators (subjective/objective). It should be noted that these factors are just important ones for the pre-selection of the group of suitable MCDM methods for the aggregation, but the final selection of the most suitable method lies beyond this circle. While there is no “best”, “correct” or perfect, universal MCDM method (methodology) to address all decision problems, there may be appropriate or suitable approaches for a particular problem at hand (Ozernoy, 1992; Tamiz et al., 1998). It means the situation of the problematic area is decisive and determining the final choice of the most suitable composite index or MCDM method. This idea is acknowledged as the underlying one for the whole selection problem highlighted in the conducted research.

Guitoni and Martel (1998), who proposed a methodological approach to select an appropriate MCDM method to a specific decision-making situation, support this opinion. Adding weight to this, Tamiz and coauthors (1998) stated that the “best” or rather the most suitable
MCDM method depends on the appropriateness of the underlying philosophy of the method with respect to the problem at hand. On the top of everything else, Mazziotta and Pareto (2013) assert that there is not a composite index and consequently MCDM approach universally valid for all areas of application, and, therefore, its validity depends on the strategic objectives of the research.

Roman et al. (2004), who advocated careful reflection of MCDM methods concerning the problem at hand, also emphasise the importance of the problem’s peculiarity. Authors stated that the very concept of searching for the “best” MCDM “method” is fundamentally flawed, mostly due to the uniqueness of every problem etc. In this research, we will develop this point of view on the selection process, in particular, when it heavily depends on the specificity of a problem and the ad hoc approach is the primal target.

It should be noted that the offered approach for the selection is applied only for the problem at hand, in particular for the primary and finalising problem of distribution of SF. There is no intention to propose a generalised MCDA method selection framework for solutions independent of the current areas of usage of MCDA methods. Besides the selection of methods can be predetermined if a DM preliminary favours a specific group of methods sorting it out from a range of plausible methods. That is why the issue of methods’ classification will be addressed superficially.

An introduction of the multi-criteria approach to the policing practices demands serious attention to the aspect of MCDM methods subjectivity as it is always implicit and neglected by developers or users of MCDM methods. In our opinion, an objectivity analysis is necessary research needed to increase the rationality of the MCDM methods application in the regional policy context. The procedure of MCDM application has to be improved to capture the objectivity perspective of rational decision-making. It may seem that the way one verified and popular amongst researchers (and practitioners) MCDM method works are the way what really is. Moreover, all the results obtained by it are truthful. So, such method claims for the status of being objective and providing correspondingly objective results. For this reason, it can be thought that all other decision-makers with their perspectives being in disagreement should be brought around: “if only this method could be followed…”. That statement is deceptive and misleading. Any DM has to be aware that any method either it is thoroughly verified, or not enough, is just one perspective on compared alternatives. It would be even correct to say “perspective on perspectives”.

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Such close attention makes subjectivity more explicit and transparent, reaching an appropriate level of DMr’s awareness and method’s justification. We believe that a thorough consideration of the subjectivity-objectivity aspect the question: “What is the most suitable decision-making method?” can be addressed. It is just a necessary and preliminary step in an attempt to answer.

However, it seems that there are just a few writers (Keeney et al., 1986; Keeney, 1992; Roy, 1993; Bana and Pirlot, 1997) in the MCDM literature who are explicitly related to the issue of subjectivity/objectivity do recognize the existence of objective and subjective information, but claim that it is not easy to distinguish between them. In their discussion of fundamental issues in MCDA, Bana e Costa and Pirlot (1997) state their conviction “… of the interconnection and inseparability of the objective and subjective elements of a decision context”.

Even though based on an assumption the choice of an MCDM method is initially made to eliminate the significant source of subjectivity in MCDM methods, such as thresholds, preference functions, subjective weights determination, a certain degree of subjectivity is still unavoidable in the decision-making process, as argued in (Buchanan et al, 1998; Olson, 2009). An unavoidable subjectivity rises from the crux of the method, from its very philosophy, form every reason causing a DM to consider this method and single out it among others. According to modern understanding expressed by, e.g., (Roy, 1993), science is characterised by the rigour of the methods and openness and exposition of the results for critical inspection and discussion. Thus, objectivity is interpreted as “having reality independent of the individual mind” (Buchanan et al., 1998). This is the conclusion of Bana e Costa and Pirlot (1997) who say: “Subjectivity is always omnipresent in decision-making”.

Therefore, it has to be accepted that any output produced by any MCDM method, such as utility value or ranking is always subjective. Such an assertion is quite realistic and pretends to be an objective statement. Buchanan et al. (1998) claim that the separation of the objective from subjective is therefore necessary for every process of decision-making. In our opinion subjectivity release is more like conditional subjectivity decrease. Total release of subjectivity seems to be impossible, which is underlined even by the definition of the decision-making process itself. The decision-maker(s) stands in the centre of the decision-making process, what is indeed reflected in the foundations of the Decision Theory literature, where a subjective utility function (Keeney, Raiffa, 1976) is the main instrument for capturing decision maker preference.
To avoid subjective believing, objectivity requires a “specifiably functioning mindless knower”, and the quest for objectivity is, however, usually thwarted by measurement difficulties, by problem complexity, and by time limitations. (Olson, David, 2009). Polanyi (1958) contended that we use apparent objectivity as a crutch, trusting that we can be relieved of all personal responsibility for our beliefs through objective criteria of validity. Nozick R. (1993) cited attempts to eliminate the personal preferences, prejudices, moods, and partiality of judges in order to attain objectivity. Meantime it is appropriate to quote Zavadskas, Turskis (2011): usually, there is no optimum solution; no alternative is the best one for each criterion. It leads to the first assumption that any point of view or decision-making method is subjective.

Objectivity is independent of the DM perception (observer) as well as independent of a method applied. The objective is something that exists without an observer and method applied as the last one is equalised with the “knower.” In other words, it is about epistemological subjectivity and constructionist point of view, that all knowledge and experience are subjectively constructed. The property is objective if a particular object can have that property regardless of any subject’s opinion derived about that object or all possible subjects (methods) perceive the object equally. Theoretically assumed situation when a unanimous (absolute) dominance of a particular alternative derived by all possible methods could be defined as a kind of objective one assuming the exhaustiveness of methods applied what is unlikely to be fulfilled in practice.

Another assumption is the bridge to the scientific world, allowing the existence of “objective” reality to describe” – a commonly shared reality, consisting of elements originating independently from us (decision-makers or observers). Thus, science is concerned with what we can know objectively from both positivism (objectivism) or subjectivism (interpretivism) or constructivism. The last epistemological position assumes that knowledge cannot be separated from what is known. This assumption about objective knowledge is additional and at the same time, contradictory to the first one. It is a pragmatic assumption, which affords a measure of comfort, as expressed by Watzlawick (Watzlawick, p. 63, 1984): “Probably the most universally accepted construction of reality rests on the supposition that the world cannot be chaotic – not because we have any proof for this view, but because chaos would simply be intolerable”. That is why within a context of MCDM methods application we conclude that any single method produces subjective results; however, the objectivity of measurement can be increased in case of similar results produced by a more significant number of methods taken into consideration.
An application of the method can be justified only within the group of methods representing the set of possible measurement perspectives. To remove (or mitigate) subjectivity and correspondingly measurement bias to an acceptable level, the pseudo-objective benchmarking has to be formed (Appendix A, fig. A.8). Below the rest of not covered yet assumptions will be introduced.

Obviously, a high number of applicable MCDM methods is at the same time is a significant source of uncertainty and an excellent ground for the further objectification of the results. One should mention that the panel of methods applied is always limited and does not include the infinity of all possible (plausible) methods. Therefore, not having fulfilled the conditions of MCDM methods exhaustiveness and outputs (utility values and ranks) unanimity obtained from selected methods, all results are considered highly subjective. Thus, the set of measurement perspectives or panel of methods plays the decisive role of a launching pad providing a pseudo-objective benchmarking or emulated reality.

Robustness of all considered alternatives (regions) measured by a panel of methods applied can be a good proxy for the measurement of pseudo-objectivity. Eventually, that method is preferred, which can measure alternatives more robustly in terms of defined criterion within an emulated pseudo-reality. What may seem confusing is that objectiveness always revolves around any subjectively defined criterion or a set of criteria defined by a DM. Bouyssou (1990) proposed a general definition of a criterion as a tool allowing a comparison of alternatives according to a particular point of view. Obviously, when constructing a criterion, all participants (actors of Cohesion Policy game) should have an agreement on it. Such criterion serves as the origin of the coordinate for the MCDM method selection process. Once the criterion is defined all alternatives under considerations can be measured, sorted, selected in relation to it. MCDM methods are called for action in this case of several essential criteria. However, a captious reader may find a vicious circle, when starting from one multi-criteria decision-making problem, we have come to another similar one but on the higher hierarchical level. Therefore, even if theoretically a set of criteria for the objectification of applied MCDM methods can be used, the complexity of such a problem is beyond the scope of the current research and will not be considered. The most straightforward case is when it is just a single criterion stemmed from a practical problem. Such an approach to methods selection based on a single criterion is followed in this research.
Relying on the problematic context given in this research, the selection of the most suitable method is driven by the best clustering structure or by the highest robustness of the method regarding the Robin Hood distribution principle. Below mentioned driving principles will be revealed in a more detailed way.

In the current research, two practical criteria will be considered separately and sequentially reducing the complexity of the selection problem to a single criterion problem. The following task is to define a criterion and to measure its value for each considered MCDM method. Thereinafter the examples of practical criteria for MCDM method’s selection will be given and visually presented. Therefore, a selection (objectiveness) criterion is chosen pragmatically; as practice (problem itself) determines the aim of the MCDM application, it should also produce the best criterion for the verification (objectification).

Starting now, we will present two selective criteria to choose an appropriate MCDM method. Selection (objectiveness) criterion is chosen pragmatically, which is on a practical basis mentioned earlier as a pragmatic assumption. As long as practice determines the aim of the MCDM methods application, it provides the best criterion for the methods’ verification (objectification). The criterion should be congruent with the way how the problem is solved.

Two practical criteria will be considered separately and sequentially reducing by this complexity of the selection problem to a single criterion problem. The sequence of steps necessary for the realisation of a selection approach guided by two different practical criteria is presented in section 2.3. Thereinafter the examples of practical criteria for MCDM method selection will be introduced and visually presented.

One possible criterion suiting the pragmatic basis of Cohesion Policy is the quality of the clustering structure produced by the MCDM method. The clustering structure obtained from utility values produced by MCDM methods is expected to be of high quality and thoroughly tested as after all it plays the role of platform for the classification of regions and distributions of funds. The principle, which underpins this criterion, is the following: “minimisation of the distance between alternatives within the cluster and maximisation of distances between clusters”. Schematically this principle is represented in fig. 1.19.

We see that different methods produce various utility values with different distances between them. It is evident that the first method classifies alternatives in two groups (clusters), in particular, alternative three is remarkably distinctive from two relatively similar alternatives 1
and 2. Method 3 measures alternatives as equally distant from each other, while method 2 distinguishes alternatives less distinctly.

The quality of the identified clustering structure should be as maximal as possible. The best genuine clustering structure serves as the indicator for the selection of the most suitable method either for the clustering or for the ranking. If a clustering structure appeared to be of maximum quality and acknowledged as the best one, then the MCDM method producing it acquires the status of the most suitable for the clustering. In the opposite case, the worst structure points at the methods having properties of the best ranking method.

fig. 1.19: Representation of clustering structures obtained from MCDM methods

![Clustering Structures](image)

Source: author

Speaking of the other possible practical criterion, it is predetermined by Robin Hood distribution principle: “taking from rich to get to the poor” (upper part of fig. 1.20). It can be rephrased economically as follows: “income is redistributed so that economic inequality is reduced”. Such a principle becomes a framework for the selection of the method and encompasses the essence of reality. An ultimate responsibility falls on the DM relying on this practical principle, that should be sure who are the rich and who are the poor. The certainty of such identification should be as maximum as possible.

As this MCDM selection step is a pre-step for the further distribution of funds, it is to ensure the precise distribution relying on ranking robustness of alternatives (regions) identified by the panel of methods. To put it differently, having used identified robustness analysis for the certainty of measurement, every applied method can be tested separately for the ability to
concentrate less spread regions (more robust) on the edges of a ranking list (fig. 1.20). It means that the ideal case would be when less developed and more developed regions are expected to be robustly measured. On the other hand, middle regions that are less likely to participate intensively in the funds’ redistribution are going to be not robust in the middle of the ranking list.

fig. 1.20: Principle of robustness measurement

Different principles will determine specifically tailored Fitness functions differently and inevitably with a high level of subjectivity. However, setting up a specific Fitness function tracing the mentioned above placement within the agreed practical approach guarantees that such a function will address the reality as it is.

The basic principles of the Fitness function construction, which lie in the basement of robustness selection approach, are the following:

– according to the Robin Hood principle two categories, namely “donors” and “recipients” should be identified with as much precision as possible to minimise an error;

– errors minimisation or placement of alternatives with the high range of possible ranks in the middle (centre) (fig. C.7, Appendix C) is being reached by the search of such aggregating perspective (MCDM method) which defines these two categories in the way they have the highest pseudo-objective robustness.
For simplicity sake, the error is counted with not original ranks, but with transformed ones allowing the shift from dichotomic “donors-recipients” division of alternatives into the one-pole division (lower left part of fig. 1.20). One-pole (flipped) division just places both opposite extreme alternatives into one side (pole) of the half-divided ranking.

1.3.3 Prerequisites for the optimisation of the Structural funds’ distribution

Nowadays, the distribution of Structural funds follows the rules taking their origin from the so-called “Berlin formula” (Wishlade, 1999) agreed in the Agenda 2000 in March 1999 in Berlin. This Berlin formula represents the allocation methodology answering to the question “How much redistribution is needed?”. It requires detailed economic calculations, which finally due to the newly released ECA (2019) became clearer and more transparent.

So far, Berlin methodology has not been substantially modified, only marginally concerning the weights and fixed initial average aid intensities. The basic structure of the Berlin methodology is presented in fig. 1.21 for the three types of regions funded from Structural funds (ERDF and ESF). The processes determining the amounts of funds allocated to the Member States is relatively complicated and depends on many factors. Further, the allocation methodology used for each category of regions is introduced.

Source: author and based on Regulation (EU) No 1303/2013
In fig. 1.21, the subjective elements are highlighted by a dotted line and by grey colour. Such subjectively defined items include: 1. demarcation threshold determining which region is less developed, transitive or more developed one; 2. GNI related coefficients used as the adjusting limits; GNI capping rate used as an additional limit but for the new member states. All these elements do not have any sound theoretical or mathematically rigorous reasoning and are subject to be substituted and tuned up by the optimisation models proposed in sub-chapter 2.4. Further, the elements of the presented distribution mechanism are revealed in detail.

The relative wealth expressed by GDP and GNI remains the criterion having the most significant effect on how much the Member States and regions receive, as EU Commission having examined alternative indicators considers GDP per capita the most neutral and reliable indicator, reflecting the needs and disparities of the regions and Member States (COM, 2014, p. 198). Other criteria are used in the allocation process, reflecting policy priorities, but these criteria have much less weight. Over previous programme periods, criteria relating to the labour market and education have been used; for the 2021-2027 period, the Commission proposes migration flows and greenhouse gas emissions as additional criteria.

MDR allocation mechanism is somewhat different from the one related to the LDR and TR. Meanwhile, the funds' allocation to the LDR remains for Cohesion Policy as a matter of the highest priority, other essential issues related (global competition in the knowledge-based economy, the shift towards the low carbon economy, educational problems, etc.) to the MDR with the average per capita aid intensity fixed at EUR 19.80. This category of regions is funded by paying attention to the range of indicators corresponding to the objectives of the Europe 2020 strategy (annexe VII, No 1303/2013): total regional population (25%), unemployment rate (20%), employment rate (20%), tertiary educational (12.5%), number of early leavers from education and training (12.5%), GDP (7.5%), population density (2.5%). Taking into account the variety of indicators and specific weights in this allocation method, MDR are going to be left out of our proposal.

The final level of financial resources for the LDR and TR is influenced by the main determinants, adjustment weights and additional factors:
1. the distance of regional GDP per capita in PPS from the average of the EU 27 determines the level of annual per capita aid intensity;
2. the weights based on the Gross National Income vary for countries with a GNI per capita of below 82% to 3.15%; between 82% and 99% to 2.70%; above 99% to 1.65%; however, coefficients were decreased for the 2020-2027 period to such as 2.8%, 1.3%, 0.9% correspondingly;
3. unemployment based premium differs from EUR1300 for LDR to EUR 1100 for TR; however, for the 2020-2027 period new premium factors were added, such as low level of education (25-64 years, greenhouse gas emission, migration);
4. capping rate gives the maximum level of transfer from the Funds to each Member State at 2.5% of the GDP of the Member State;
5. allocation to the TR are subject to the maximum intensity limitation at 40% cutting off share and minimum intensity as €18 per year and per head multiplied by the regional population (MDR method).

The allocation process with details for the latest period (2020-2027) is presented in fig. A.5 (Appendix A). Simply saying, the allocations for LDR are determined in three steps:
1. Measurement of a difference between the region’s GDP per capita and the EU average (the prosperity gap) multiplied by the population of the region.
2. Correction of a multiplied prosperity gap by the GNI related coefficients depending on the wealth of the Member State where the region is located. A poor region in a developing country, therefore, receives more than an equally poor region in more developed country.
3. Determination of additional premium relating to socio-economic and environmental factors: unemployment and youth unemployment specifically, educational attainment, greenhouse gas emissions and migration.

A more detailed description of the current allocation method of ESI, including cohesion CPF, can be found with the latest changes in ECA (2019) and COM (2018). Not saying that this methodology is perceived as a largely unpredictable and opaque mix of political and technical ingredients (Bachtler, Wishlade, 2004), a general reflection on it brings us to the following conclusion by pointing out the main drawbacks.

First of all, it is appeared to be a drawback in an essential degree of subjectivity in the determination of GNI weights or national caps; secondly, weights play the same role as the capping rate does, thus they are used interchangeably and replicate each other to some extent; thirdly, calculation methods for the LDR and TR seem to have the same base as GDP per capita,
but they are different due to the min and max limits defined basing on the LDR and MDR calculating methods. Additional attention to these points will be paid below.

The first indicator, the distance between GDP per capita and EU 27 average, appears to be a reasonable indicator, as this reacts automatically to increases of a region’s prosperity, leading then to a decline in allocated funds. The present scaling of the national prosperity coefficients is the main cause for a (politically desirable) unequal treatment of regions with a comparable prosperity level: regions in poorer Member States thus get higher transfers than regions with an identical GDP per capita in PPS which are located in richer Member States (Osterloh, 2009). Even though the precise choice of GNI coefficient has a potentially significant impact on outcomes, it is not specified whether national prosperity is measured in purchasing power parities or Euros; and it is also not clear whether the latest data should be used, or the same period for which regional GDP data is available (Bachtler, Wishlade, 2004). All in all, the question arises as to whether equally lagging LDR should be treated differently if they belong to different Member States with dissimilar prosperity. It appears that the elimination of GNI coefficients present in the allocation method could exclude the subjective differentiation between regions and provide fair conditions for all regions claiming for the SF support. It is possible only in a situation when the regional allocations are proportionally defined depending on regional needs reflecting regional welfare.

Similar discrimination is present within the allocation method for the TR. The dominance of the GDP indicator for the TR differs from the methodology used for LDR and depends in some way on the theoretical allocations for MDR. The usage of the same calculating method for both TR and LDR will simplify the procedure and again equitable and homogeneous way of the distribution based only on the GDP per capita.

As Breuss and Eller (2004) state, the exact optimal amount of EU involvement needed at each stage can be determined by neither theory nor empirics; so practical solutions will have to be worked out in agreement with these general principles that can follow a more political inspiration. Therefore, as a matter of fact, there is no economic way to establish the shares of the EU budget to be allocated to each category of regions. Moreover, the theoretical and empirical basis for determining the amount of money a country should spend on cohesion is very thin. Therefore, the decision, which depends on matching the recipients’ demands (level of disparities) and the donors’ willingness to pay, is challenging to make and the outcome has mostly been a
political decision. Eventually, it appears to be only logical that the bulk of the SF is spent in regions with a level of development (GDP/P) below the EU average.

Research (Bayoumi and Masson, 1995; Kandogan, 2000) shows that indeed, both power (votes) and regional needs seem to be an important determinant factor influencing the number of funds redistributed. In addition, the needs criterion is limited by the absorption capacity. To avoid creating major macroeconomic and institutional unbalances, the EU set up a capping rate for the total share of its aid to the GDP of 2.5 per cent.

Regarding the total budget of the EU, it has been capping at some 1 per cent of the total GDP of the EU. This deduction rate as well is not economically founded, and a further increase of this ceiling requires unanimous consent of all member states.

The analysis of the current allocation mechanism revealed two components relevant to explain the different levels of funds allocated to the Member States: first, the ceiling due to limited absorption capacity and second, the modified “Berlin formula” (Osterloh, 2009). Bachtler and Wishlade (2004) state that exactly the capping rate determines the allocation of new EU Member States containing a lot of LDR. The application of the bottom-up Berlin methodology turns out to be the functioning limit for more developed Member States containing much less LDR. Uniformity of ceilings or capping rates reached by the same calculating method as well could simplify Berlin methodology principles and ensure the equal treatment of both richer and poorer Member States.

The further simplification and improvements of the Berlin methodology are grounded on the mentioned above drawbacks. The simplification is going to be realised due to the introduction of optimisation models (sub-chapter 3.3) encompassing all suggested above changes. However, such subjectivity sources as 1. deduction rate to form SF form the EU Budget; 2. capping rate to receive SF / National capping rate; 3. regional demarcation threshold are left without specification and subject to fitting and finding the optimal values during simulation of different distribution strategies.

The improvements related to the suggested optimisation models (sec. 2.4.1, 2.4.2), will comply with the “rules of game” embodied into the parameters of the model. These rules limit the distribution possibilities and form an essential part of the model constraints. The set of rules in a simplified way can be described by three “policy” parameters, establishing:

1. $\alpha$ – deduction rate or “how much (maximum) will be taken away?”,
2. $\beta$ – capping or absorption rate “how much (maximum) will be given?”;
3. $\gamma$ – demarcation threshold or “who will be a donor or recipient?”.

All parameters limit the amount of funds but in a different way. Firstly, potential payments from any region are restricted by alpha. Secondly, the number of donors is defined by parameter gamma and in the final turn beta parameter cuts the incoming amount of funds to the recipients. One should notice that only two parameters cut of the amount of funds for the redistribution and they are alpha and gamma. Beta in its turn makes only a ceiling for the allocations extracted from already formed funds.

When the gamma is taken into account, all regions according to the gamma level are divided into two groups: donors donating and forming the SF and recipients only able to receive the aid. It means that regions eligible for funds according to the gamma threshold do not contribute to the SF. Consequently, the higher gamma as a threshold for the recipient status, the fewer regions left to be donors and fewer funds can be gathered and redistributed. When gamma is not considered in the model, all regions are not pre-classified, and genuine recipients are defined as the least developed regions. The funds allocated to these regions can decrease the variance of GDP per capita most efficiently, and the main priority here is the diminishing of the variance of GDP per capita, making the regional level more equal. There are no regions blocked by high gamma criterion and region can play any role freely depending on its relative economic status. Namely, this set of distributional rules can provide the most effective distribution, but it does not have the precise nominal differentiation between donors and recipients as made in the current practice.

Saying in another way, in the first case with defined gamma, the set of regions will be strictly cut for the donors and recipients with optimised aids in the scope of contributions shaped under the lead of alpha and gamma. The second case without gamma has the greater ceteris paribus optimised amount of deductions and therefore, allocations. Graphically all essential parts of the redistribution foundation necessary for the development (in sub-chapter 2.4) of optimisation models are presented in fig. 1.22.
In the 2.4 sub-chapter, three optimisation models with all necessary theoretical argumentations will be presented in detail. All of them will address the discussed shortcomings. The models will differ according to the basic idea underlying the distribution. The first min-variance model (sec. 2.4.1) as the pure improvement of presented Berlin formula. The second model (sec. 2.4.2) is the extension of the first one but allowing the incorporation of the measurement results obtained from the MCDM methods. The third model will go further and suggest the solution to the free-rider problem of lagging regions (sec. 2.4.3).

**Conclusions to chapter 1**

During the analysis of the literature devoted to the application of quantitative methods in the Cohesion policy field, the following the most essential gaps were discovered: 1. effectiveness in contrast to an efficiency is not taken into account; 2. interaction and synergies between criteria describing regional performance are not measured; 3. there are no effective combination of methods and techniques which would widen analytical picture; 4. hierarchical levels such as NUTS 1 and NUTS 2 are not considered together; 5. no comparison of compromise MCDM methods concerning their ranking or clustering power; 6. no approach to select the most suitable MCDM method for the posterior funds' distribution considering the robustness of ranks; 7. no objective verifying approach to choose the best clustering method for the regional classification; 8. no alternative points of view on SF distribution considering different conceptual and
methodological approaches; 9. finally, no systemic view on the decision-making process sequentially and coherently solving all problems underlying the distribution of funds. All these gaps formed the grounded platform for the new original contribution made in this research.

The analysis of the current ESI distribution mechanism (sub-chapter 1.2) highlighted the two main controls explaining the different amount of funds allocated to the Member States. The first one is the absorption capacity or capping rate and the second one – the “Berlin formula”. The capping rate determines the allocation of new EU Member States containing a lot of LDR. From the opposite side, the Berlin formula limits allocation to more developed Member States containing much less LDR. In addition, it was found that equally poor regions belonging to different member states are treated eventually differently because of their national affiliation. Overall, three primary sources of subjectivity are defined: 1. deduction rate to form SF form the EU Budget; 2. capping rate to receive SF / National capping rate; 3. regional classification threshold. The simplification and improvement distribution of SF, as the most significant part (60 %) of ESI is going to be realised due to the introduction of optimisation models (sub-chapter 3.3) encompassing all suggested above drawbacks.

In the sub-chapter 1.3, the essential assumptions and principles of the IMC approach were put forward and discussed. The first part of objectivity related assumptions such as epistemological subjectivity and “objective” reality to describe” identifies the selection problem and its pseudo-objective plane (benchmarking). Within this plane, the following pragmatic block of assumptions consisting of the pre-selected methods’ exhaustiveness, unanimity of results and pragmatic assumption allows the analysis of the method’s robustness and then choice the most suitable one. The correctly solved problems guarantee the appropriate application of the suggested IMC approach, which results heavily depend on the cautiously selected MCDM methods. Thus, the third set of operational assumptions includes context relevancy, unsupervised objectivity, and sequential consistency. All sets of assumptions are responsible for the coordinated application of all selected methods and models together realising the function of one IMC approach.
2. METHODOLOGICAL FOUNDATION OF THE INTERRELATED MULTI-CRITERIA APPROACH

In this chapter, the methodological platform of the current research is presented. The chapter provides for the discussion the existent in the literature objective MCDM methods (sub-chapter 2.1) and developed measurement methods (sub-chapter 2.2), selection approaches (sub-chapter 2.3) and optimisation models (sub-chapter 2.4) necessary for the solution of the range of methodological problems underlying the distribution of SF. The main attention has fallen on such problems, as measurement and classification of regional performance intertwined with optimisation and methods’ selection.

2.1 Basic multi-criteria decision-making methods applicable to regional performance measurement

This sub-chapter introduces the variety of the multi-criteria decision-making methods applicable to the solution of measurement problems within the context of Cohesion policy. Reviewed methods are divided into existent methods that are considered as appropriate ones (because of their minimum subjectivity) for this context and developed in sub-chapter 2.1.5 methods and measurement approaches. The latter ones are elaborated based on the defined in the literature gaps and disadvantages of the existent methods. Together they present a rational methodological ensemble of methods and approaches covering different aspects of regional performance measurement.

2.1.1 Brief review and classification of the existent and developed methods

Classification of MCDM methods can be made in different ways (Hwang and Yoon 1981; Larichev 2000; Figueira et al. 2005). For instance, Belton and Stewart (2002) offered the following classification of MCDM methods: 1) value measurement models; 2) goal, aspiration, and reference level models; 3) outranking models (the French school). That is why Multi-Attribute Utility Theory (MAUT) based MCDM methods, which are intended to have total objectivity as an ideal, are the main course of application. In this research within the proposed working classification, plausible MCDM methods are classified into five groups presented in fig. 2.1. Compiling the set of methods to be explored, the objectivity requirement was considered. It
serves as a significant sorting barrier accepting methods with minimum subjectivity level. Therefore, all methods, as well as weights determination, is expected to be as much data-driven as possible, leaving the DM suspended and minimally involved. It explains why some famous enough methods that as AHP, ANP, DEMATEL, COPRAS-G, WINGS are left aside.

fig. 2.1: Working classification of MCDM methods

All methods presented are classified by pointed characteristics and highlighted groups according to which the methods will be presented below.

The first group of non-weighted methods includes two of them, which are contradictory by their nature. The DP2 method does not use weights directly but counts the standard deviation of the criteria. At the same time, reduces non-unique variance by excluding some redundant criteria. Eventually, it uses all valuable information provided by partial indicators, meantime eliminating redundant variance and leaving just the unique one. Simple additive weighting sum (SAW), in particular, affiliating to this group, and its derivative with equal weights or average weighting (AV) on the contrary pay attention to all of the criteria treating them equally with the same weights. In this case, some criteria can be redundant, and any of them are less important.

Second compromise distance-based group of the methods has such a distinctive feature as the compromise between strength and weaknesses of the alternatives. Every method included in this group has its aggregating function allowing it to blind all criteria in its specific way, counting regret factor differently.
The third fuzzy group is one, which allows flexibility in consideration of weights. The weights can be changed according to the stated by DM optimistic condition (expressed by linguistic quantifiers) conditions or by the identified in data or DM preference synergies of criteria. The last ones allow counting indicators much more extensively and in connection to each other, while all other methods count criteria only in separate ways assuming preferential independence, which is often not the case and therefore leads to a false violated aggregation.

Fourth ratio-based group reveals new perspectives of measurement encompassing broader characteristics of the performance presented by ratios, neglecting the absolute scale of measurement and focusing only on relative features, The last ones eventually allow to measure efficiency or effectiveness of the performance, as they are by nature the sophisticated relative features.

The last fifth group of methods plays the role of aiding the source of methodological elements needed for the newly made hybrid methods. These methods, due to their subjectivity based on the thresholds and preference functions to be established by the DM. In some cases, these additional methodological features can serve a great benefit; however, in the research, it only produces a new subjectivity, which is assumed to be avoided.

The higher degree of their feasibility and usability in the research is highlighted by grey colour. Highlighted by grey MCDM methods are those that are applied in the current research and have been explored to determine the most suitable from them. These grey methods are of particular practical interest. Almost all of them are referred to a bigger MAUT group except for Data Envelopment Analysis, which is classified as a non-parametric linear programming methodology to measure the efficiency of multiple decision-making units (DMUs). Even though this methodology does not have such features of subjectivity as preference functions and thresholds, so from first glance, it seems to be satisfying preliminary objectivity conditions. Meantime, how the weights are determined under the optimality search is not quite acceptable in Cohesion Policy practice. Weights are assigned purposely to maximise efficiency but not in a data-driven fashion. This way of weight determination seems to be not realistic and applicable in the context of further funds’ distribution problem. Therefore, it will be excluded from the panel of MCDM methods, which will be analysed to choose the most suitable MCDM method. Nevertheless, DEA will be applied within the frame of the proposed resonance approach to the measurement of an intensive aspect of regional performance.
As for the other methods belonging to the outranking group, they encompass a certain level of subjectivity embodied into the thresholds and preference function. Therefore, they are not going to be included in the panel of compared MCDM methods as well. However, some elements of ELECTRE and PROMETHEE methods will serve as a source for the further methodological hybridisation of compromise MCDM methods. The other methods, namely OWA (ordered weighting average), SAW (simple additive weighted sum) and Equal weights are used to a full extent, but just for the method’s profile construction. It will be used for the analysis of the relative properties and behaviour of MCDM methods.

2.1.2 Methods dealing with dependency/independency of criteria

This sub-chapter having presented the proto MCDM method called Simple Additive Weighting method (SAW), further gives the panel of methods which are combined by their ability to deal with uncertainty in weights of criteria (Ordered Weighted Average), the interaction between criteria (Choquet integral) and a correlation between criteria (DP-2). All of them have their advantages and restrictions narrowing their application to a specific problem. Some of the disadvantages and limitations will be overcome by the proposed approaches and improvements suiting original methods for the specific Cohesion Policy needs (sub-chapter 2.2).

2.1.2.1 Simple Additive Weighting method as a classic framework for independent criteria

Before we introduce any suitable aggregating operators considered as more advanced and featured explicitly for the particular problem, let us introduces the Multi-Attribute Utility Theory (MAUT) (Keeney, Raiffa, 1993). This multi-criteria platform is the most suitable to start. The most widely used method so far in MCDM is the Simple Additive Weighting method (SAW) (Fishburn, 1977) or Weighted Arithmetic Mean (WAM). The description of the multiple criteria problem starts from the following conditions: 1. the finite set of alternatives (regions) \( A = \{a_1,a_2,\ldots,a_m\} \); 2. finite set of criteria or attributes \( C = \{c_1,c_2,\ldots,c_n\} \) describing the \( A \); as a result each \( a_i \) is described by a performance matrix or profile \( X = \{x_i^k, x_i^2,\ldots,x_i^n\} \in \mathbb{R}^q \), where \( x_i^k \) – is a partial score of alternative \( a_k \) related to \( i \)-th criterion for all \( i = 1\ldots q \) with \( x_i^k \in X_i \subseteq \mathbb{R} \), while the same linear transformation is applied to \( X \), or the same interval scale is typical.
The aim of multi-attributive theory (MAUT) is to model the preference of the DM, which is given by a binary relation \( \geq \) on \( X \) with the help of utility function \( U \) mapping \( X \rightarrow \mathbb{R} \), such that if \( x \geq y \Rightarrow U(x) \geq U(y) \) \( \forall x, y \in X \).

To each alternative’s profile, a global score or a rank can be associated due to the application of an aggregation operator \( F \) based on utility function \( U \) in the form of a more general transitive decomposable model (Krantz et al., 1971; Bouyssou, Pirlot, 2004):

\[
U^k(x^k) := F(u_1(x_1^k), u_1(x_1^k), \ldots, u_n(x_n^k)),
\]

where \( u_i(x_i^k) : X^k \rightarrow R \) is a utility function;

\( F : R^q \rightarrow R \) is a no decreasing aggregation operator.

The form of utility function depends on the conditions (relations between criteria) used for the multi-attributive decision-making problem. In the case of independent criteria or mutual preferential independence assumption (Vincke, 1992), the additive function is appropriate what invokes WAM:

\[
WAM^k(x_1^k, x_1^k, \ldots, x_n^k) = \sum_{i=1}^{n} x_i^k \times w_i \rightarrow \max.
\]

Verbally, a utility value can be perceived as a representation of decision maker’s preferences over alternatives, with one preferred to another if and only if its expected utility is greater. The best alternative \( a^* \) is defined as:

\[
a^* = \left\{ U_k(x) \mid \max_k U_k(x) \right\}.
\]

The linear additive function correctly integrates the preferences of DM into a total utility value only when the independence assumptions (Keeney, Raiffa, 1993) are being met. Therefore, now the most intuitive framework easy dealing with multiple criteria problems:

\[
U_k = \sum_{j=1}^{n} w_j r_{kj}(x),
\]

where \( U_k \) – the utility of the \( k \)-th alternative and w.r.t. \( j \)-th criterion;

\( w_j \) – weight of \( j \)-th \( (j = 1, \ldots, n) \) criteria under the condition of \( \sum_{j=1}^{n} w_j = 1 \);

\( r_{kj}(x) \) – the normalised value of actual value \( x \), in terms of the \( k \)-th alternative \((k = 1, \ldots, m)\) and \( j \)-th criterion \((j = 1, \ldots, n)\).
However, the independence axiom is rarely holding and verified in practice. Usually, researchers simply assume it, what eventually distorts the modelled picture of the reality. Grabisch, M. and Labreuche, C. (2005) noticed that some interactions between criteria (as favour high scores; focus on weak points) are not possible to be captured by SAW method, however, they can be handled by a weighted sum on the ordered list of scores in increasing order (the ordered weighted average – OWA; while such interactions as to eliminate alternative if criterion 3 is not well satisfied or if criteria 1 and 2 are satisfied, do not overestimate their importance, etc. are not treated, neither by the weighted sum nor by an OWA (Grabisch, Labreuche, 2005). It requires a more extended and developed operator called Choquet. These two more powerful operators will be presented below.

The weights or importance of indicators is the crucial step in applying any MCDM methods. One should mention that there is a wide variety of methods to define the weights of criteria. However, being guided by the principle of maximum objectivity, it was decided to choose the Entropy method, which produces the weights without the intrusion of a DM.

In this research, the priority is given to the objective method of weights determination called Entropy method (Zanakis et al., 1998) which will be applied for the all MCDM methods in the following way:

step 1: normalise an initial data matrix $X_y$:

$$p_y = x_y / \sum_{i=1}^{n} x_y, \text{ for } j \in M,$$

where $x_{ij}$ – $j$-th attribute of the $i^{th}$ region, $i = 1, 2, \ldots, m$ (number of regions).

step 2: calculate the Entropy ($E_j$) of $j^{th}$ criterion:

$$E_y = -1 / \ln(N) \times \sum_{i=1}^{n} p_y \ln(p_y), \text{ for } j \in M,$$

step 3: determine the weight ($w_j$) of $j^{th}$ criterion:

$$w_j = (1 - E_j) / \sum_{j=1}^{M} (1 - E_j), \text{ for } j \in M.$$

According to this method, for instance, if the values of particular criteria are relatively similar for a set of given alternatives, their entropy will be higher, and therefore the importance of such a criterion is smaller. This is the case when a criterion is recommended to be dropped because of low relevance. In the opposite case, highly varying values provide low entropy and
correspondingly higher weights. This method is sound for the situations with a relatively big data sample and when the experts are not able to establish the importance of criteria.

2.1.2.2 Ordered Weighted Average Operator dealing with different optimistic degree assuming uncertainty of criteria weights

The OWA operator (Yager, 1988) provides a parameterised family of aggregation operators between the minimum and the maximum, which have been used in many applications. The weights of criteria are determined by the operator for an alternative depending on the performance of that alternative relative to others. Thus, as opposed to weighted sum aggregation, the weight of a criterion depends on the nature of the criterion.

The principal interest to this operator lies in the fact that it can express vague quantifiers, as: “at least some criteria are met” or “at least one” (corresponds to a disjunctive or \textit{max} behaviour). It is worth noticing that OWA incorporates many basic functions, such as:
- the "Max" function, with weight vector $W = (0,0, \ldots, 1)$;
- the "Min" function, with weight vector $W = (1, \ldots, 0, 0)$;
- the «average» or arithmetic mean, over the $n$ criterions, with weight vector $W = (1/n, \ldots, 1/n)$.

It is the only thing shared with OWA, however, these two operators can be considered as orthogonal in terms of intuitive understanding.

Numerous instances from above originate from the field of fuzzy logic. The operator can be defined as follows. An OWA operator of dimension $n$ is a mapping OWA: $R^n \rightarrow R$ that has an associated weighting vector $W$ of dimension $n$ having the properties:

(1) $w_j \in [0,1]$; (2) $\sum_{j=1}^{n} w_j = 1$, such that

$$OWA_W(b_1,b_2,\ldots,b_n) = \sum_{j=1}^{n} w_j b_{(j)},$$

where $W = (w_1,w_2,\ldots,w_n)$ is a weight vector satisfying property 1 and 2 for all $j$;

$(b_{(1)},b_{(2)},\ldots,b_{(n)})$ is the vector of scores rearranged in no decreasing order;

notation $(B)$ refers to the permutation of indices $B = (b_1,b_2,\ldots,b_n)$, satisfying $b_{(1)} \leq b_{(2)} \ldots \leq b_{(n)}$.

One should keep in mind that $w_j$ is the order weight of weight on the rank of scores, so it differs from the weight on criteria. The order of weights is, in fact, the function of DM’s risk.
attitude. The most frequently used method for the order weights determination is the one proposed by Yager (1993, 1996) which based on linguistic quantifiers (Zadeh, 1983) $Q(\frac{i}{n})$:

$$w_j = Q(\frac{i}{n}) - Q(\frac{i-1}{n}), i = 1, \ldots, n \text{ while } Q(0) = 0$$ (2.9)

where $n$ - is the number of criteria.

This quantifier, facilitating the conversion from the natural language form, such as “a few”, “most” etc. to a mathematical one, serves as an interpreter for the policy-makers following different risk strategies (correspondingly risk lover or risk-averse).

Order weights are influenced by the “optimistic degree” or Orness degree ($\theta$) given by the DM, which in term depends on the “optimism” coefficient ($\alpha$) (Yager, 1996). To measure “optimistic degree” ($\theta$) the following formula is used (Yager, 1988):

$$\theta = \frac{1}{n-1} \sum_{i=1}^{n} (n-i) \times w_j, \text{ while } 0 \leq \theta \leq 1$$ (2.10)

$$w_j = (\frac{i}{n})^\alpha - Q(\frac{i-1}{n})^\alpha, i = 1, \ldots, n.$$ (2.11)

If the Orness degree ($\theta$) is equal 1, the optimism position of the DM is at maximum indication the highest level of risk due to the favouring exclusively strengths; the value 0 points at the opposite priority with weaknesses considered. The neutral position ($\theta =0.5$) implies both strengths and weaknesses considered. Theoretical and practical evidence of presented relations between Orness and priorities can be found in (Bodily, 1985; Mellers and Chang, 1994).

Zarghami M. and Szidarovszky F. (2008) proposed their vision of relations between linguistic quantifiers, optimistic conditions, optimism coefficient and Orness degree (fig. 2.1). table 2.1: Different optimistic degrees within OWA

<table>
<thead>
<tr>
<th>Linguistic quantifiers</th>
<th>Optimistic coefficient ($\alpha$)</th>
<th>Optimism degree ($\theta$)</th>
<th>Optimistic condition</th>
</tr>
</thead>
<tbody>
<tr>
<td>At least one</td>
<td>$\alpha \rightarrow 0.0, (\alpha = 0.01)$</td>
<td>0.999</td>
<td>Very optimistic</td>
</tr>
<tr>
<td>At least a few</td>
<td>0.10</td>
<td>0.909</td>
<td>Optimistic</td>
</tr>
<tr>
<td>A few</td>
<td>0.50</td>
<td>0.667</td>
<td>Fairly optimistic</td>
</tr>
<tr>
<td>Half</td>
<td>1.00</td>
<td>0.500</td>
<td>Neutral</td>
</tr>
<tr>
<td>Most</td>
<td>2.00</td>
<td>0.333</td>
<td>Fairly pessimistic</td>
</tr>
<tr>
<td>Almost all</td>
<td>10.00</td>
<td>0.091</td>
<td>Pessimistic</td>
</tr>
<tr>
<td>All</td>
<td>$\alpha \rightarrow \infty$</td>
<td>0.001</td>
<td>Very pessimistic</td>
</tr>
</tbody>
</table>


Note that different properties can be studied such as the distinction between descending and ascending orders, different measures for characterising the weighting vector and different
families of OWA operators. From a generalised view of the reordering step, it is possible to
differentiate between the descendent OWA (DOWA) operator and the ascending OWA (AOWA)
operator. Note that the weights of these two operators are related by \( w_j = w^*_{n-j+1} \), where \( w_j \) is
the \( j \)-th weight of the DOWA and \( w^*_{n-j+1} \) is the \( j \)-th weight of the AOWA operator.

It is worth noticing that OWA incorporates many basic functions, such as Max, Min, etc.
and all they depend on Orness degree:
- if the DM has an optimistic view, then larger weights will be assigned to the first ranks in the
OWA operator, and therefore the alternative will have a larger value: the «Max» function, with
weight vector \( W = (0,0,...,1) \);
- a pessimistic DM acts inversely: the «Min» function, with weight vector \( W = (1,...,0,0) \);
- other neutral attitude favours neither weaknesses not strengths: the «simple average» or
arithmetic mean, over the \( n \) criterions, with weight vector \( W = (1/n,...,1/n) \):

\[
F_B(b_1,b_2,\ldots,b_n) = \frac{1}{n} \sum_{j=1}^{n} b_j.
\]  

(2.12)

It is the only thing shared with OWA; however, these two operators can be considered as
orthogonal in terms of intuitive understanding.

One should note that OWA is commutative, monotonic, bounded and idempotent. For
further properties and applications on the OWA operator, see (Beliakov, 2007; Yager, Kacprzyk,
1997; Wei, 2010; Zhou, Chen, 2010). Surely, OWA has its drawbacks. On the one hand, large
families do not possess all desirable properties (e.g. quasi-arithmetic means are not stable under
positive linear transformation), and on the other hand, small families seem to be too restrictive
(arithmetic sums, OWA, etc.) (Grabisch, 1996). OWA operator is not able to model the
interaction between criteria, such as mutual reinforcing in case of positive synergy and
weakening in case of negative synergy. While this interaction is out of consideration,
correspondingly under- and overestimation are unavoidable. That is why the next method to be
introduced is the fuzzy integral, which constitutes a new large family of aggregation operators,
without mentioned drawbacks.

2.1.2.3 Choquet integral counting synergy interaction effects between criteria

A suitable operator, which generalises WAM and OWA, is a discrete Choquet integral.
Proposed in capacity theory (Choquet, 1953), the concept of Choquet integral has been
considered and applied in many various contexts. To explain the essence of this method, the concept of fuzzy measures has to be introduced.

A fuzzy measure or capacity on $N$ is a mapping $\mu : 2^N \rightarrow [0,1]$, which satisfies the following conditions:
- $\mu(\emptyset) = 0$ and $\mu(N) = 1$;
- for any $S, T \subseteq C$, $S \subseteq T \Rightarrow \mu(S) \leq \mu(T)$ (monotonicity);
- additive if $S, T \subseteq C$, $S \subseteq T \Rightarrow \mu(S \cup T) = \mu(S) + \mu(T)$ for all disjoint subsets $S, T$.

where $\mu(S)$ can be interpreted as the weight or importance of $S$, while $S$ is a criteria subset of initial criteria $C$.

Monotonicity of fuzzy measure means that the weight of the criteria subset cannot decrease if new criteria are being added.

It is evident that for the criteria interaction modelling not only the importance of criteria must be taken into account, but also the importance of each subset of criteria. For this purpose, it has been proposed to substitute a monotone set function on $C$, called capacity (Choquet, 1953) or fuzzy measure (Sugeno, 1974), to the weight vector involved in the calculation of weighted sums. In other words, using a capacity (fuzzy measures) makes possible modelling of criteria subsets importance. This, at the same time, allows doing naturally an extension of WAM to the Choquet integral. According to (Grabisch, Kojadinovic, Meyer, 2008) capacities can be regarded as generalisations of weighting vectors involved in the calculation of weighted sums.

Following (Grabisch, 1995) and (Marichal, 2000), Choquet integral is viewed here as an $n$-variable aggregation function with a function-like notation instead of the usual integral form.

The discrete Choquet integral of a function $x : C \rightarrow \mathbb{R}$ concerning $\mu$ is defined by:

$$C^\mu(x^k) = \sum_{i=1}^{n} (x^k_i - x^k_{i-1}) \times \mu(A_{(i)})$$

where $x^k = (x^k_1, \ldots, x^k_n)$ is a profile of commensurate partial scores of alternative $a_k$ with regard to $n$ criteria;

$(\cdot)$ is the subscript pointing at the permutation of indices $i = 1, \ldots, n$ such as $x^k$ is sorted in ascending order $x^k_{(1)} \leq x^k_{(2)} \leq \ldots \leq x^k_{(n)}$;

$A_{(i)}$ is a subset of $C$ such as $A_{(i)} = \{c_{(i)}, \ldots, c_{(n)}\} \subseteq C$. 

80
Choquet collapses into the weighted arithmetic mean (discrete Lebesque integral) if the fuzzy measure $\mu$ is additive, that is $\mu(S \cup T) = \mu(S) + \mu(T)$, when $S \cap T = \emptyset$ (Marichal, 2000). For the better differentiation and understanding of intuition of both integrals, their graphical interpretation is given in fig. 2.2.

**fig. 2.2:** Graphical representation of aggregating integrals

![Graphical representation of aggregating integrals](image)

*Source: author*

From the left part of the figure, we see that SAW aggregates areas formed by multiplication of the criteria value on its weights, meantime the Choquet integral builds aggregated areas differently considering the importance of criteria coalitions. For instance, the lowest area represents the coalitions of all criteria.

Having the following:
- the monotonic fuzzy measures are, $\mu(A_{(1)})$, $\ldots$, $\mu(A_{(2)})$, $\mu(A_{(n-1)})$, $\mu(A_{(n)})$.
- the 1st rectangular area $x_{(1)} \cdot \mu(A_{(1)}) = x_{(1)} \cdot \mu([x_1, x_2, \ldots, x_{n-1}, x_n])$;
- the 2nd rectangular area $(x_{(2)} - x_{(1)}) \cdot \mu(A_{(2)}) = (x_{(2)} - x_{(1)}) \cdot \mu([x_2, \ldots, x_{n-1}, x_n])$;
- the 3rd rectangular area $(x_{(n-1)} - x_{(n-2)}) \cdot \mu(A_{(n-1)}) = (x_{(n-1)} - x_{(n-2)}) \cdot \mu([x_{n-1}, x_n])$;
- the 4th rectangular area $(x_{(n)} - x_{(n-1)}) \cdot \mu(A_{(n)}) = (x_{(n)} - x_{(n-1)}) \cdot \mu([x_n])$.

The Choquet integral or the sum of all areas would be defined as follows:
\begin{align*}
(c) \int f d\mu &= \sum_{i=1}^{n} (x_{i} - x_{(i-1)}) \cdot \mu(A_{i}) = x_{(1)} \cdot \mu(A_{(1)}) + (x_{(2)} - x_{(1)}) \cdot \mu(A_{(2)}) + \\
&\quad + (x_{(n-1)} - x_{(n-2)}) \cdot \mu(A_{(n-1)}) + (x_{(n)} - x_{(n-1)}) \cdot \mu(A_{(n)}) 
\end{align*}

The Choquet integral has been well-researched in the context of MCDA due to its ability to account for any form of criteria interaction (Marichal, Roubens, 2000), of which there are three distinct types: correlation, substitutiveness / complementarity, and preferential dependence (Marichal, 2000).

From the example in fig. B.1 (Appendix B) we see that two first pairs of criteria create a negative effect, however, the third pair of human resources (HRST) and unemployment (UN) gives the positive effect, as their correlation is almost equal to 0. A high positive correlation says that the criteria are just redundant to each other. Eventually, it is evident that the weight of coalition is greater than the additive sum of criteria: \( \mu(UN \cup HRST) > \mu(HRST) + \mu(UN) \) or numerically, respectively \((3.14 + 57) > 57\). To implement the Choquet method, it is necessary to develop the fuzzy identification method for the transformation of the correlation between criteria into the fuzzy measures of criteria combinations.

2.1.2.4 DP-2 method processing redundancy and complementarities in criteria set

The DP-2 method proposed by Pena (1977) is a synthetic indicator, which is widely used to measure the quality of life on the level of countries. It is designed to make inter-spatial and inter-temporary comparisons. In addition to this, it can filter duplicity of information, which makes it particularly valuable compare to other similar multi-dimensional methods. Importance of the DP-2 method’s capability to escape duplicity of information in regional studies is proved by the presence of articles where the methods were used for the measurement of life quality or social well-being (Somarriba, Pena, 2009; Zarzosa, Somarriba, 2013), social and economic regional development (Martín, Molina, Fernández, 2012), regional performance and development (Sánchez-Domínguez, Ruiz-Martos, 2012, 2014) have been measured.

The DP-2 method in its nature is not “exclusive” as the PCA method, but “exhaustive” meaning that it uses all valuable information provided by partial indicators, meantime eliminating redundant variance due to the consideration correlation between indicators. The only objective limitation of this method is its time-consuming usage as its algorithm is iterative. This is explained by its nature motivating to include as many as possible indicators, which is entirely benevolent for the final result, which will get a higher degree of exhaustiveness in this case.
The general final form of DP-2 index is the following:

\[
DP_{2(i)} = \sum_{i=1}^{n} \left\{ \frac{d_i}{\sigma_i} \left(1 - R_{i-1,...,1}^2 \right) \right\}, \quad \text{while } d_i = |x_{ij} - x_{ij}^*| \tag{2.15}
\]

where \( x_{ij} \) – is the value of the variable (indicator) \( x \) describing the \( i \)-th attribute of \( j \)-th alternative for \( i = 1, \ldots, n \) and \( j = 1, \ldots, m \);

\( x_{ij}^* \) – is the etalon value of the variable (indicator) \( x \) describing \( i \)-th attribute of the actual or fictitious alternative serving as a reference base \( X_* = (x_{1*}, \ldots, x_{n*}) \);

\( \sigma_i \) – the standard deviation of \( i \)-th variable;

\( R_{i-1,...,1}^2 \) – the coefficient of determination in the regression of \( X_i \) over \( X_{i-1}, X_{i-2}, \ldots, X_1 \).

There are three methodological elements, which are worth further discussion. First, the presence of a corrective mechanism \((1 - R_{i-1,...,1}^2)\) makes this method stand out from all other similar aggregating indices. Due to this part index retains the new information contributed by \( i \)-th variable and neglects its redundant part. Then with the help of \( d_i / \sigma_i \) the new bit of information is weighted and multiplied by the difference in target achievement.

Concerning the weighting of included variables (attributes), the problem is solved by multiplying the difference \( d_i \) between actual and fictitious values by an inversed standard deviation \( 1/\sigma_i \) of the corresponding variable. The logic applied here is the higher the difference, the lower weight of the variable will be. This seems to be controversial, as high standard deviation can also point at the variable of a specific interest that is hard to control and necessary to improve. Thus, this inverse weighting scheme leaves space for further considerations and perhaps rises the necessity to justify such logic if the method is due to be applied.

The last point to discuss relates to the correction mechanism springing from Pearson’s correlation. This concept while being widely used and practically useful remains the limitation itself, as all possible non-linear relationships between variables that are not under the jurisdiction of Pearson’s’ correlation are left beyond the analysis and cannot be processed by this index.

The index does not end at this point, as other additional and enriching sub-functions of it are proposed. Thus, to analyse discriminant power of each variable on the final index discrimination coefficient \( DC_i \) is used with the help of Gini index \( G \) :
\[ DC_i = 2 \frac{n}{(n-1)} G_i. \]  

This coefficient ranges between 0 and 2, while extreme values mean 0 and maximum discriminating power pointing at how different \( i \)-th variable across all alternatives.

Thereinafter the procedure of evaluating DP-2 index is presented repetitively by the following stages:

1. the departing point is the formation of a matrix \( X=(x_{ij},\ldots,x_{im}) \) describing \( i = 1,\ldots,n \) conditions of \( j = 1,\ldots,m \) alternatives. If included indicators are negatively related to the meaning of the whole synthetic index, their sign is changed into the opposed.

2. the reference base \( X_*=(x_{1*},\ldots,x_{n*}) \) calibration assuming either creating or changing any already existent standard. A reference value for each variable must follow the same logic of comparison, such as \( \geq, \leq, \min, \max \) of values observed in the sample. For example, if region development is measured, the reference base will be presented as min theoretical values presenting the worst scenario of regional performance. Cost indicators are required to be multiplied by -1.

3. distance matrix \( D_j=(d_{ij},\ldots,d_{mj}) \) calculation, where \( d_{ij}=|x_{ij}-x_{i*}| \) is the difference between actual values of the \( j \)-th region and values belonging to the reference base.

4. Measurement of the first preliminary composite index which is called Frechet index:

\[ DF_j = \sum_{j=1}^{m} \frac{d_{ij}}{\sigma_i} \text{ for all } j = 1,\ldots,m. \]  

One should understand that the contribution of each distanced variable is strictly proportional to the standard deviation of the variable. Besides, such ration implies that Frechet index is measured in abstract units; however, it is nor free of duplicated information unless all variables are not correlated. Because of this dependence effect, the forthcoming steps are devoted to the correction mechanism leading to a solution to this problem.

5. Calculating the Pearson’s correlation \( r_i^n (DF^n;X_i) \) between the obtained Frechet index and included variables.

6. Making a descending ranking of the correlations measured in the previous stage \( ranking^{r^n} (r_i^n (DF^n;X_i)) \).

7. Getting the first, second, third, etc. order DP-2 index based on the including variables according to the order (ranking) obtained in the previous stage. For example, according to the
ranking, the indicator taking the first position will contribute all its information \((d_{ij}/\sigma_i)\cdot 1\) to the synthetic index, as the \((1-R^2_i)=1\). The second indicator will be included just partly \((d_{ij}/\sigma_j)\cdot (1-R^2_{z,i})\), multiplier \((1-R^2_{z,i})<1\) saying that first and second indicators are not complete correlated. Similarly, the third multiplier is \((1-R^2_{z,2,i})<(1-R^2_{z,1,i})<1\), pointing at even smaller active part of the third indicator in a synthetic index. The dimension of the whole vector of correction multipliers \(\{1-R^2_{z,1,i}\};\{1-R^2_{z,2,i}\};\ldots;\{1-R^2_{z,n-1,i}\}\) is relative to the dimension of vector of attributes (indicators, variables) considered, such as \(i = 1,\ldots, n\). The vector of DP-2 index formed by the conduction of all necessary iterations is the following \(DF = \{DF^1;DF^2;\ldots;DF^{(n-1)};DF^{(n-th)}\}\).

8. Stabilisation of iterations. It happens when the ranking obtained on \(\text{ranking}^{(n-th)}(t_i^{(n-th)};DF^{(n-th)};X_i)) = \text{ranking}^{(n-1)th}(t_i^{(n-1)th}(DF^{(n-1)-th};X_i))\) \(n\)-th iteration does not differentiate from the order at \((n-1)\)-th iteration, so there is no need to continue.

9. Final converged \(n\)-th order DP-2 index obtainment.

The example in fig. B.2 (Appendix B) shows that according to the DP-2 method, just 84\% of unemployment is considered in measurement, while another part of the criterion already contains in the GDP as duplicated. Being very informative in terms of unique information and methodologically rich about an excellent filtering ability to decrease the redundancy this method remains as an improved version of the SAW method, as it is not able to consider the interaction between criteria and cannot follow particular compromise aggregation strategy. The last can be managed by compromise distance-based based methods presented in the following subsection.

### 2.1.3 Distance-based methods suitable for a compromise solution with different risk attitude

Below we describe three basic methods stressing out their peculiarities and disadvantages, which will be eliminated due to the introducing of outranking elements in section 2.2.1. All presented MCDM methods are based on the distance function but with specific differences in the perception of the ideal point, which creates the range of different evaluating strategies. The application of the TOPSIS and VIKOR methods helps in the resolution of a conflict. The compromise solution is based on the negotiation leading to an agreement established by mutual concessions. The TOPSIS method is based on the principle that the optimal point is expected to
have the shortest distance from the positive ideal solution and the farthest from the negative ideal solution. Thus, this method is suitable for cautious decision-makers not only making as much profit as possible, but also avoiding risk as much as possible. The VIKOR method considering just “closeness” to the positive ideal solution is influenced by the minimum of individual regret and suitable for the decision-makers aimed more at the maximum profit than interested in risk avoidance. In contrast to previous methods, Hellwig’s method is oriented just on the group utility maximisation what suits better to the “risk lovers” or the situation when the risk or regret is left out of the attention. Based on the mentioned above disadvantages and different aggregating functions, the hybridisation of these methods is considered necessary.

Let us suppose that the MCDM problem can be described by \( m \) alternatives \((A_1, A_2, ..., A_m)\) presenting the NUTS 2 regions and \( n \) criteria \((C_1, C_2, ..., C_n)\) characterising the performance of the regions. The performance matrix \( X = [x_{ij}]_{m \times n} \) shows all values assigned to the alternatives relating to each criterion. The weights of criteria have been denoted by
\[
W = [w_1, w_2, ..., w_n]
\]
under the condition of \( \sum_{j=1}^{n} w_j = 1 \).

All three methods presented provide a different background for the compromise solution. A different perspective on the ideal point lays the foundation for the calculating scheme of the ranking index produced by each method. While Hellwig’s method accounts only the closest Euclidean distance to the best-desired levels of criteria, the VIKOR method considers the mutual concession between a maximum utility of the majority and a minimum individual regret of the opponent calculated using \( L_p \)-metric. The TOPSIS method seeks for the compromise solution based on the shortest distance to the ideal point and the farthest to the negative ideal one. All the methods presented below work with the initial (given) weights, which in this current research will be calculated by the Entropy method (Hwang and Yoon, 1981; Zanakis et al., 1998). Commonly this method is recommended in cases where a DM has no reason to prefer one criterion to others.

2.1.3.1 Hellwig’s method for the risk-loving aggregation strategy

The first method to describe is Hellwig’s method. This method is aimed at the measuring of the degree of development in regions and detecting homogenous groups (Harman, H.H., 1976; Hellwig, Z., 1968; Pluta W., 1977) due to the Hellwig’s synthetic indicator. Within this
methodology, using the principle of a shortest (taxonomical) distance of an ideal point, as a result, we calculate the coefficients describing the development of resources belonged to the analysed regions. The steps of the introduced method are the following.

Step 1: form an initial matrix of data and to normalise it:

\[ Z_{ij} = \left( x_{ij} - \bar{x}_j \right) / S_j, \]  \hspace{1cm} (2.18)

Step 2: determine an etalon \( E_o (Z_{01},...,Z_{0n}) \) in accord to the min-max criterion;

Step 3: calculate the distances from the etalon:

\[ c_{io} = \left[ \sum_{j=1}^{n} (z_{ij} - z_{oij})^2 \right]^{1/2}, \]  \hspace{1cm} (2.19)

Step 4: calculate the upper limits \( C_o \) (critical distance) of the options using:

\[ c_0 = \bar{c}_0 + 2S_0, \]  \hspace{1cm} (2.20)

\[ \bar{c}_0 = \frac{1}{m} \sum_{i=1}^{m} c_{i0}, \]  \hspace{1cm} (2.21)

\[ S_o = \left[ \frac{1}{m} \sum_{i=1}^{m} (c_{io} - \bar{c}_o)^2 \right]^{1/2}. \]  \hspace{1cm} (2.22)

Step 5: to calculate the development score \( (d_i) \) of the options using:

\[ d_i = 1 - \frac{c_i}{c_0}, \]  \hspace{1cm} (2.23)

where: \( x_{ij} \) – \( j^{th} \) attribute of the \( i^{th} \) region, \( i = 1,2,\ldots,m \) (number of regions);

\( j = 1,2,\ldots,n \) (number of attributes);

\( z_{oij} \) – normalized coordinate of the etalon;

\( Z_{ik} \) – normalized value of \( k^{th} \) variable in the \( i^{th} \) region;

\( S_o \) – standard deviation of the distances.

The main feature of this method is the single orientation of the aggregation function just on the maximum group utility of the majority (distance to the positive etalon) (fig. 2.3a). Any consideration of additional factors such as risk or regret is left out making this method suitable for such strategy, as “risk-loving”.

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fig. 2.3: Graphical representation of compromise concept

![Graphical representation of compromise concept](image)

a. Hellwig’s foundation  
b. TOPSIS foundation

*Source: author*

In contrast to other distance-based methods, Hellwig’s method is oriented just on the group utility maximisation what suits better to the “risk lovers” or the situation when the risk or regret is left out of the attention.

### 2.1.3.2 TOPSIS method for the risk-avoiding compromise aggregation

The following MCDM method is the TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) (Hwang, Yoon, 1981) method, determining the similarity to the “double-side” ideal solution (fig. 2.3b). It determines the ideal and anti-ideal points, finding the alternative with the closest Euclidean distance from the ideal point, but at the same time, the farthest Euclidean distance from the anti-ideal point.

In contrast to the previous method, it is positioned as the one oriented on the “risk-averse” decision-making due to the counting of the negative ideal. The realisation of the method is done by the following procedure.

**Step 1:** to calculate the normalised decision matrix \( R = [r_{ij}]_{m \times n} \) with the normalised value \( r_{ij} \) calculated as follows:

\[
r_{ij} = x_{ij} / \sqrt{\sum_{i=1}^{m} x_{ij}^2}, \quad i = 1, 2, \ldots, m \text{ and } j = 1, 2, \ldots, n.
\]  

(2.24)

**Step 2:** Calculate the weighted normalised decision matrix. The weighted normalised value \( v_{ij} \) is calculated as follows:
\[ v_y = r_y \times w_j, \quad i = 1, 2, ..., m \quad \text{and} \quad j = 1, 2, ..., n. \] (2.25)

Step 3: Determine the ideal \((A^+)\) and negative ideal \((A^-)\) solutions:
\[
A^+ = \{(\max_i v_y | j \in C^{\text{benefit}}), (\min_i v_y | j \in C^{\text{cost}})\} = \{v_j^+ | j = 1, 2, ..., n\};
\] (2.26)
\[
A^- = \{(\min_i v_y | j \in C^{\text{benefit}}), (\max_i v_y | j \in C^{\text{cost}})\} = \{v_j^- | j = 1, 2, ..., n\}.
\] (2.27)

Step 4: Calculate the separation measures using the m-dimensional Euclidean distance. The separation measures of each alternative from the ideal \((S^*_i)\) and negative ideal \((S^-_i)\) solution, correspondingly, are as follows:
\[
S^*_i = \sqrt{\sum_{j=1}^{n} (v_y - v_j^*)^2}
\] (2.28)
\[
S^-_i = \sqrt{\sum_{j=1}^{n} (v_y - v_j^-)^2}
\] (2.29)

Step 5: Calculate the relative closeness \((C^*_i)\) to the ideal solution and rank the preference order. The relative closeness of the alternative \(a_i\) with respect to \(A^+\) is defined as follows:
\[
C^*_i = \frac{S^-_i}{S^-_i + S^*_i}.
\] (2.30)

The TOPSIS method is based on the principle that the optimal point should have the shortest distance from the positive ideal solution and the farthest from the negative ideal solution. Thus, this method is suitable for cautious decision-makers not only making as much profit as possible, but also avoiding risk as much as possible.

To conclude, this method determines a solution with the shortest distance from the ideal solution and the farthest distance from the negative ideal solution, but it does not consider the relative importance of these distances (Hwang, Yoon, 1981; Yoon, 1987), that is considered as a main drawback of the method.

2.1.3.3 VIKOR method for the compromise aggregation based on moderate risk

The last but not least method is the VIKOR (VinseKriterijumska Optimizacija I Kompromisno Resenje). It is as well a compromise ranking method developed by Opricovic (1998). Its role is to find a multi-criteria ranking index based on a particular measure of closeness to the ideal solution (Opricovic, 1998), providing a maximum group utility of the majority and a
minimum of the individual regret of the opponent (Opricovic, Tzeng, 2004). It is placed as a “moderate risk-averse” method, as it counts not full negative ideal, but just a minimum of the individual regret of the opponent. The mathematical procedure of VIKOR has four main steps.

Step 1: to determine the best (desired) $f^*_j$, and the worst (tolerable) $f^-_j$ values of all criterion functions:

$$ f^*_j = \{ \left( \max_i f^i_y \right) \left| j \in C^{benefit} \right\}, \left( \min_i f^i_y \right) \left| j \in C^{cost} \right\} = \{ f^*_j \} \left| j = 1,2,\ldots,n \right\} $$ (2.31)

$$ f^-_j = \{ \left( \min_i f^i_y \right) \left| j \in C^{benefit} \right\}, \left( \max_i f^i_y \right) \left| j \in C^{cost} \right\} = \{ f^-_j \} \left| j = 1,2,\ldots,n \right\} $$ (2.32)

Step 2: to calculate the maximum utility of the majority $(\min S_i)$ and a minimum individual regret of the opponent $(\min R_i)$ from the $L_p$-metric:

$$ L_{p,i} = \left\{ \sum_{j=1}^n w_j (f^*_j - f^i_y) / (f^*_j - f^-_j) \right\}^{1/p} , 1 \leq p \leq \infty, i = 1,2,\ldots,m, $$ (2.33)

$$ S_i = \sum_{j=1}^n w_j (f^*_j - f^i_y) / (f^*_j - f^-_j), i = 1,2,\ldots,m, $$ (2.34)

$$ R_i = \max \left\{ w_j (f^*_j - f^i_y) / (f^*_j - f^-_j) \right\} , i = 1,2,\ldots,m. $$ (2.35)

Both $S_i$ and $R_i$ are measured from 0 to 1 when 0 means that it reached the best level.

Step 3: to compute the best and the worst values:

$$ S^* = \min S_i, S^- = \max S_i, i = 1,2,\ldots,m $$

$$ R^* = \min R_i, R^- = \max R_i, i = 1,2,\ldots,m. $$

Step 4: to determine the value $Q_i$ representing the compromise solution, integrated by the maximum utility of the majority $(S_i)$ and minimum individual regret of the opponent $(R_i)$ as the base for an agreement established by mutual concessions:

$$ Q_i = v \left[ S_i - S^- \right] + (1-v) \left[ R^* - R_i \right] , i = 1,2,\ldots,m. $$ (2.36)

where $v$ is the balance parameter following the strategy of maximum group utility (if $v > 0.5$) or the strategy supporting negative individual regret (if $v < 0.5$).

In this research, equal importance is given to both strategies and $v = 0.5$. In this research, equal importance is given to both strategies and $v = 0.5$. However, the balance parameter leaves the space for changes and not stable results influencing the final score of the alternatives. The presence of this parameter is considered as the drawback of the method on the way of its application for the lagging regions’ determination.
2.1.4 Data envelopment analysis for technical efficiency measurement

To evaluate the technical efficiency of resource usage, we apply a non-parametric method such as Data Envelopment Analysis (DEA), which was introduced by Charnes, Cooper, and Rhodes (1978). This method allows for measuring the intensive dimension of RC. The backbone of the DEA methodology is linear programming based on an optimisation platform. DEA models can generate new alternatives to improve performance compared to other techniques.

The DEA models can generate new alternatives to improve performance compared to other techniques. Hence, what differentiates the DEA from the other methods is that it identifies the optimal ways of performance rather than the averages. The identification of an optimal performance leads to the benchmarking in a normative way.

The DMUs are usually characterised by \( m \) inputs that are utilised for producing \( s \) outputs. The efficiency coefficient is the ratio between the weighted sum of outputs and the weighted sum of inputs. We can write an input matrix \( X = \{ x_{ij}, \, i=1, 2, \ldots, \, m; \, j=1, 2, \ldots, \, n \} \) and output matrix \( Y = \{ y_{ij}, \, i=1, 2, \ldots, \, s; \, j=1, 2, \ldots, \, n \} \). The \( q \)-th line – i.e. \( X_q \) and \( Y_q \) – of these matrixes shows quantified inputs/outputs of units DMU\(_q\). The efficiency rate in a general way can be expressed by:

\[
\frac{\text{weighted sum of outputs}}{\text{weighted sum of inputs}} = \frac{\sum_{i=1}^{s} u_i y_{iq}}{\sum_{j=1}^{m} v_j x_{jq}},
\]

(2.37)

where \( v_j \) – are weights assigned to \( j \)-th input, when \( j=1, 2, \ldots, \, m; \)

\( u_i \) – are weights assigned to \( i \)-th input, when \( i=1, 2, \ldots, \, s. \)

Each region selects input and output weights that maximise its efficiency score. DMU is efficient if the observed data correspond to testing whether the DMU is on the imaginary production possibility frontier. All other DMUs are merely inefficient. The best practice units are used as a reference for the evaluation of the other group units.

The aim of this method is to divide regions into effective and non-effective ones by the number of consumed inputs and produced outputs and finally, to obtain the respective efficiency coefficients for each region. The efficiency coefficient is the ratio between the weighted sum of
outputs and the weighted sum of inputs. Armed with two basic DEA models (input or output-oriented), it is worth mentioning that regional level efficiency could more likely be achieved by growing outputs than by decreasing inputs (Schaffer et al., 2011). We share this position, adding that economic resources in a region should not be decreased, and vice versa, regions should try to create more considerable resource abilities in order to expand markets and be more influential economically. A multiplier output-oriented model with a constant return to scale (CCR) is used:

$$\min q = \sum_{i=1}^{m} v_i x_{i0},$$

$$s.t.: \sum_{i=1}^{m} v_i x_{ij} - \sum_{r=1}^{s} \mu_r y_{rj} \geq 0, \mu_r, v_i > 0, \sum_{r=1}^{s} \mu_r y_{rj} = 1,$$

where $o$ is the region being evaluated;
$s$ – number of outputs, $r=1,2\ldots s$;
$m$ – number of inputs, $i=1,2\ldots m$;
$y_{rj}$, $x_{ij}$ – the amount of output $r$ (input $i$) from region $j$;
$\mu_r$ and $v_i$ are the weights given to output $r$ and input $i$, respectively.

When the number of regions is higher than the number of outputs, a dual model is used for computational reasons, giving efficiency scores from 0 to 1. However, this method suffers from one severe limitation related to the necessity of having large enough numbers of DMUs to get a well-differentiated efficiency score. According to a “rule of thumb,” the number of Ukrainian regions (26) is not sufficient concerning the initial number of inputs and outputs (9). To solve this problem, a taxonomy method was used to aggregate all inputs into one synthetic index.

Different assumptions regarding the frontier can be made: the underlying technology is characterised by constant returns to scale (CRS), assuming that all companies are operating under the optimal size (see Charnes et al., 1978, who first derived the DEA under CRS). Undoubtedly, the assumption of variable returns to scale suggests a more realistic description of economic reality engaging a multitude of activities existing in the region. The variable return to scale (VRS) approach assumes that scale inefficiencies in the industry are present (see Banker et al., 1984, who first allow for VRS). In VRS point of view, it is possible to distinguish between various returns to scale decreasing (DRS), increasing (IRS), non-increasing (NIRS), and non-decreasing returns to scale (NDRS), modifying the restrictions in the linear optimisation problem.
(see Cooper et al., 2007, for a summary of assumptions). To determine efficiency measures under the variable returns to scale (VRS) assumption, a further convexity constraint $\sum \lambda = 1$ must be considered. On balance of pointed above, we are inclined to apply both assumptions and to choose convenient and appropriate results. However, quite often, VRS causes the situation when there are too many DMUs on the efficient frontier, which makes the results of analysis not informative and eventually leads to the rejection of the VRS model.

2.2 Developed methods and approaches to measurement and analysis of different aspects of regional performance

This sub-chapter consists of four sections providing the developed methods and approaches to the measurement of specific aspects of regional performance, extending the possible range of managerial decisions. Section 2.2.1 describes the group of MCDM methods able to measure regional performance concerning different risk attitude embodied in aggregations functions of different distance-based compromise methods. Section 2.2.2 offers the way to transform correlation into the fuzzy measures necessary for the application of Choquet integral (presented in sec. 2.1.2.3), which will measure the interaction of criteria for the consideration of synergy effects. Section 2.2.3 suggests the methods capable of measuring such missing in regional analysis aspect of performance, as effectiveness. The last section 2.2.4 provides the non-compensatory hierarchical resonance approach measuring the competitiveness of regions concerning the coincidence of weaknesses between different NUTS1 and NUTS 2 hierarchical regional levels.

2.2.1 Two-factor outranking approach to compromise distance-based methods for the lagging regions’ determination concerning risk attitude

The proposed approach fits the scenario of multi-dimensional measurement presented in sec. 1.3.1 (blocks 1.2-4.2, fig. 1.17). In particular, this approach belongs to block 2.2, assuming multiple complementing applications of MCDM methods.

The first group of methods to be applied is the compromise distance-based methods measuring with different risk attitude. The Hellwig’s method provides the risk-loving aggregating strategy, paying attention only to the distance to positive etalon. While the TOPSIS (VIKOR) follows a risk-averse (risk moderate) strategy and considers both positive and negative etalons.
However, as was shown in the previous 2.1.3 subsection, compromise distance-based MCDM methods have different aggregation mechanisms. Consequently, utility values are obtained on a different basis, and this is often the reason for critique. So, it was decided to hybridise them and apply a single well-grounded function based on adopted elements from outranking group. The common aggregating function will unify the process of utility values formation.

Meanwhile, the nature of original compromise methods must be preserved, and their highlighted disadvantages need to be eliminated. For this purpose, the hybridisation of these methods, implying the usage of outranking principles is considered necessary. The practical outcome of the hybridisation is the possibility to predefine the lagging cluster of regions by the adoption of the “net flow” index.

It is customary to distinguish two schools of thoughts, producing the different basis for the decision-making process, in particular, French school (Roy, 1968) propagating outranking concept and American school based on the multi-attribute value functions and multi-attribute utility theory (MAUT) (Keeney, Raiffa, 1976). In this section to some extent, we will combine two these groups, enriching the original compromise MCDM methods by outranking elements.

We can state that in general outranking methods have some features pushing them out from the usage in the regional studies practice. The advantages of outranking methods prevent themselves from becoming frequently used in regional studies. Neither qualitative nor uncertain and fuzzy information is often used in regional decision-making. In addition, there is some essential level of subjectivity, because it is hard to define the threshold for the values of criteria and level of incomparability between alternatives. Nevertheless, outranking methods are designed to decrease the compensatory effect, and that is why are characterised by the limited degree to which a disadvantage on a particular viewpoint may be compensated by advantages on other viewpoints (Pirlot, 1997). In such a way, the compensatory effect being present in MAUT methods is considerably decreased. This advantage of outranking methods in the light of binary preference relations can enrich the practice of the clusters’ determination. The advantage of outranking methods can be transferred to the MAUT methods due to the approach presented hereinafter.

Outranking methods indicate the degree of dominance of one alternative over another (Rogers, Bruen, 1998). Providing the set of preference relations between alternatives, the outranking methods reveal the very different from MAUT logic. The question is, whether there is
enough information to state that one alternative is at least as good as another is. The rational of outranking methods is similar to the voting theory (Vincke, 1992), where the alternative \( a \) is considered to be better than alternative \( b \) if the number of votes (or criteria) in favour of alternative \( a \) exceeds the number of votes supporting the opposite statement. Preferences in ELECTRE methods are modelled by using binary outranking relations, \( S \), whose meaning is “at least as good as”. Considering two actions \( a \) and \( b \), four situations may occur (Roy, 1991):

- \( aPb \) (\( a \) is strictly preferred to \( b \)), when \( aSb \) and not \( bSa \),
- \( bPa \) (\( b \) is strictly preferred to \( a \)), when \( bSa \) and not \( aSb \),
- \( aIb \) (\( a \) is indifferent to \( b \)), when \( aSb \) and \( bSa \),
- \( aRb \) (\( a \) is incomparable to \( b \)), when not \( aSb \) and not \( bSa \).

It seems that the exploitation of expressed preference relations can give principally new results compare to the MAUT MCDM methods. In this research, such an approach will be utilised in not full extent, as it is done in the outranking methods, but just partially in the selected MCDM methods. The steps of the mentioned two factors outranking (TFO) approach are introduced after this.

The 1st step. The Regret (R) criterion is introduced as an additional factor. It serves to eliminate the compensating effect present in, for example, Hellwig’s method. This factor accounts the worst criterion influencing the estimation of the alternative. In this way, apart from the main index (distance to the positive ideal) produced by the basic method, we equally care about the minimisation of the regret that the ideal solution cannot be reached. The basic idea of the Regret additional factor originates from the VIKOR method, but its calculation depends on the basic method:

- for the Hellwig’s method, it is absent as the nature of the method implies the maximum compensation corresponding to the “risk-loving” strategy;
- for the TOPSIS method, it is the farthest distance from the negative ideal solution;
- for the VIKOR method, it is the regret factor suggested in the original formulation.

The 2nd step. To make a comparison between alternatives stricter, we conduct it simultaneously for both main and additional criteria. Let us denote values of \( i \)-th criteria (\( i = 1,\ldots,m \), where in our case \( m = 2 \), namely main factor – \( M \) and regret factor – \( R \)) for \( j \)-th alternative as \( y_{ji} \), \( j = 1,\ldots,N \). Thus, for each pair of alternatives \( j, k \) the set of criteria \( I = \{1,\ldots,m\} \) is divided into three groups corresponding to the binary outranking relations:
$I_{jk}^+ = \{ i \in I \mid y_{ji} > y_{ki} \}$, includes criteria for which $j$-th alternative is better than $k$-th;

$I_{jk}^- = \{ i \in I \mid y_{ji} < y_{ki} \}$, includes criteria for which $j$-th alternative is worse than $k$-th;

$I_{jk}^0 = \{ i \in I \mid y_{ji} \approx y_{ki} \}$, includes criteria for which $j$-th and $k$-th alternatives are equal.

The ELECTRE III method, in which the criteria of the set of decisional alternatives are compared using a binary relationship (defined as “outranking relationship”), is more “flexible” than the ones based on a multi-objective approach (Maystre L. et al., 1994).

An economic interpretation of the development scores for all methods is measured from 0 to 1, and the maximum value in this interval indicates the highest level of development (in VIKOR vice versa). Speaking in terms of $M$ and $R$ nature, for Hellwig’s and VIKOR method, they both are going to be minimised. In contrast, $M$ indicator from the TOPSIS method is presented as a benefit criterion. The transfer of $M$ and $R$ indicators from the methods is the following:

- from the TOPSIS method $M_i = S_i^* \rightarrow \min$ and $R_i = S_i^- \rightarrow \max$;
- from the VIKOR method $M_i = S_i \rightarrow \min$ and $R_i \rightarrow \min$.

Thus, the alternatives are pairwise compared concerning two criteria keeping the following conditions for the VIKOR method:

- $a \succ b$, if $M_a < M_b \land R_a < R_b$ (alternative $a$ outranks $b$);
- $a \sim b$, if $M_a < M_b \land R_a > R_b$ or $M_a > M_b \land R_a < R_b$ (alternative $a$ indifferent to $b$);
- $a \prec b$, if $M_a > M_b \land R_a > R_b$ (alternative $b$ outranks $a$).

For a hybrid version of the TOSIS method, this preference model for two criteria can be easily adjusted just changing the orientation of the $R$ criterion from the minimisation to the maximisation by analogy to the shown above idea.

The 3rd step. If the DM considers the imperfect character of the evaluation of actions, it is necessary to use the discrimination indifference and preference thresholds. This leads to a pseudo-criterion model on each criterion, helping account the imperfect nature of the evaluations and avoid a small difference between values, which can influence the decision-making process. This makes decision-making less sensitive to small differences. An increase in the accuracy of the comparisons between alternatives is reached due to the introduction of pseudo-criteria (fig. 2.4) (Brans et al., 1986) with intrinsic preference ($p$) and indifference ($q$) thresholds. In our case,
the same formula for the $M$ and $R$ criteria is used having indifference and preference thresholds equal:

$$q(M) = p(M) = \frac{M_{j}^{\text{max}} - M_{j}^{\text{min}}}{n-1} \quad \text{alternatively,} \quad \text{st.dev.}$$

(2.41)

fig. 2.4: Preference function

Eventually, the comprehensive model of preferences will provide us with three types of relations, in particular, Strong preference ($P$), Weak preference ($Q$), and Indifference ($I$), which together with pseudo-criterion were adopted from the outranking methods. Speaking of each type of preference, we have the following preferences conditioned (table B.1, Appendix B):

For instance, if the DM finds the difference between alternatives with respect to both criteria greater than the defined threshold, then such relation is perceived as a strong preference. If one of the criteria is strongly preferred, while the difference between another one is not higher than the threshold, then we get a weak preference relation. If the difference between both criteria is less, then alternatives are defined as indifferent, and a DM hesitates with the conclusion and accepts indifference.

The 4th step. To measure (quantify) the preference degree of the statements about relations between alternatives we need to quantify outranking relations or define their values. The preference degree or the strength of alternative is computed based on the preference function giving four types of degrees rising from the accounting both $M$ and $R$ criteria:

$$F(a,b) = \begin{cases} 
1 & \text{if } aP^+b \text{ or } -1 \text{ bP } a; \\
0.5 & \text{if } aQ^+b \text{ or } -0.5 \text{ bQ } a; \\
0 & \text{if } aIb. 
\end{cases}$$

(2.42)

The 5th step is specified to aggregate the preference degrees between alternatives using the “net flow” concept, which was introduced in the PROMETHEE method by Brans, Mareschal and
Vince (1984). Aggregation is done by the calculating of the positive or dominance ($\Phi^+_j$) and negative or sub-dominance flows ($\Phi^-_j$) and resulting net preference flow or global ($\Phi_j$), which leads to the complete ranking. Compare to the ELECTRE method, the incomparable status does not exist here. Based on this, the aggregating utility function is calculated as the row summation of preference degrees within the matrix of alternatives $N \times N$:

$$\Phi_j = \Phi^+_j + \Phi^-_j, \quad j=1,\ldots,N,$$

(2.43)

The final 6th step is to define the relative net flow ($\Phi^{+/−}_j$) showing the per cent of the dominance or sub dominance of the alternatives. In the context of regional performance, the closer to the -100 %, the less region is developed.

$$\Phi^{+/−}_j = \frac{\sum_{j=1}^n F^+_j + \sum_{j=1}^n F^-_j}{n-1}.$$  

(2.44)

Besides, the sub-utility function can be obtained based on strong preferences ($\Phi^p_j$):

$$\Phi^{p+/−}_j = \frac{\sum_{j=1}^n F^p_j + \sum_{j=1}^n F^-_j}{n-1}.$$  

(2.45)

To summarise the introduced elements, the fig. 2.5 presents all elements of the hybridisation process.

fig. 2.5: Hybridization of MCDM methods

Source: author
From the picture, we see that elements from two groups, namely MAUT based and outranking one, have been combined in producing their hybrid modifications. It should be noticed, that the standard aggregation functions (L_p-metric) in original methods are substituted by the presented above two-factor outranking approach including modelling of binary preference relations, thresholds and “net-flow” index.

The suggested approach is going to be applied to EU regional data in section 3.1.1.

2.2.2 Unsupervised correlation-based fuzzy identification method for criteria interaction measurement

The proposed in this section method allows identifying the fuzzy measures necessary for the application of the Choquet method for the multi-dimensional scenario (blocks 1.2-4.2 in fig. 1.17) of regional performance measurement (block 2.2). The importance of the Choquet method is explained by its power to count interaction between criteria, what is rarely investigated by researchers in regional studies.

During the last two decades, a great deal of various fuzzy measure identification methods has been proposed in the literature. M. Grabisch (1996) classified identification methods into three essential groups. The first group implies the presence of semantic considerations leading to the reasoning about fuzzy measures based on the negligible amount of experience (Takahagi, 2000; Takahagi 2008; Larbani, Huang, Tzeng 2011; Wu, Yang, Zhang, Ding, 2015; Bernal et al. 2016). While the first group is entirely dependent on a decision maker’s experience the second group (Grabisch, 1996; Grabisch, Kojadinovic, Meyer, 2008; Grabisch, Labreuche, 2008) of data-driven methods delivers him/her from burdensome considerations and relies on the learning data or training set providing all the necessary information. Usually, the fuzzy measures are calculated by applying superior artificial intelligence or machine learning methods (Li, Yao, Sun, Wu 2017), such as neural networks (Klir, Wang, Harmanec, 1997) or a genetic algorithm (Shi, Liu, Gao, & Zhang, 2011). Considering the fact that these methods are quite time-consuming and seem “much more related to the field of estimation theory” (Grabisch, Labreuche, 2008) the following third group (Yoneda, Fukami, and Grabisch, 1993; Marichal, Roubens, 2000; Angilella, et al. 2004; Kojadinovic, 2007; Merad et al. 2013; Hsu et al. 2013) is presented as mixture of previous ones and considering both subjective and subjective aspects remains the mainstream.

One should notice that even being the mainstream, this group of methods is the most difficult for
the practitioners practical because of its high cognitive capacity required. A new alternative direction in fuzzy determination methods resulted due to the need for managing the situation when there is no opportunity to rely on the learning set as well as experts’ consideration. The only rescue is to rely on a provided data set. Besides, methods dealing with such kinds of problems seem to elude such time and brain-consuming tasks having been addressed by mentioned earlier groups of methods. To cope with this type of problem, Kojadinovic (2004) was the first author to propose the unsupervised identification method based probabilistic view on the estimation of fuzzy measure coefficients by information-theoretic functions.

Summing up all the advantages and disadvantages listed in table B.2 (Appendix B) we can state, that the main feature from all already existent approaches is the intermediary concept representing fuzzy measures. As a rule, this concept originates from an extraneous involved theory or a method. Even though such involvement makes its necessary contribution, we consider it as an extra element making new approaches more complicated for the comprehension.

On the contrary, the proposed approach does not call for help any theory or method. It is just based on the fundamental geometrical representation of criteria relations in the vector form in two-dimensional space. For the better distinction among the approaches, on the figure below all distinctive features are presented. From fig. A.4 (Appendix A) we see that the essential difference is that the proposed approach does not involve any methods or theories to identify fuzzy measures; moreover, it deals with fuzzy measures directly without any intermediaries.

The input data for the method is the initial weights of criteria obtained by the extraneous method, i.e. the Entropy method and the Pearson’s correlation. On this basis, the well-known geometric figure will be used. Triangular will serve as a natural prototype for the interaction model finding the underlying cause of the very essence of criteria interaction explaining the relative nature of the interaction effect. Therefore, the descriptive conceptual triad of the proposed method is “correlation-triangular-relative interaction effect.” The most distinctive feature of the proposed approach is its cognitive, conceptual (triangular based) and methodological (basic trigonometric function paired with an optimisation model) simplicity providing at the same time the capability to reveal the geometrical rudiments of the criteria interaction effect. After all, fuzzy measures are obtained by solving a non-convex quadratic optimisation problem. The essential steps of the Choquet method application are presented in fig. 2.6.
fig. 2.6: Sequence of steps to apply the Choquet method

Within these steps, the 3rd one is devoted to the suggested geometrically based approach to fuzzy measures determination incorporating the given correlation between criteria under consideration. The details of the suggested approach will be shown below.

Having searched possible natural constructs able to represent the interaction between two elements straightforwardly, we focused our attention on nothing but merely a triangle. This plane figure with three straight sides and three angles can be symbolically and functionally interpreted as two interacting $a$ and $b$ sides (elements) producing the mutual result embodied in the third side $c$. In terms of the decision-making process, the third one is the offspring of a two sides’ combination. The combination of one and another produces a new form of being altogether. Philosophically, it can be interpreted as the rise or appearance of creativity or just interaction producing some constructive or destroying energy, synergy effect, etc. Not digging into the symbolism and philosophical interpretations the triangle is assumed the best natural model to be tested for the further analysis of an interaction between two criteria.

After this, the symbolic triangle model will be quantified using geometry and trigonometry. Let us have a closer look at a triangle presented in a vector space $\mathbb{R}^2$ (fig. B.3, Appendix B). Two elements being in certain relations can be represented as two vectors $\vec{a}$ and $\vec{b}$ producing the resulting vector $\vec{c}$, which is merely the manifestation of the interaction of the side, including an interaction effect. Henceforward we will use the words “side” and “element” interchangeably as synonyms in the context of interaction. Algebraically and geometrically, this interaction process gradually can be derived by the following transformations:
\[ \vec{c} \cdot \vec{c} = |\vec{c}|^2 \]  
\[ |\vec{c}|^2 = (\vec{b} - \vec{a}) \cdot (\vec{b} - \vec{a}) = |\vec{b}|^2 - 2 \vec{b} \cdot \vec{a} + |\vec{a}|^2 \]  
\[ 2 \cdot \vec{b} \cdot \vec{a} = 2 \cdot |\vec{b}| \cdot |\vec{a}| \cdot \cos \gamma \]  

By definition, multiplication of two vectors can be presented as their dot product consisting of vectors’ magnitude and cosine of the \( \gamma \) angle between sides. Afterwards, equations from above lead us to the core expression describing the relation between triangle sides or the interaction of elements in the systemic context. In trigonometry, this expression is called the “law of cosine” and has the following view (Saville, Graham, 1991):

\[ |\vec{c}|^2 = |\vec{a}|^2 + |\vec{b}|^2 - 2 |\vec{a}| |\vec{b}| \cos \gamma \]  

It has an underlying simple principle at work, which in detail is going to be explained below. One should notice that the law of cosine could be seen as the generalisation of the well-known Pythagorean Theorem when the angle between sides equals to 90 degrees and cosine becomes 0 vanishing the deduction part in eq. (2.49).

“What happens when two elements \( e_i \) and \( e_j \) create a coalition and produce a systemic result (\( R_{ij} \)) as the consequence of their combined efforts?” Surely, we can assume that the result of the elements’ mutual actions:

1. equals to the sum of efforts made by elements, however in practice it appears as a particularly rare case;

2. does not equal to the additive sum of their contributions \( R_{ij} \neq \sum_{i=1}^{n} e_i \).

Obviously, elements “working” together under the different conditions make us count for the synergetic interaction effect (\( \lambda_{ij} \)) arising between them:

\[ R_{ij} = e_i + e_j + \lambda_{ij} \]  

It is necessary to discern strictly such terms as interaction and interaction effect. The former says simply about the kind of action that occurs as two or more objects affect one another. The latter is the quantitative contribution, result or consequence of an interaction. It is fairly, perhaps tautologically to state that the interaction effect is the result of the interaction. The current research is targeted at the determination of the synergetic interaction effect.
There can be two different types of interaction. For instance, elements might hamper each other (negative effect) or vice versa to find ways for effective collaboration (positive effect). Thus, taking (2.49) as a framework and assuming two extreme and straightforward cases of perfect (+) and imperfect (−) compliance of elements the total result of their mutual work gets the form:

\[ R_{ij}^2 = e_i^2 + e_j^2 - 2 \cdot e_i \cdot e_j \]  

(2.51)

A multiplication operator is used for the description of the interaction act. The graphical disaggregation of the total result by areas is displayed in fig. 2.7.

fig. 2.7: Disaggregated areas of the squared total result

<p>| | |</p>
<table>
<thead>
<tr>
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<tbody>
<tr>
<td>$e_i \cdot e_j$</td>
<td>$e_i^2$</td>
</tr>
<tr>
<td>$e_j^2$</td>
<td>$e_i \cdot e_j$</td>
</tr>
</tbody>
</table>

Source: author

The areas presented are the following: $2 \cdot e_i \cdot e_j$ – maximum cross interaction effect ($CI_{ij}$), $e_i^2$, $e_j^2$ – self-interaction ($SI$) of elements $i$, $j$, correspondingly. The example of two opposite cases with perfect (-1) and imperfect (+1) interaction of elements 3 and 6 is given below correspondingly:

\[
R(3;6)^{\text{perfect}} = \sqrt{3^2 + 6^2 - 2 \cdot 3 \cdot 6 \cdot (-1)} = \sqrt{(6 + 3)^2} ; \\
R(3;6)^{\text{imperfect}} = \sqrt{3^2 + 6^2 - 2 \cdot 3 \cdot 6 \cdot (+1)} = \sqrt{(6 - 3)^2} .
\]

The numbers corresponding to perfect and imperfect conditions can be puzzling, though the logic of a sign is simply explained. In parenthesis “−” relates to the situation when elements are entirely different, what points at unique information supplied by elements meaning as well that there is no duplicated information. Sign “+” on the contrary indicates that elements are repeating themselves with no contribution at all, leaving the coalition with the 6-3=3 part of unique information. However, if conditions are not so “black and white” like with perfect and imperfect relations, then (2.49) comes into play with a “rescuing” cosine embodied into the dot product. Its principal function is to measure similarities by accumulation interactions in matching
directions. Due to the cosine representing the overlap between vectors, the cross-interaction effect is accurately measured:

\[ CI_{ij} = -2 \cdot e_i \cdot e_j \cdot \cos \gamma_{ij} \]  

(2.52)

To put in another way with trigonometric terms, the cosine can be perceived as the multiplying factor representing the percentage of the cross interaction of elements predefined by \( \gamma_{ij} \). The greater a cross interaction effect is, the higher the actual total result interaction \( R \).

\[ R_{ij} = \sqrt{SI_i^2 + SI_j^2 + CI_{ij}} \]  

(2.53)

Further down the properties and nature of \( \lambda_{ij} \) is going to be defined following the geometrical interpretation. Turning back to the basic triangular model, let us specify it, adding some interaction related details explained earlier (fig. 2.8).

fig. 2.8: Specified triangular vector model

Having two vectors \( w_1 (OB) \) and \( w_2 (OA*=OA=OA+) \) explicitly, it is possible to discuss an interaction effect in the following way. If it is assumed that the diversity of vectors spurs a positive synergetic effect, a newly obtained vector is \( AB \). This vector incorporates an actual interaction effect \( (E_{actual}) \), which explicitly is presented as \( AE \). If vectors were orthogonal to each other (the case without any interaction) the explicit effect would be \( A*E^* \). The actual implicit interaction effect \( (\Delta E) \) can be found as a difference between actual \( E_{actual} \) and hypothetical \( E_{hypoth} \) explicit effects \( (AE-A*E^*) \). It is evident, that there is another more direct way of calculating
addressing per se the newly obtained vector (side) $AB$ and the hypothetical side $BA^*$, in this case, hypotenuse, serving as a benchmarking reference base $BA^*$:

$$\Delta E = \lambda = E_\text{actual} - E_\text{hypoth} = BA - BA^*$$  \hspace{1cm} (2.54)

Saying generally, an interaction effect equals to a difference between the actual side ($S^a$), representing newly formed vector and reference base or hypothetical side ($S^h$) represented by the side formed due to an arbitrarily chosen angle between vectors under consideration.

$$\Delta E = \lambda = S_\text{actual} - S_\text{hypoth}.$$  \hspace{1cm} (2.55)

However, one should keep in mind that a newly obtained vector $BA$ depends on the input data, such as importance criteria (weights) and a correlation between them. Thus, depending on input data, there is only one possible output vector $AB$. On the contrary, the placement of a reference point or a hypothetical benchmarking side does not have any particular based on input data reason to define it in a certain way. It raises the question of whether a particular position of a reference side is better than the other one. The simplest and perhaps the most sensible solution is to assume arbitrary placement of the reference side, implying arbitrary reference correlation between criteria and as a result an arbitrary angle between vectors in the graphical model.

Therefore, a hypothetical benchmarking side can be formed with any angle between two initial vectors varying from 0 to 180 degrees and correspondingly the cosine takes value from -1 to 1. As it is shown in fig. 2.9 the hypothetical benchmarking side may take any form, such as $BA^+, BA, BA^{**}, BA^*, BA^{*-}, BA^{***}, BA^-$ depending on an angle.

fig. 2.9: Variability of a reference side

Source: author

A hypothetical reference side, depending on the decision maker’s choice of a reference angle, is for example: 1. if vectors are orthogonal with an angle 90 degrees it is $BA^*$; 2. if vectors...
are fully opposite to each other with an angle 180 degrees it is BA−; 3. if vectors are fully co-directed, with an angle 0 degrees it is BA+. Another aspect, which has not been covered yet, is the preference of a DM regarding the nature of two interacting vectors. There can be two opposite situations; in particular, when aligned vectors are favoured and when differently directed are preferred (negative correlation). In the first situation, positive correlation or similarities lead to better cooperation, while in the second negative correlation or dissimilarities increase the effectiveness of the working together. Considering these two situations, the vector model becomes as in fig. 2.10.

fig. 2.10: Complete vector model

Source: author

One can notice from the figure that in case of positive correlation preferred, the interaction vector would be OA_b, while in another situation, it will be BA. It is evident that in the first case, the length of the vector is more prominent, which also means that the interaction effect is more significant as well as keeping the same reference point. Therefore, depending on interaction preferences, a particular wing is used for the effect’s representation. At this step of the investigation, the nature of the interaction effect is appropriate to define it. The interaction effect is a relative effect arising from two interacting elements which mutual efforts lead to either cooperation (with non-additive positive effect) or hindrance (with non-additive negative effect).

From the presented complete vector model (fig. 2.10) and through behavioural analysis, it was concluded that magnitude and sign of an interaction effect are under the direct influence of:

1. ratio between weights – the more equal criteria are, the higher interaction effect will be;
2. correlation – the higher a correlation, the stronger an absolute interaction effect will be;

3. direction of correlation – if similarities (dissimilarities) between the criteria are favoured, then the positive (negative) correlation will lead to the positive interaction effect.

4. chosen reference base – this factor overlies on the previous one and says that if dissimilarities (similarities) are favoured, then changing the reference base from -1 to 1 will create the more positive (negative) effect.

Let us briefly review the basic definitions and properties of fuzzy measures. Considering a set of criteria (elements) \( E = \{e_i | i = 1, n\} \) capacity (Choquet, 1953) or a fuzzy measure (Sugeno, 1974) on \( E \) is a mapping \( \mu: 2^E \rightarrow [0,1] \) satisfying the following conditions:

1. \( \mu(\emptyset) = 0, \mu(N) = 1 \) (boundary condition);

2. if \( S \subseteq A \subseteq B \) implies \( \mu(S) \leq \mu(B) \) (monotonicity condition).

In MCDM context each subset of criteria \( A \subseteq B \), \( \mu(A) \) can be considered as the weight or importance of \( A \). Having \( S \cap T = \emptyset \) fuzzy measure can be of three types depending on the interaction effect (\( \lambda_{ij} \)) expressing the interdependence between subsets of criteria \( S \) and \( T \):

1. capacity is an additive one, when \( \mu(S \cup T) = \mu(S) + \mu(T) \) and \( \lambda_{ST} = 0 \);

2. capacity is non-additive, but super-additive when \( \mu(S \cup T) > \mu(S) + \mu(T) \) or \( \mu(S \cup T) = \mu(S) + \mu(T) + \lambda_{ST} \);

3. capacity is non-additive, but sub-additive when \( \mu(S \cup T) < \mu(S) + \mu(T) \) or \( \mu(S \cup T) = \mu(S) + \mu(T) + (-\lambda_{ST}) \).

Based on eq. (2.49) and other aspects stated above, the formula for the determination of the relative interaction effect (\( \lambda_{ij} \)) between \( i \)-th and \( j \)-th criteria is:

\[
\lambda_{ij} = \sqrt{\mu(i)^2 + \mu(j)^2 - 2 \cdot \mu(i) \cdot \mu(j) \cdot \rho_{Eij}} - \sqrt{\mu(i)^2 + \mu(j)^2 - 2 \cdot \mu(i) \cdot \mu(j) \cdot \rho_{Eij}^\text{etalon}.} \tag{2.56}
\]

The new variable (\( \rho_{Eij}^\text{etalon} \)) being the cosine varies from -1 to 1 and represents the \( X \) variable. Thus, depending on its value, fuzzy measures are determined. Respecting all optimisation and fuzzy conditions, the unique optimal solution is found by the solving of the following optimisation problem:
Objective function: \( \sum_{j=1}^{n} \lambda_{ij} \rightarrow \min \) (balancing condition);

while \( x = \cos \theta = \rho_{xij}^{\text{etalon}} \in [-1;1] \) (\( \theta \) - an angle for a hypothetical reference side);

s.t.: 1. \( \sum_{i=1}^{n} w_{i} = 1 \) (weights’ sum condition); (2.58)

2. \( \mu(E) = \sum_{i} w_{i} + \sum_{j} \lambda_{ij} \leq 1 \) for all \( i, j \) (boundary condition for all criteria); (2.59)

3. \( 0 \leq \mu\{e_{i}, e_{j}\}^{\perp} = w_{i} + w_{j} + \lambda_{ij} \leq 1, \) for all \( \mu\{e_{i}, e_{j}\}^{\perp} i \neq j \) (boundary condition for all criteria pairs); (2.60)

4. \( \lambda_{ij} + \sum (w_{i}; w_{j}) \geq \max(w_{i}; w_{j}) \) (maximum weight condition). (2.61)

It should be noticed that the optimisation problem presented by inequalities above always produces a unique optimal solution with optimally chosen \( \cos \theta = \rho_{xij}^{\text{etalon}} \) for the minimised total effect \( \sum_{j=1}^{n} \lambda_{ij} \) when \( \mu(E) \) reaches 1. This solution is characterised by the correct processing of preferences (correct Shapley values) as the full realisation of interaction effect is made. It is because of sum condition is followed, and the total effect is equal 0, what together automatically leads to zero slack of interaction effect. That is why the slack condition is not pointed out in the optimisation model. Thus, the model is searching just for the reference base neutralising all synergy effects what causes total interaction effect and automatically slacks to be zero. As a result, preferences are considered correct, and there is no bias in measurement.

Having defined interaction effects by the suggested optimisation model, we can apply the Choquet method using k-additive fuzzy measures Grabisch (1997). It means that fuzzy representation is being truncated up to some sufficient level, providing minimum losses of information and maximum simplicity in calculations. Usually, this level is taken when \( k=2 \), meaning that relations to which attention is paid are the pairs of criteria, while \( k=1 \) reduces fuzzy measures to the vector of importance weights.

To calculate the Choquet integral based on 2-additive fuzzy measures expressing complementarities and redundancies within possible pairs of criteria, we have to incorporate interaction effects obtained before by proposed correlation-based unsupervised method takes the
following form. The calculation of 2-additive Choquet integral proceeds by the following steps (Grabisch, 2013).

1. Determination of Shapley (Shapley, 1953) importance index $\phi_i(\mu)$ for criterion $i$ as a weighted average of the difference $\mu(A \cup i) - \mu(A)$ taken over all possible $A \subseteq N \setminus i$:

$$
\phi_i(\mu) = \sum_{A \subseteq N \setminus i} \frac{|A|!(n-|A|-1)!}{n!} (\mu(A \cup i) - \mu(A))
$$

(2.62)

However, as certain Shapley values can originate from different fuzzy measures, they cannot be considered as a tool for the direct representation of fuzzy measures. It means that the description of fuzzy measures has to be enriched by the following step.

2. Calculation of an interaction index $I_{ij}(\mu)$ (Murofushi, Soneda 1993) is done by taking for all possible groups $A \subseteq N \setminus \{i, j\}$ a weighted average of the difference between mutual satisfaction of criteria $\mu(A \cup \{i, j\}) - \mu(A)$ and sum of their separated satisfactions, namely $\mu(A \cup i) - \mu(A)$ for $i$-th criterion and $\mu(A \cup j) - \mu(A)$ for $j$-th criterion:

$$
I_{ij}(\mu) = \sum_{A \subseteq N \setminus \{i, j\}} \frac{|A|!(n-|A|-2)!}{n-1!} (\mu(A \cup \{i, j\}) - \mu(A))
$$

(2.63)

Having measured all necessary characteristics, such as importance and interaction index, the total score of alternatives can be measured.

3. Measurement of the 2-additive Choquet integral ($Ch_\mu$):

$$
Ch_\mu^{2\text{-additive}}(a_1, \ldots, a_n) = \sum_{i,j} (a_i \wedge a_j) \cdot I_{ij} + \sum_{i,j} (a_i \vee a_j) \cdot I_{ij} + \sum_{i} a_i \cdot (\phi_i - \sum_{j \neq i} |I_{ij}|)
$$

(2.64)

where $I_{ij}$, $\phi$ are the interaction index and Shapley value respectively;

$\vee, \wedge$ stand for minimum and maximum, respectively.

The main limitation of the method is invoked from the correspondent limitations of the Pearson correlation coefficient – its linear nature. It is the central assumption of the method. If the variables are independent, Pearson's correlation coefficient is 0, but the converse is not true because the correlation coefficient detects only linear dependencies between two variables.

The proposed fuzzy identification method will be used in section 3.2.2 within the application of the Choquet method included in an inclusive panel of MCDM methods for the measurement of regional performance of 273 EU NUTS 2 regions.
2.2.3 Ratio Additive Weighting method for the unorthodox measurement of the effectiveness

The proposed RAW method allows measurement of the effectiveness of regional performance. This aspect of measurement goes in line with the unorthodox synthetic scenario (blocks 1.3 in fig. 1.17) assuming the application (block 2.3) of non-conventional MCDM methods.

The “effectiveness” is the vague concept originally appeared in the managerial context of organisational performance measurement. There were many debates devoted to this concept, which successfully have been finished with some consensus bounding the set of accepted approaches being appropriate for a specific situation (Cameron, 1984). Despite the high interest and variety of the conceptual approaches (Henri, 2004; Love, Skitmore, 1996; Mette A, Joseph, David, 2007; Oghojafor, Muo, Aduloju, 2012) to effectiveness, no one to the best of our knowledge was quantified and embedded into by the particular methodology.

On the contrary, all efforts are focused on the measurement of other aspects of performance. For instance, the term “efficiency” is used sometimes as a synonym to “effectiveness”. In this case, the criteria should follow the input-output structure, and non-parametric Data Envelopment Analysis (DEA) is applied for the efficiency measuring (Charnes, Cooper, Rhodes, 1978). Both these terms reflect two different complementary aspects revealing the performance of the alternative. If the “efficiency” is about “doing things right”, the “effectiveness” is about “doing right things” (Anthony, Govindarajan, etc. 2014).

Meanwhile, another generic and less specific approach exists. Its focus is related to the bald “having things done” without any other additional aspects of analysis. Usually, this approach is applied to measure different synthetic properties, such as “level of development”, “quality of life”, etc. It does not require any relations between its substitutes and the SAW (Fishburn, 1977) from multi-attribute value theory (MAUT) theory that can be appropriately used.

It is necessary to mention that the performance context is not the only one appropriate for the exploitation of effectiveness. In the broadest sense, the effectiveness can be analysed from passive and active points of view. Active is about how an alternative performed, passive – how an alternative should be designed. Having stressed this point, the broad application of this term, discovering the aspect “doing right things” in different fields is unquestionable. Moreover, it is
fair to say that any analysis of the performance following both directions, for example, efficiency via effectiveness, always tends to be more comprehensive and informative.

After getting to know the term, let us move on to the three main conceptual approaches to its analysis. The goal-attainment approach (Etzioni, 1964) to effectiveness has been the most widely discussed, and it defines effectiveness as a degree to which targets are achieved. In contrast to the goal attainment, the systems’ resource approach does not ignore goals; but views them as one element of a set of complex criteria, that will increase the long-term survival of the organisation (Yutchman & Seashore, 1967). In essence, the systems approach focuses not so much on specific ends, but on the means needed for achieving these ends. The competing values approach assumes that there is “no best” criteria that are valued and used in assessing operational effectiveness (Quinn and Rohrbaugh, 1981). This approach uses both means, ends, and therefore overcomes the limitations associated with previous approaches.

There has been much debate among scholars, and because of non-conceptual harmony, this concept did not get its mathematical materialisation in the field of quantitative methods, and the methodological gap eventually was not filled in. Considering the fact of the variety of conceptual approaches to the effectiveness measurement, the most discussed and widely used remains the “Goal attainment” approach (Goodman, Pennings, 1977) focused on the ends exclusively, namely on the achievement of goals, objectives, targets, etc. (Henri, 2004). Meantime if to apply “Occam’s razor” (fig. B.4, Appendix B), we can easily notice that all approaches could be reduced to the single one – generic Goal Attainment approach with possible input-output-outcome division converging to primal target closing the chain of the less and more valuable goals. According to this approach, effectiveness is defined as the degree to which targets achieved (Etzioni, 1964). In our research, this definition is the starting point for the development of the method for the effectiveness measurement. Even though effectiveness originates from plenty of conceptual approaches, none of them was quantified by some grounded methodology. Based on this, the aim of this subsection is the development of the method for the effectiveness measurement based on the “Goal attainment” approach.

The effectiveness as a multi-dimensional phenomenon requires some aggregating function to be processed. If we focus just on the absolute level of targets and their importance, we easily can apply the SAW method and measure, for example, aggregated indicators such as “level of development”, “synthetic performance”, “quality of life”. However, in real-world problems,
mutual independence preference condition is held quite rarely and very often ignored by decision-makers. The investigation of criteria proportions for the measurement of the level of targets’ attainment causes the violation of utility independence, and as a result, the SAW method fails.

In many practical applications, including regional studies, the decision criteria contain some interaction effects. The most common effects to consider are a correlation (Grabisch, 1996) and preferential independence (Fishburn, 1970; Keeney and Raiffa, 1976). However, the correlation phenomenon is perhaps the most intuitively understandable. For example, if criteria are perceived as mutually exclusive, such as economic and ecological development, then higher values of both imply some positive synergy effect to count. Three types of relations can be presented through the correlation: 1. in case of a positive correlation between \( j \) and \( i \) criteria, their total interaction can be modelled as \( v(i, j) < v(i) + v(j) \); negative as \( v(i, j) > v(i) + v(j) \); additive as \( v(i, j) = v(i) + v(j) \).

Preferential dependence is explained in the following way. The subset \( S \) of criteria as preferentially independent of \( N \setminus S \) if, for all \( x, x^*, y, z \in \mathbb{R}^n \) we have \( xSy \geq x^*Sy \iff xSz \geq x^*Sy \). In this case whole set of criteria \( N \) is said to be mutually preferentially independent is \( S \) is preferentially independent of \( N \setminus S \) for every \( S \subseteq N \). Thus, the existence of preferential independence would exclude the use of the SAW method. However, mutual preference independence is not sufficient, but a necessary condition for using an additive operator.

The springboard of the further analysis is the basic definition of the effectiveness. As stated above, according to the “goal-attainment” approach, the effectiveness is the degree to which targets are achieved. We will slightly enrich this ultimately simple definition, making it more precise. The effectiveness is the relative degree to which targets (uniformly) are achieved with respect to the priority vector. Relying on this working definition, the following pre-conditions are listed and should be considered in the method:

1. The focus is on the quality of performance (or design). Effectiveness is a relative phenomenon, expressing the concept of “doing right things” with the emphasis on the character of the “things”. It is not just benchmarking of performance, aggregating attributes of alternatives. It is the comparison between “things” (targets) being more or less done according to preferences.

2. Comparison between target attainments, not between absolute values of initial criteria. The Effectiveness measurement method is aimed at the analysis of proportions.
3. No compensation between absolute values. More favourite targets have a higher priority in an evaluation. A higher value of the less critical target attainment cannot compensate for the lower value of the more important one as it is allowed in the SAW method.

4. The degree of the right target attainment is measured. The targets of alternative are fulfilled when the proportions between target attainments are defined according to the vector of weights.

5. Uniformity could be important (optionally). Fragmentary compliance with the right proportions does not allow to a full extent the exploration of the effectiveness. The uniformity of targets achievements could be a constituent of the effectiveness concept and another aspect to be considered.

Before we start introducing methodological elements of the proposed method, let us present its conceptual framework. The theoretical core of the proposed Ratio Additive Weighting approach is a generic approach of Goal Attainment manifested in the “input-output-outcome” ratio framework. The purpose of the approach is not only to measure effectiveness but also to measure all possible ratio-based conceptual variations, including also efficiency. The underlying idea and the nature of all possible ratio-based concepts within the framework “input-output-outcome” are displayed in fig. 2.11.

fig. 2.11: Conceptual ratio based structure of input-output-outcome relations

<table>
<thead>
<tr>
<th>Groups of targets</th>
<th>Dominating Importance (6—the highest)</th>
<th>Inputs (I)</th>
<th>Outputs (Op)</th>
<th>Outcomes (Oc)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dominated</td>
<td></td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Inputs (I)</td>
<td></td>
<td></td>
<td>A</td>
<td>B</td>
</tr>
<tr>
<td>Outputs (Op)</td>
<td></td>
<td>3</td>
<td>C</td>
<td>E</td>
</tr>
<tr>
<td>Outcomes (Oc)</td>
<td></td>
<td>5</td>
<td>F</td>
<td></td>
</tr>
</tbody>
</table>

Source: author

From the figure above we can conclude that any ratio based concept either efficiency or effectiveness can be derived just through elements’ intersection being in the research focus. Analysis of possible combinations covers the following types of relationships: A. within inputs group effectiveness; B. classic between groups’ efficiency (outputs to inputs); C. within outputs group effectiveness; D. between groups’ efficiency (outcomes to inputs); E. classic between groups’ effectiveness (outcomes to outputs); F. within outcomes group effectiveness. Of course,
it is necessary to notice that the primal target of the suggested method to grasp all presented sectors to measure complete effectiveness. However, any sectors can be considered for a specific aim.

The most well-known and formalised concepts such as B (classic efficiency) and E (classic effectiveness) are dealt with DEA analysis. However, as we see, there are other crossed combinations to be analysed and bring a certain value into an understanding of the performance. Moreover, ratios between all prioritised elements can be aggregated into one composite index. Prioritised means that a DM is capable to define priorities within the group as well as priorities between the groups. In other words, for the full prioritising, the vector of weight coefficients should be defined as follows: $w_6 > w_5 > ... > w_1$ and

$$\sum_{\text{inputs}} w_j < \sum_{\text{outputs}} w_m < \sum_{\text{outcomes}} w_k \mid j, m, k \in N.$$  

In other words, outcomes are more important than outputs, while the last ones – than inputs. If to assume that all elements are prioritised as goals to be reached, then all possible combinations can be reduced to effectiveness analysis implying the answering to the question “how are targets fulfilled?” However, the answer as a possible solution comes from a relative point of view, when the levels of targets’ achievement are defined as self-oriented meaning in the form of ratios between each other. The example of criteria relations according to the importance vector is given in fig. B.6 (appendix B) concerning innovative effectiveness. The importance vector of the innovative effectiveness shows that the exported goods are more important than innovative goods sold, a number of innovative processes, a number of innovative enterprises, and so on. Once the relations are established the decomposition of criteria is made in fashion showed in fig. B.5.

In fig. 2.12 we showed the how input-output-outcome framework could be used to explore efficiency or/and effectiveness applying two different approaches of analysis, in particular, frontier best practice analysis (DEA) and MAUT based approach.

Three types of algorithms are presented depending on a degree of decision maker’s awareness of targets’ priorities. In this research, we are interested mainly in two extreme cases. The first is based on full awareness of priorities when weights of all criteria are wholly defined. The second one is with full uncertainty in terms of priorities when a DM is not able to define weights calling for additional uncertainty analysis, such as OWA method.
fig. 2.12: Effectiveness measurement depending on decision maker’s priorities

Source: author
The remaining case of semi-defined priorities, when it is just known that outputs are preferred to inputs falls into the area of DEA analysis or frontier best practice analysis. It is so because the weights of targets (inputs, outputs, ratios) are not defined a priori and are obtained due to optimising calculations.

From the economic point of view in the regional policy field, such practice of priority determination underlying the measurement of regional performance cannot be regarded as appropriate for the policy further policy implications. It is so because weights (target priorities) are defined somewhat artificially utilising just strength of alternatives then following a realistic and comprehensive benchmarking approach. Meantime one should notice that the DEA approach, being non-parametric linear optimisation technique follows presented above the input-output-outcome framework for the measurement of ratios. However, it covers only a part of possible ratios falling into a sector B of classic efficiency.

It is interesting to note that according to the work of Wu, D., Liang, L., Huang, Z., & Li, S. X. (2005) it is proved that basic CCR model measuring efficiency can be reduced to the aggregated ratio model, where DMUo is ratio efficient if there exists an optimal solution \( \{p^*_l : l \in L\} \) with \( p^*_l > 0 \) such that \( p^* = 1 \):

\[
p^* = \max \ p = \sum p_l w_{l0}
\]

\[
\sum_{l \in L} p_l w_{lj} \leq 1, j = 1, \ldots, n,
\]

s.t.

\[
p_l \geq \varepsilon, l \in L, \text{ while}
\]

\[
W_i = \{w_{lj} : l = 1, \ldots, m \times s\} = \left\{ \frac{y_{lj}}{x_{lj}} : i = 1, \ldots, m, r = 1, \ldots, s \right\}
\]

where \( \varepsilon \) – non-Archimedean small quantity \( \varepsilon > 0 \);

\( x_{lj}, y_{lj}, \) – the amount of \( i \)-th input (\( r \)-th output) consumed (produced) by \( j \)-th DMU respectively, \( x_{lj}, y_{lj} > 0 \).

However, according to the operational definition of effectiveness (level of relative targets’ achievements) and leaving aside the best practice frontier analysis targeted at optimal weights this model takes the form of a trivial MAUT approach and is itself the specific case of the more generalised effectiveness measurement problem. Thus, the development of the method measuring the full range of ratios reflecting the total effectiveness will be presented below. The focus of the following investigation is the measurement of effectiveness through the MAUT (multi-attribute
utility theory) approach, the capability of which is revealed by the introduction of ratio decomposition.

The logic of ratio decomposition for the utility independent proportions’ measurement will be presented further. The MCDM problem is described as follows: initial set of alternatives \( A = \{ a_k | k = 1, m \} \), set of criteria \( C = \{ c_j | j = 1, n \} \) characterising the performance (design) of alternatives, performance matrix \( X = [x_{kj}]_{m \times n} \), showing all values assigned to the alternatives relating to each criterion and weights of criteria denoted by \( W = \{ w_j | j = 1, n \} \).

Taking the SAW method as a basis for the effectiveness measurement, utility independence is going to be violated. It appears that effectiveness \((E)\) according to its definition is a concept which cannot be measured based on a weighted additive aggregation of its initial criteria (goals), as sub-utility \( e_{kj} = f(X) \) representing the level of \( j \)-th target achievement of \( k \)-th alternative occurs to be dependent on all other criteria:

\[
E_k(x_{k1}, \ldots, x_{kn}) = f[e_1(x_{k1}), \ldots, e_n(x_{kn})] \neq \sum_{j=1}^{n} w_j \cdot e_{kj}(x_{kj}).
\tag{2.68}
\]

Indeed, the calculation of shares (or proportions) of target achievement levels creates a dependency between single utility functions and that is why all initial absolute criteria are not mutual preferentially independent. The easiest way to move forward is to focus on the derived set of criteria based on the formation of ratios reflecting the relations between criteria and relative level of targets’ achievement. Thus, such transfer from initial absolute to relative criteria with their further aggregation is supposed to solve the problem of preference dependence.

To solve this problem and avoid using the non-additive value function, the transformation of the SAW has to be done. Let us suppose that the original criteria set \( C = \{ c_j | j = 1, n \} \) is decomposed to get new extended superset \( \bigcup_{j=2}^{n} C_{\tau(j) > \tau(v)} \), where \( \tau(j), \tau(v) \) is the permutation on \( W \), that is \( w_{\tau(j)} < w_{\tau(v)} < w_{\tau(v)} \) for \( j, v = 1, n \). Decomposition implies \( n \) criteria to be extended into the \( n-1 \) subsets of sub-criteria composing the superset

\[
\bigcup_{j=2}^{n} C^*_{\tau(j) > \tau(v)} = C_{\tau(2), \tau(v)} \cup \ldots \cup C_{\tau(j), \tau(v)} \ldots \cup C_{\tau(n), \tau(v)} \quad j, v = 1, n: j > v
\]

derived from the lower triangular matrix \((C \times C)\) (fig. B.5, Appendix B). Its elements \( C_{\tau(j)/\tau(v)} \) (the same as \( C_{\tau(j) > \tau(v)} \)) denote preference relations between \( j \)-th (more important) and \( v \)-th (less important) criteria. We
see that \( c_{\tau(2)} \) is more important than \( c_{\tau(1)} \), consequently from the intersection, we have new-paired sub-criterion \( C_{\tau(2)/\tau(1)} \). Altogether, subsets count \( (n^2-n)/2 \) new benefit paired sub-criteria.

The new extended superset \( \bigcup_{j=2}^{5} C_{\tau(j)\tau(v)}^* \) is derived from initial \( C = \{c_{j,v} \mid j, v = \overline{1,n} \} \) by ratio decomposition, when \( j > v \). Having defined the weights of all initial criteria, they are placed in the rows and columns such as \( w_{\tau(i)} < w_{\tau(j)} < w_{\tau(n)} \) for \( j, v = \overline{1,n} \). At the intersection of each row and column, we obtain the ratio between more important criteria (nominators) and less important ones (denominators). All these intersections give the platform for the new-paired sub-criteria and new sub-weights. All the new benefit paired sub-criteria are presented by \( n-1 \) subsets

\[
\bigcup_{j=1}^{j-1} C_{\tau(j)\tau(v)} = \{c_{\tau(j)/\tau(l)}, \ldots, c_{\tau(j)/\tau(v)}, \ldots, c_{\tau(j)/\tau(j-1)} \}
\]

with \( j = \overline{2,n} : j > v \). For example, from fig. B.5 (Appendix B) we see that \( c_{\tau(2)} \) is more important than \( c_{\tau(1)} \), consequently from the intersection, we have new-paired sub-criterion \( C_{\tau(2)/\tau(1)} \). Having decomposed the set of original criteria, the normalised performance matrix \( L = [l_{ij}]_{n \times n} \) and weights \( w = \{w_j \mid j = \overline{1,n} \} \) are respectively decomposed for the extension similarly as above, but using the difference operator:

\[
I_{\tau(j)/\tau(v)} = I_{\tau(j)} - I_{\tau(v)}, \text{ but for } w_{\tau(j),\tau(v)} = w_{\tau(j)} - w_{\tau(v)}.
\]  

(2.69)

The difference operator is used for sub-weights determination, as the ratio between weights does not make any sense in both mathematical and logical ways of consideration.

For example, we know that criteria weights have been defined such as \( w_2 > w_1 \), meaning higher importance of gross fixed capital formation (\( c_2 \) – nominator) over economically active population (\( c_1 \) – denominator). It means that the higher priority in targets’ achievement should be given to the \( c_2 \). The weight of the new obtained sub-criterion \( c_{2,1} \) is \( w_{2,1} = 0.07-0.04 = 0.03 \). If \( I_{\tau(2)/\tau(1)} \) for the 1st region is lower than for the 2nd one, the latter has better (more effective) proportions, even though absolute values of \( c_1 \) and \( c_2 \) from the 1st region are higher. In other words, the 2nd region achieves targets better or does “right things” in terms of etalon proportions established by weights. To remind one more time, just proportions (ratios) are the subject for the measurement in the frame of the effectiveness analysis. The benefit subset is the sum of the ratios between nominator (representing a more important criterion) and denominator (representing a
less important one). However, the multiple participation of the nominator is accompanied by its cost participation as well, when it plays the role of the denominator in the subset initiated by other more important criteria unless it is the last n-th the most important criterion. By such decomposition, the participation of each original criterion is accounted for both benefit and cost sides separately. Thus, presented in eq. (2.68) utility dependence and dual nature (cost and benefit) of original criteria can be avoided due to the decomposition and formation of new-paired sub-criteria. To give more visibility to the presented idea of the ratio decomposition, we have pictured geometrical representation of the classic SAW method (fig. B.7, Appendix B). It can be seen easily, that total utility geometrically represented is just a sum of areas (OAA₀, OBB₀, OCC₀) of up-ward slope triangles, where their areas are obtained by multiplication of their heights (normalised value) on weights.

The idea of the proposed ratio approach is visualised in fig. 2.13.

fig. 2.13: Ratio decomposition approach to measure the total utility

![Diagram showing ratio values and weights](image)

*Source: author*

The heights of newly appeared triangles are formed by ratios obtained from all possible pairs of arranges in weights ascending order sub-criteria (for \(j, v = 1, n : j > v\)); meantime bases of triangles are formed by the differences of their respective weights. In the frame of this approach, the total utility function is represented by the sum of areas of up-ward slope triangles \(A_0 B_A B_0\), \(A_0 C_A C_0\), \(B_0 C_B C_0\). Based on the preconditions mentioned above the following targets should be reached by the developed method:

1. to catch the relative proportions of target attainments;
2. to measure the degree of right target attainment;
3. to consider the uniformity target attainment degree as an additional factor of effectiveness (optionally).

To sum up, the methodological contribution of the proposed Ratio Additive Weighting method (RAW) for the effectiveness measurement is steamed out from the ratio decomposition approach introduced earlier (fig. 2.11) and embedded into the SAW method frame (Fishburn, 1977). Further, we present steps of the suggested new RAW method:

1. to determine the initial set of alternatives \( A = \{a_k | k = 1, m\} \).
2. having selected original criteria \( C = \{c_j | j = 1, n\} \), to decompose it to the extended set of sub-criteria \( \bigcup_{j=2}^{n} C^*_j \) for \( i, v = \overline{1, n} : i > v \), where \( \tau(i), \tau(v) \) is the permutation on weights \( (W) \), that is \( w_{\tau(1)} < w_{\tau(i)} < w_{\tau(n)} \).
3. to form the performance matrix \( X = [x_{ki}]_{m \times n} \) showing all values assigned to the alternatives relating to each criterion.
4. having obtained the initial set of weights denoted by \( W = \{w_j | j = 1, n\} \), to decompose it using difference operator obtaining new extended \( n-1 \) subsets \( W_{\tau(i)-\tau(v)} \) for \( i = 2, n : i > v \) with sub-weights \( w^*_{\tau(i)-\tau(v)} \) calculated by:

\[
W^*_{\tau(i)-\tau(v)} = W_{\tau(i)} - W_{\tau(v)}. \tag{2.70}
\]

An original set of weights can be obtained by different objective data-driven methods, such as Entropy method based on eq. (2.5)-(2.7) or by subjective methods. For example, this is one of the simplest subjective methods, called Ordering method and based on ascending ranks ratio:

\[
w_j = \frac{\text{rank}_i}{\sum_{j=1}^{n} \text{rank}_j} \tag{2.71}
\]

This method perfectly suits the situation when a DM is aware of the targets to be reached and able to form clearly the preferences.

5. to normalise the new extended sub-weights \( w^*_{\tau(i)-\tau(v)} \) obtaining 1 as the sum of \( w^*_{\tau(i)/\tau(v)} \):

\[
W^*_{\tau(i)-\tau(v)} = \frac{w_{\tau(i)} - w_{\tau(v)}}{\sum_{i=2}^{n-1} \sum_{v=1}^{i-1} (w_{\tau(i)} - w_{\tau(v)})} \tag{2.72}
\]

6. to normalise initial performance values \( x_{ki} \) obtaining \( l_{ki} \) for the \( k \)-th alternative and \( i \)-th criterion using modified linear max normalisation producing values from 1 to 10:
\[ I_{ki} = \begin{cases} 1 & \text{if } (x_{ki} \cdot 10 / x_{\text{max}}^i) < 1 \\ (x_{ki} \cdot 10 / x_{\text{max}}^i). & \end{cases} \] (2.73)

Many other normalising and standardising procedures can be applied; however, due to the specific properties, this method of normalisation was preferred in this research. The only requirement relates to the final value, which should not be less than 1.

7. to decompose levels of target achievement \( I_{ki} \) using ratio operator for obtaining new extended target achievements \( I_{k,\tau(i)/\tau(v)} \), encompassing relations between two criteria:

\[ I_{k,\tau(i)/\tau(v)} = \frac{I_{k,\tau(i)}}{I_{k,\tau(v)}} \text{ for } i = 2, n : i > v. \] (2.74)

8. to standardise decomposed levels of target achievement obtaining their z-values \( I_{k,\tau(i)/\tau(v)}^* \) for \( \sigma(i)/\sigma(v) \)-th criterion among \( m \) alternatives:

\[ I_{k,\tau(i)/\tau(v)}^* = \frac{I_{k,\tau(i)/\tau(v)} - \overline{I}_{\tau(i)/\tau(v)}}{S_{\tau(i)/\tau(v)}}, \] (2.75)

where \( \overline{I}_{\tau(i)/\tau(v)} \) – the average value of target achievement,

\( S_{\tau(i)/\tau(v)} \) – the standard deviation of target achievement.

9. to calculate effectiveness \( E_k \) representing the decision maker’s preferences over \( k \)-th alternative considering the extended weighted target achievements:

\[ E_k = \sum_{i=2}^{n} \sum_{v=1}^{i-1} I_{k,\tau(i)/\tau(v)}^* \times w_{\tau(i)/\tau(v)}^* \text{ for } i = 2, n : i > v. \] (2.76)

10. calculate the coefficient of variation \( CV_k \) of extended weighted target achievements \( lw_{k,\tau(j)/\tau(v)} \) to measure their uniformity:

\[ CV_k = \frac{\sigma(lw_{k,\tau(j)/\tau(v)})}{\overline{lw}_{k,\tau(j)/\tau(v)}} \text{ for } k = 1, \ldots, m. \] (2.77)

where \( \overline{lw}_{k,\tau(j)/\tau(v)} \) – the average value of weighted target achievements,

\( \sigma(lw_{k,\tau(j)/\tau(v)}) \) – the standard deviation of weighted target achievements.

11. calculate the balanced \( E_k^b \) using \( CV_k \) as follows (uniformity aspect):

\[ E_k^b = \frac{E_k}{CV_k}. \] (2.79)

The developed method will be applied to EU NUTS 2 regions in section 3.1.2.
2.2.4 Non-compensatory resonance approach to measure competitiveness

The proposed resonance approach to the measurement of intensive and extensive aspects regional performance fits the multi-dimensional scenario (blocks 1.2-4.2 in fig. 1.17) including the application of MCDM methods based on methodological pluralism.

The poly-pillar compensatory measurement approach using a single, very often linear aggregating methodology as in (Annoni, Kozovska, 2010; Annoni, Dijsktra, Kozovska, 2011; Annoni, Dijsktra, 2013; Gábor, Ottaviano, 2015; Snieška, Bruneckienė, 2009) can be perceived as the factor, which decreases the precision (because of high compensatory effect) and usefulness of competitiveness for the policy-makers. Pillars encompassing basic indicators should be structured and precisely reflect areas of regional performance, representing the essence of the competitiveness. In the case of developing countries, regional performance and competitiveness should be based mostly on business and labour (working) factors, which allows decreasing the number of essential pillars included in analysis. That is why we decided to focus on the simplified and, at the same time, clear “magnetic” vision of competitiveness. Following this vision, Annoni and Dijkstra (2013) define RC as “the regional ability to offer an attractive and sustainable environment for firms and residents to live and work.”

The “magnetic” view, meaning that a competitive region attracts human capital and businesses, is supported by a great number of definitions and descriptions of competitiveness (Poot, 2000; Porter and Ketels, 2003; Cooke, 2004; Aiginger, K., 2006; Pessoa A., 2013). It should be noted that while RC has been measured in different ways, the “magnetic” perception has remained only as a definition and has not been quantified. Moreover, in our opinion, such a poly-dimensional phenomenon as RC should be analysed based on the synthesis of methods suited specifically to each aspect of performance.

From a policy-making perspective, the usefulness of CI is limited to choosing “winners and losers”, where the last ones are subject to the policy interventions. The recipe is simple: the more lagging a region is, the more “medicine” it requires. This is the most straightforward rule, making competitiveness usable for regional policy-makers. However, such a simple approach, no matter which aggregating technique has been used, does not pay attention to the following spatial and hierarchical specifics while determining the targets. As there is a significant spatial correlation between neighbouring NUTS 2 regions, the corresponding NUTS 1 regions can considerably influence their performance. This means that paying attention to the hierarchical
interconnectedness of NUTS 1 and NUTS 2 regions can lead to important synergetic effects while establishing the targets. Therefore, the complexity of the system requires a more differential approach to the investigation of the system’s characteristics should be applied for policy-making; instead of just an aggregation procedure leading to the composite CI.

The core of the resonance approach is formulated in the following way: if the weaknesses of lagging NUTS 2 regions coincide with the corresponding NUTS 1 region, then neighbouring regions with such weakness coincidence requires homogeneous resonance interventions forming a synergetic effect in their regional performance. Simply put, the “weakness coincidence” at the two NUTS levels is the base for policy-making within this approach. The bigger the area with homogenous weakness coincidences the stronger resonance effect will be from policy interventions. Regional weakness is defined as the explored composite characteristic presented as a component of competitiveness (sub-indicator) that has been ranked as the worst compared to other characteristics within the same region. For the sake of formalisation, we provide definitions of the interventions analysed further:

a) the resonance interventions (RI) assume hierarchical coincidence between NUTS 1 and included NUTS 2 regional weaknesses.

b) the homogeneous RI imply not only hierarchical but also spatial coincidence of weaknesses between NUTS 2 and corresponding NUTS 1 region. In other words, the synergy effect caused by these interventions is based on the double weakness coincidence defined in spatial and hierarchical form.

c) the ordered RI presuppose a series of consecutive RI, based on double coincidence and strict succession of ranks.

The combined effect of the homogeneous RI based on territorial synergy will be greater than interventions elaborated for each region in isolation. Simply said, what is profitable for a NUTS 2 region should also be a priority for the system (NUTS 1 region). No region has enough potential to realise a maximum positive effect while in horizontal (between NUTS 2 regions) or hierarchical (NUTS 2 and NUTS 1) isolation.

The rationale of the suggested resonance intervention approach is based on the following assumptions revealing the cornerstones of the framework. The assumptions are divided into two blocks. The first three assumptions are about the particularities of competitiveness measurement and the three final ones directly related to the resonance approach:
1. the set of pillars is based on the “magnetic vision of RC.” In particular, the number of pillars is reduced to human capital, business and meso-level. These pillars describe the performance of the two main consumers of RC, those that primarily form competitiveness in the developing countries;

2. pillars are measured from a two-dimension perspective following input and output division, in particular, intensive (technical efficiency) and extensive (resource level);

3. aspects (pillars) and dimensions are the same at both NUTS 1 and NUTS 2 hierarchical levels. The fractal principle is adhered to as the basic underlying principle. It simplifies the competitiveness benchmarking at NUTS 1, 2 levels, keeping the composition of components scale-free (similar);

4. the NUTS 1 division of the country is assumed to be a functional division;

5. in lagging regions, policy interventions focus on the “weak link,” or the regional weakness that, when dealt with, represents a trigger for competitiveness improvements and local potential realisation;

6. the efficiency of policy-making focused on lagging regions can be increased with the homogeneous RI.

Below, we present the set of hypotheses, which are entirely consistent with the introduced types of interventions. The set is made up of the following hypotheses: determination of RI by the level of total competitiveness (A), determination of RI by the components of competitiveness (B), the presence of a homogeneous (C) and ordered area of RI (D).

A: \( H_0 \): RI to the NUTS 2 regions are not determined by their level of total competitiveness or economic development (GDP/capita).

\( H_{alt} \): RI to the NUTS 2 regions are determined by competitiveness.

B: \( H_0 \): RI to the NUTS 2 regions are not determined by the level of competitiveness components.

\( H_{alt} \): RI to the NUTS 2 regions are determined by competitiveness components.

C: \( H_0 \): there are no equal RI to the regions neighbouring to each other.

\( H_{alt} \): there is a homogeneous area (spatial coincidence) of RI targeted at neighbouring NUTS 2 regions.

D: \( H_0 \): there are no consecutively ranked RI in the homogeneous area.

\( H_{alt} \): RI in the homogeneous area are ranked in a series.
Al hypotheses will be tested in subsection 3.1.3.

The full extent argumentation of the resonance approach in detail can be found in (Guliak, 2017). From a practical point of view, the best way to show the essential link between competitiveness and policy-making will be to simultaneously outline three essential aspects describing competitiveness interwoven into a policy-making process (fig. B.8, Appendix B).

The methodological aspect revealed by the question “Which methodology to use for regional competitiveness (RC) measurement?” is the most important to discuss here. The answer, in our opinion, should be based on methodological pluralism (Flood and Jackson, 1991; Jackson, 1991; Flood and Romm, 1996; Mingers and Gill, 1997). The wider the range of available methods, the more flexible and responsive our systemic practice can be. No single methodology can make a comprehensive analysis of phenomena, especially when it comes to RC. Therefore, being able to draw upon multiple methods from different paradigmatic sources can enhance the system’s thinking resource we have available for intervention (Midgley G., 2014). To measure RC in different dimensions, we use three methods dealing with input and output categories. The last aspect is “What is the best place or territory (region) for receiving the interventions?” The rationale of the answer to this question is given within the suggested resonance approach assuming the importance of the coincident of the intervention targets between NUTS 1 and NUTS 2 levels.

Following the analysis of the first resource component, we get answers to the question: “What does a region perform with?” The second technical efficiency component answers the question: “Is regional performance efficient enough to produce maximum outputs from the given quantity of inputs?” Finally, the third structural effectiveness component answers the question: “Is a way of performance effective enough to produce indented or expected results?” This set of dimensions through which competitiveness is going to be studied requires corresponding methodological tools. All methods used in this approach comply with the theoretical framework of RC investigation and reflect the specific traits of the highlighted conceptual dimensions (fig. 2.14). To uncover the extensive dimension, we aggregated initial inputs by the distance-based Hellwig’s method (sec. 2.1.3.1), using a synthetic indicator to measure the level of regional resources (extensive component). The DEA method (sec. 2.1.4) is focused on the technical efficiency of the region and aggregates inputs and outputs (outcomes) reflecting the intensive dimension of competitiveness. To our knowledge, DEA and Hellwig’s indices have never been
combined in similar studies to investigate these intensive and extensive aspects. The structural effectiveness is measured by the RAW method suggested in sec. 2.2.3.

fig. 2.14: Methods applied in the resonance approach

The expected hierarchical structure of indicators and composite indices obtained from the presented methods is shown in fig. B.9 (Appendix B). Having applied all the methods and to compute the synthetic competitiveness indicator (CI), its components have to be aggregated at least by the SAW method. After that for the examination, the variability of ranks, a simple simulation procedure has to be conducted, where the parity of weights will serve as the starting point of sensitivity analysis. All 6 sub-indicators will be transformed into a [0;1] variability range using the step $\frac{1}{k \times p}$ (where p is 10) turning k-1 sub-indicators in equal proportion. Having formed the 61 sets of technically admissible weights for each sub-indicator, we obtained 6×61 sets in total and consequently, the same number of sets of ranks. For every $j$-th NUTS 2 region we found mean rank ($\bar{r}_j$), standard deviation ($\sigma_j$), max rank ($r_{j}^{\text{max}}$) and min rank ($r_{j}^{\text{min}}$). The variability of ranks is analysed using two approaches, namely the max-min and standard deviation approach. Correspondingly, robustness ($\bar{R}$) can be measured in two ways:

$$\bar{R}^{\text{max-min}} = 1 - \frac{\sum_{i=1}^{n} r_{i}^{\text{max}} - r_{i}^{\text{min}}}{n^2};$$  \hspace{1cm} (2.80)

$$\bar{R}^{\sigma} = 1 - \frac{\sum_{i=1}^{n} 2 \times \sigma_i}{n^2}. \hspace{1cm} (2.81)$$

In the case of low robustness, the non-compensatory resonance approach for the determination of lagging regional policy interventions gets its actuality. It is because the
resonance approach is a non-compensatory approach based on the resonance principle applied to both NUTS 1 and NUTS 2 levels representing the administrative division of European regions. The procedure of the suggested method, which combines measurement results into one compromise resonance solution, is provided below:

1. definition of alternatives according to the E (technical efficiency), R (resource level) and St. (structural effectiveness) dimensions of competitiveness and according to the two external G, S managerial levels and one internal L level;
   1.1 decision matrices $G^E$ and $G^R$ are $(F\times K)$ matrices in which elements $g^E_{mj}$ and $g^R_{mj}$ separately indicate the performance of alternative $G_m$ (NUTS 1 region) for $m=1,...,F$ according to E and R dimensions;
   1.2 decision matrices $S^E$ and $S^R$ are $(N\times K)$ matrices in which element $s^E_{ij}$ and $s^R_{ij}$ separately indicate the performance of alternative $S_i$ (NUTS 2 region) for $i=1,...,N$ according to E and R dimensions, when $S = \{s_i\} = \bigcup_{gsG} g | N > F$;
   1.3 decision matrix $L$ constitutes $(N\times K)$ matrices in which element $l_{ij}$ indicates the performance of alternative $L_i$ (NUTS 2 region) for $i=1,...,N$ according to the St. (structural effectiveness) dimension;

2. definition of criteria $C_j$ based on the aspects of competitiveness measurement, namely human, business and meso-level group (table 3.4). Alternatives $G_m, S_i, L_i$ are evaluated in terms of decision criteria $C_j$ for $j=1,...,K$;

3. transformation of original matrices into ranked ones according to $E$, $R$, $St.$ dimensions separately, where the highest rank is assigned to the lowest value (Appendix C, Table C.12);
   3.1 transformation of $G$ matrix into the ranked matrix $G^r$ in which elements $g^r_{mj}$ indicate the performance of $m$-th alternative measured in ranks $(r^g_m)$, so as $g^r_{mj} = \{r^g_m\}$;
   3.2 transformation of $S$ matrix into the ranked matrix $S^r$ in which elements $s^r_{ij}$ indicate the performance of $i$-th alternative measured in ranks $(r^s_i)$, so that $s^r_{ij} = \{r^s_i\}$;
3.3 transformation of \( L \) matrix into the ranked matrix \( L' \) in which elements indicate the performance of \( i \)-th alternative measured in ranks \( (r_i') \), so that \( l_i' = l(r_i') \);

4. to define weaknesses for \( E, R, St. \) dimensions separately for matrices \( G', S', L' \) (table 3.5);
   4.1 from the matrix \( G' \) to define the weaknesses \( g_i \) choosing minimal rank \( (\min g_{ij}^r) \) for \( m \)-th alternative with respect to criterion \( C_j^e \);
   4.2 from the matrix \( S' \) to define the weaknesses \( s_i \) choosing minimal rank \( (\min s_{ij}^r) \) for \( i \)-th alternative with respect to criterion \( C_j^s \);
   4.3 from the matrix \( L' \) to define the weaknesses \( l_i \) choosing minimal rank \( (\min l_{ij}^r) \) for \( i \)-th alternative with respect to criterion \( C_j^l \);

5. with respect to \( E \) and \( R \) dimensions to define correspondingly possible resonance combinations \( M_i^e \) and \( M_i^r \) for all alternatives as a coincidence of weaknesses criteria \( C_j \) between \( g_i, s_i, l_i \) using match function \( (M) \) leading to the different resonance combination (table 3.5):

\[
M_i = M(g_m, s_i, l_i) = \begin{cases} 
C_j(G, S, L) & \text{if } C_j^e \equiv C_j^s \equiv C_j^l; \\
C_j(G, S) & \text{if } C_j^e \equiv C_j^s; \\
C_j(G, L) & \text{if } C_j^e \equiv C_j^l; \\
C_j(S) & \text{if } C_j^e \neq C_j^s \land C_j^e \neq C_j^l.
\end{cases}
\]

6. to define \( R^* \) as a \( \max_r \) \( M_i \) following the resonance preferences \( (G, S, L) \succ (G, S) \succ (G, L) \) (table 3.6);

7. to define ranks \( (r_{ij}^M) \) of alternatives \( M_i^* \) in accordance with resonance preferences and finding maximum rank at \( G, S \) and \( L \) levels \( \max_m \max_r \max M_i^* \);

8. to determine the homogeneous RI \( \{M_i^w\}^{\text{homog.}} \) (fig. 3.5) which have spatial contiguity of the \( M^*_i \) with the same coincidence criteria \( C_{ij}^{M^*} \):

1.1 can be defined visually by mapping.
1.2 can be defined analytically by constructing the \((N \times N)\) matrix \(M^W\) for which rows are computed as a product of coincidence criterion \(C_{ij}^M\) and row \((1 \times n)\) vector 
\[ w_i = (w_1, \ldots, w_n) \]
for which values equal 1 (if regional contiguity) or 0 (if discontinuity):
\[
M^W = \begin{pmatrix}
C_{i1}^M \times w_1; \\
\vdots \\
C_{in}^M \times w_n;
\end{pmatrix}, \text{ where contiguous } C_{ij}^M \text{ to be found;}
\]

9. to define the series of rank-ordered homogeneous RI \( \{M_i^W\}_{\text{ordered homog.}} \).

Six steps of the given algorithm are presented graphically in fig. 2.15. The highest priority is given to the region having the highest resonance GSL index-combination. The GSL combination points at the match in weaknesses in efficiency dimension of meso-group at both NUTS 1 and NUTS 2 hierarchical levels.

fig. 2.15: Determination of resonance index-combinations

Source: author

As we can see the main idea of resonance approach is the weakness coincidence at the two NUTS levels: if the weakness of lower NUTS 2 level coincides with the weakness of respective NUTS 1 region, then neighbouring regions with such coincidence require homogenous resonance
interventions. The application of a given approach will be made for the Ukrainian regions in section 3.1.3.

2.3 Pragmatic approaches to selection and profiling of the most appropriate multi-criteria decision-making method

The set of assumptions guiding how the selection problem is solved was presented in the 1.3 sub-chapter. All these assumptions found its methodological embodiment in the current sub-chapter. Hereinafter the necessary steps and formulae are given for the selection of the MCDM method based on practical criteria and correspondingly problems at hand, such as the classification of regions and funds’ distribution. The presented approaches to select the MCDM method are just an alternative way to choose a more suitable and appropriate method. Moreover, the suggested approaches are applied exclusively in the context of SF distribution and do not pretend on the paramount and general applicability.

The complexity of the practical problems to be solved determines a composition of criteria used for the selection problem. As it was pointed out in sub-chapter 1.3, we stick to the most uncomplicated case with just a single criterion stemming from practical problems. Such a simplified situation does not require the solution of a multi-criteria problem at the higher hieratical level. Thus, the problem of methods selection is reduced to a single criterion problem. The following task is to measure the value of this criterion for each considered MCDM method. The conceptual idea of practical criteria for MCDM methods’ selection is described and visually presented in sub-chapter 1.3. The sequence of steps necessary for the realisation of the selection approach guided by two different practical criteria is given in fig. B.10 (Appendix B). Thereinafter the examples of practical criteria for MCDM method’s selection are discussed and formalised into the developed selection approaches (sec. 2.3.1, 2.3.2). However, the justified choice of MCDM method has to be accomplished by the understanding of its peculiarities and characteristic features. For that, the approach to MCDM profile construction was proposed in sec. 2.3.3.
2.3.1 Approach to the method’s selection based on the clustering structure analysis

The proposed selective approach follows the scenario of multi-dimensional measurement presented in sec. 1.3.1 (blocks 1.2-4.2, fig. 1.17). This approach belongs to block 3.2, necessary for the selection of the most suitable method from the panel of applied MCDM methods.

The first practical criterion to be further discussed and methodologically described is based on the practical classification problem being solved by clustering methods. The quality of the clustering structure obtained after the application of clustering methods is the identifier of the most suitable MCDM method. One should notice that the clustering structure differs according to its ranking (high similarities between clusters and low similarities within clusters) or clustering properties (high similarities within clusters and low similarities between clusters). The features are displayed in a graph (fig. 2.16), where it is seen that the best clustering structure possesses the lowest dissimilarities within the cluster and the highest dissimilarity between the clusters.

**fig. 2.16**: The relations between clustering structure properties

![Graph showing the relations between clustering structure properties](image)

*Source: author*

Just for reminding, if the clustering structure possesses the highest quality, then the MCDM method providing the utility values for the clustering is the most suitable for the clustering and correspondingly for classification purpose. In this case, alternatives within the cluster are measured as almost similar ones, while clusters ought to be at most dissimilar to each other, showing the principal difference between belonging to them alternatives. In the opposite case, with low quality, the MCDM method seems to be the best for the ranking of alternatives (regions) differentiating them from each other the most. Considering said above, the suggested
below methodology using the quality of the clustering structure has to measure the differentiating power of the MCDM method producing utility values.

To start the discussion about clustering based on MCDM methods, one should mention that while MCDM methods construct an ideal point or etalon from the alternatives’ attributes expressed in the best way, the clustering methods have nothing to do with that. On the contrary, they pay maximum attention to the attributes of each alternative and measure the distance between alternatives to find the similarities for the cluster identification. MCDM methods, in turn, measure the distance to the pure etalon producing the corresponding vector of final scores. It means that MCDM based clustering does not pay explicitly (considering each attribute separately) attention to the neighbours concerning the distance to them. The distance between neighbours is accounted for indirectly utilising the distances to the etalon or aggregated utility value (fig. B.11, Appendix B). Such a way of similarity measurement can be called quasi-clustering or radial one, what per se has the right to exist and requires further steps of analysis suggested below.

Speaking of clustering parameters taken into account in the current research (table 2.2), all of them have advantages and disadvantages, discussion of which is not worth conducting due to the limited scope of the research. Moreover, it would not make any added value, as the set of 15 validating criteria is going to be used to make the final selection.

<table>
<thead>
<tr>
<th>Distance measure</th>
<th>Linkage method</th>
<th>Clustering method</th>
<th>Validating criteria</th>
<th>Number of clusters</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Manhattan distance</td>
<td>1. Single</td>
<td>1. k-means</td>
<td>1. &quot;ch&quot;</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>2. Complete</td>
<td></td>
<td>2. &quot;cindex&quot;</td>
<td>2</td>
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</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>15. &quot;hartigan&quot;</td>
<td>10</td>
</tr>
</tbody>
</table>

Nevertheless, the procedures of two frequently used clustering methods, namely, k-means and hierarchical clustering, are presented below. Hierarchical algorithms, in particular, have been dominant in the literature (Kassambara, 2017). At the same time, the k-means method considered the most popular clustering technique (Henning et al., 2015). Frequent usage of these techniques underpinned out choice for mentioned clustering methods.
The general task for the clustering: considering the sets of alternatives \( A = \{a_i | i = 1, n \} \), clusters \( C = \{c_k | k = 1, f \} \), \( f \leq n \) and MCDM methods \( M = \{m_p | p = 1, l \} \), the task for the clustering is to find the optimal number of clusters \( k^* \leq n \) at the \( z \)-th step related to the \( p \)-th MCDM method.

K-means algorithm can be summarised as follow:

1. Specify the number of clusters (K) to be created (by the analyst)
2. Select randomly \( k \) objects from the data set as the initial cluster centres or means
3. Assigns each observation to their closest centroid, based on the Euclidean distance between the object and the centroid
4. For each of the \( k \) clusters update the cluster centroid by calculating the new mean values of all the data points in the cluster. The centroid of a \( k \)-th cluster is a vector of length \( p \) containing the means of all variables for the observations in the \( k \)-th cluster; \( p \) is the number of variables.
5. Iteratively minimise the total within the sum of square. That is, iterate steps 3 and 4 until the cluster assignments stop changing or the maximum number of iterations is reached.

Mathematically, each observation \((x_i)\) is assigned to a given cluster such that the sum of squares (SS) distance of the observation to their assigned cluster centres \( \mu_k \) is a minimum. We define the total within-cluster variation as follow:

\[
\text{tot.within} = \sum_{k=1}^{k} W(C_k) = \sum_{k=1}^{k} \sum_{i \in C_k} (x_i - \mu_k)^2 \rightarrow \min.
\] (2.82)

The total within-cluster sum of square measures the compactness (i.e. goodness) of the clustering, and we want it to be as small as possible (Kassambara, 2017).

The focus of this research is on agglomerative clustering. It works in a “bottom-up” manner by the following steps:

1. Initialisation. To start by assigning each item to each own cluster so as \( k = n \). Thus each object is initially considered as a single-element cluster (leaf).
2. Iteration.
   2.1 The first step is to compute a dissimilarity/distance matrix from the original data matrix. Working with the vector space, a traditional way to measure distances is to use the Minkowski distance function, which is a family of metrics:
\[ L_p(x_a, x_b, ) = \left( \sum_{i=1}^{d} |x_{i,a} - x_{i,b}|^p \right)^{1/p}, \forall p \geq 1, p \in \mathbb{Z} \] (2.83)

Having instead of vector space just one variable – utility value, the clustering becomes monothetic when the most straightforward distance measure will be the Manhattan \((p=1)\).

2. 2 Relying on the fusion strategy (linkage method) to merge two clusters into one. The most common linkage methods are the following:

- single-link distance between clusters \(C_i\) and \(C_j\) is the minimum distance between any object in \(C_i\) and any object in \(C_j\). Distance is defined by the two most similar objects as

\[
D_s(C_i, C_j) = \min_{x,y} \{d(x,y) | x \in C_i, y \in C_j \} \tag{2.84}
\]

- complete-link distance between clusters \(C_i\) and \(C_j\) is the maximum distance between any object in \(C_i\) and any object in \(C_j\). The distance is defined by the two most dissimilar objects as

\[
D_c(C_i, C_j) = \max_{x,y} \{d(x,y) | x \in C_i, y \in C_j \} \tag{2.85}
\]

- group average distance between clusters \(C_i\) and \(C_j\) is the average distance between any object in \(C_i\) and any object in \(C_j\). The distance is defined by the two most dissimilar objects as

\[
D_{avg}(C_i, C_j) = \frac{1}{|C_i| \times |C_j|} \sum_{x \in C_i, y \in C_j} d(x,y) \tag{2.86}
\]

2. 3 linkage method verification. If the investigator does not have strong priorities for the specific linkage method, the cophenetic correlation can be used to choose the most appropriate linkage method:

\[
D_{avg}(C_i, C_j) = \frac{1}{|C_i| \times |C_j|} \sum_{x \in C_i, y \in C_j} d(x,y) \tag{2.87}
\]

If the clustering is valid, the linking of all objects into the cluster tree should have a strong correlation between the cophenetic distances and the original distance measured by the Minkowski distance function. The closer the value of the correlation coefficient is to 1, the more accurately the clustering solution reflects the data (Kassambara, 2017).

The 15 indices (Charrad et al., 2014) will determine the number of clusters and propose the best clustering scheme from the different results obtained by varying all combinations of clusters’ numbers, distance measures, and clustering methods. The list of 15 validating indices with their optimal values is presented in Table B.3 (Appendix B).
The validating criteria are capable of measuring differently the quality of the clustering structure and by this to select the best clustering structure based on a pair of correspondingly best clustering and MCDM methods. Even though the validating indices work with slight differences, they count the same properties of the clustering structure (fig. 2.16) and find their compromise solution with the optimal number of clusters. A remarkable feature of validating indices application is that they help solve at the same time several selecting problems, namely aimed at the choice of the best clustering structure. Using these indices, based on two characteristics (Tan et al., 2005), such as compactness (how near the data points in a cluster are to the cluster centroid) and isolation or separation (how far away the different cluster centroids from one another) of clusters, we can solve several tasks:

1. to choose the best MCDM method representing particular aggregating strategy and providing data (utility values) for the clustering;
2. to choose the best clustering method directly processing utility values;
3. to choose the optimal number and distribution of clusters and by this the genuine classification.

Finally, the additional decisive criteria measuring discrimination power ($D$) of each MCDM method coupled with the clustering method, is calculated as follows:

$$D_{\%} = \frac{10 \sum_{i=2}^{10} n_{i,\text{opt}} \times f_{i,\text{opt}}}{n \times 10} \times 100\%.$$  \hspace{1cm} (2.88)

where $n_{i,\text{opt}}$ – the optimal number of clusters, $i = 2, \ldots, 10$.

$f_{i,\text{opt}}$ – the number of times, when the optimal number occurred,

$n$ – number of validating indices used.

The presented indicator measuring the discriminating power is proposed as the identifier of methods’ tendency to produce the clustering structure with a certain number of clusters when the number of possible clusters varies from 10 to 2. Thus the lower the discriminating power is, the more reasons to identify this combination of clustering and MCDM methods as oriented on the optimal structure with fewer clusters. Such methods’ combination with the lowest discrimination power points at the genuine clustering structure.

The suggested approach is going to be applied to the EU NUTS 1 regions in section 3.2.1.
2.3.2 Approach to the method’s selection based on analysis of ranks’ robustness

The proposed selective approach is congruent with the scenario of multi-dimensional measurement presented in sec. 1.3.1 (blocks 1.2-4.2, fig. 1.17). Particularly, this approach belongs to block 3.2, responsible for the selection of the most suitable method from the panel of applied MCDM methods. As opposed to the previously introduced criterion of clustering structure quality, this one is based on the robustness of the MCDM methods in terms of identified ranks. It presents another foundation for the selection problem predetermined by the following optimisation problem. Robustness is measured with the connection of ranked alternatives suitable for the further fund’s distribution made under the banner of “Robin Hood principle”. To remind, considering the richest and the poorest regions, measured by the MCDM method, the range of their possible ranks according to other methods has to be minimal. For example, the poorest (last position) region by the \( i \)-th method has the range of possible ranks equal to 30, while by \( j \)-th method the poorest region has the range of 10 ranks. By comparison, the \( j \)-th method provides a more robust measurement for the proceeding optimisation problem. Such logic makes sure that the more robust method will have the minimum (centred) measurement error (fig. C.7, Appendix C) proved by the majority of the methods. Saying differently, if the method puts on the leading positions regions with a narrower range of possible ranks, it has a higher fitness score and is considered robust.

As practice (distribution of funds) determines the final exploitation aim of the MCDM methods’ application, it also produces the best criterion for the verification (objectification). Therefore, a selection (objective choice) – is made pragmatically and is congruent with how the further problem (optimisation) is solved. Considering the inputs and outputs of the proposed selection process based on the robustness, the following elements have to be defined:

1. Inputs.
   1.1. Set of alternatives \( \left\langle A \right\rangle \), where \( a_i | i = 1..n \) is an \( i \)-th alternative (region).

1.2. Set (panel) of MCDM methods.
   1.2.1. Set of application MCDM methods \( \left\langle M_{\text{applic}} \right\rangle \), where \( m_g | g = 1..k \) – is the \( g \)-th MCDM method at the application step.
   1.2.2. Set of selecting MCDM methods \( \left\langle M_{\text{select}} \right\rangle \), where \( m_l | l = 1..m \) – is the \( l \)-th MCDM method at the selection step.
1.3. Set of criteria.

1.3.1. Set of application criteria \( \{ C_{\text{applic}} \} \), where \( c_b | b = 1 \ldots d \) is the \( b \)-th criterion taken into account at the application step for the set of alternatives \( \{ A \} \).

1.3.2. Set of selecting (practical) criteria \( \{ C_{\text{select}} \} \), where \( c_e | e = 1 \ldots f \) is the \( e \)-th criterion taken into account at the selecting step for the set of application MCDM methods \( \{ M_{\text{applic}} \} \).

1.4. Set of application values \( \{ V \} \), where \( v_{ib} | i = 1 \ldots n, b = 1 \ldots d \) is the value of \( i \)-th alternative with \( b \)-th application criterion.

1.5. Set of weights.

1.5.1. Set of application weights \( \{ W_{\text{applic}} \} \), where \( w_b | b = 1 \ldots d \) is the weight of \( b \)-th criterion taken into account at the application step for the set of alternatives \( \{ A \} \).

1.5.2. Set of selecting weights \( \{ W_{\text{select}} \} \), where \( w_e | e = 1 \ldots f \) is the weight of \( e \)-th criterion taken into account at the selecting step for the set of application MCDM methods \( \{ M_{\text{applic}} \} \).

2. Outputs related to \( i \)-th alternative and obtained by the \( g \)-th application MCDM method.

2.1. Set of utility values \( \{ U_{\text{applic}} \} \), where \( u_{ig} | i = 1 \ldots n, g = 1 \ldots k \) is the utility value of \( i \)-th alternative obtained by \( g \)-th application MCDM method.

2.2. Set of ranks \( \{ R_{\text{applic}} \} \), where \( r_{ig} | i = 1 \ldots n \) is the rank of \( i \)-th alternative obtained by \( g \)-th application MCDM method.

3. Outcomes related to the \( g \)-th MCMD application method and obtained by \( l \)-th selecting MCDM method.

3.1. Set of utility values \( \{ U_{\text{select}} \} \), where \( u_{lg} | g = 1 \ldots k, l = 1 \ldots m \) is the utility value of the \( g \)-th application method obtained by \( l \)-th selecting the MCDM method.

3.2. Set of ranks \( \{ R_{\text{select}} \} \), where \( r_{lg} | g = 1 \ldots k, l = 1 \ldots m \) is the rank of \( g \)-th application method obtained by \( l \)-th selecting MCDM method.

Outputs from the application step and outcomes from the selection step can be presented as the following functions

\( \{ U, R_{\text{applic}} \} = f_{\text{applic}} (A, M_{\text{applic}}, C_{\text{applic}}, W_{\text{applic}}) \) and
\[ \langle U, R^{\text{select}} \rangle = f^{\text{select}}(U^{\text{applic}}, R^{\text{applic}}, M^{\text{select}}, C^{\text{select}}, W^{\text{select}}) \] correspondingly, where \( f^{\text{applic}} \) and \( f^{\text{select}} \) are transforming functions at the application and selecting steps correspondingly.

Graphically the sequence of selection process helping define the most suitable MCDM method in terms of inputs, outputs and outcomes is presented in fig. 2.17.

The inputs are all sources of uncertainty and subjectivity on the application step of every single method. Moreover, to the inputs of the selection process, we will add outputs of the application step, namely ranks and utility values. The outcome will be the most suitable method finally selected, while ranks or utility values produced by it are considered the most qualified, the most suitable or better representing the reality.

The central selective position taken in this research is that the current trend in the MCDM application field and the exceptional popularity of some MCDM methods does not influence and rule the choice of the MCDM method for the solution of practical problems, such as measurement and classification of regional performance. Only the researcher drives the choice of a starting conceptual point. In this relation, we try to avoid the affection to a specific MCDM method with the help of robustness analysis allowing the objective choice of the most suitable method regarding the following optimisation problem.

fig. 2.17: Sequence of steps of the selective MCDM methods process

Source: author
The panel of MCDM methods consists of three groups, in particular, compromise methods (VIKOR, Hellwig’s, TOPSIS), weighted methods (Additive Weighting Sum, Choquet), not weighted (Pena’s DP2, Equal weighting). An exactly active panel including seven basic MCDM methods creates the foundation for the simulated objectivity, which further will serve as the background for the calculation of Fitness function and the best method selection. Thus, the best method selection is predetermined by the two main factors, namely the panel of methods a constructed fitness function modelled for the specific practical situation causing the problem to be solved. Thereinafter all methods used at the selection step are divided into two sets. The MCDM methods, which will be compared, are mentioned as initial measuring perspectives. The aggregating derivatives from the basic Equal weighting method based on OWA operator are called as basic sub-perspectives.

The selection process is conducted by the following steps:
1. to measure subjectively (by specific MCDM method) the ranks of alternatives;
2. to measure pseudo-objectivity by calculating for each alternative the range (robustness) of all possible ranks received from all methods;
3. to normalise pseudo-objective robustness;
4. to transform the possible obtained ranks according to the fitness function reflecting the practical specificities of the problem;
5. to define importance (weight) of each transformed rank assigned to the alternatives;
6. to measure the fitness function as the product of standardised ranges and their weights.

First of all, pseudo-objective robustness ($R_i$) analysis takes into account the range $r_i$ of min and max ranks assigned to an alternative $i$ after the application of MCDM methods’ panel:

$$R_i = 1 - \frac{r_i}{n}, \quad i = 1...n.$$ (2.89)

$$r_i = rank_{rank_{max}}^i - rank_{min}^i$$ (2.90)

where $n$ – number of alternatives.

Both the pseudo-objective robustness measured by a panel of MCDM methods and the specific rank obtained from the particular method relate to each other as a general and particular. Therefore, this comparison gives us the foundation to compare them also as pseudo-objective (full possible range of ranks) and subjective (particular rank given by a certain method). So by
the consideration of possible ranks obtained by different MCDM methods, we emulate objective decision-making reality to find the most objective method.

The normalisation of \( R_i \) is often known as feature scaling when the values of a numeric range of robustness are reduced to a scale between 0 and 1. The choice of normalisation technique is not restricted to the min-max case. It can be also max, Z or average normalisation. However, the normalisation techniques being characterised by different levels of sensitivity to outliers also influence the sensitivity of the robustness measurement, making differences between MCDM methods more or less noticeable. When the MCDM methods produce very similar rankings, the higher sensitivity appears to be a great help for the selection problem. Thus, the min-max method was chosen because of its higher sensitivity to outliers and correspondingly higher discriminating power during the robustness analysis. It is achieved as follows:

\[
norm.R_i = \frac{R_i - \min(R_i)}{\max(R_i) - \min(R_i)}, \quad i = 1..n.
\]

To measure the level of methods’ similarity within the panel of MCDM methods, the following formula is used:

\[
av.R = 1 - \frac{\sum_{i=1}^{n} r_i^2}{n^2}
\]

Speaking of the subjective measurement related to each MCDM method, the ranks obtained have to be transformed, allowing the later application of the “Robin Hood” distribution principle. Based on this, the ranks of the donors and recipients must not be placed in a dichotomic way, but mixed in one side of the ranking list, while central regions are moved to the other. Such transformation of original ranks is conducted by the following formula:

\[
rank_i^* = abs \left| rank_i - \frac{n + 1}{2} \right|, \quad i = 1..n.
\]

where \( rank_i^* \) – transformed rank if \( i \)-th alternative, \( t = 0..m \), while \( m = \frac{n - 1}{2} \).

After the replacement of alternatives by the transformation, it is necessary to define their importance coefficients (weights) by the simple optimisation model presented below. The rank standing further from 0 has to have higher importance as alternatives taking it are referred to as key players (either donors or recipients) that are intensively involved in the distribution process. Thus weights \( (w_i) \) are calculated as follows:
$$w_i = (1 - \lambda) \times \lambda^\varphi,$$

(2.94)

The following optimisation model helps identify the optimal $\lambda$ parameter:

$$\sum_{i=1}^{m} w_i - \sum_{i=1}^{m} (w_{i+1} - w_i) \rightarrow \max,$$

(2.95)

$$\sum_{i=1}^{m} (w_{i+1} - w_i)$$

(2.96)

$$\text{when } \varphi = m - t,$$

(2.97)

where: $w_i$ – importance coefficient of $t$-th transformed rank;

$\lambda$ – the constant parameter being optimised;

$\varphi$ – variable parameter assigned to a corresponding importance coefficient;

$m$ – a number of transformed ranks equal to $\frac{n-1}{2}$.

The selection process eventually converges to the calculation of the fitness score. Now it is time to define which method is the most robust and more applicable in terms of preciseness to the distribution of funds. For this, the fitness function ($F_l$) for each MCDM method as a sum of products of weight on alternative’s normalised robustness is calculated:

$$F_l = \sum_{i=1}^{m} w_i \times \text{norm}.R_i \rightarrow \max, \ t = 1..m.$$

(2.98)

where $\text{norm}.R_i$ – normalised robustness of $i$-th region (alternative);

$F_l$ – fitness score of $l$-th MCDM method, $l = 1..q$.

The higher the value of the fitness function, the more suitable this method is. It is worth noticing that $F_l$ for the convenience’s sake can be min-max normalised to obtain scaled values varying from 0 to 1. The MCDM method possessing the highest value 1, is considered the most suitable for the following optimisation problem. The suitability of the method is defined by its ability to define absolute (with higher weights) recipients and donors among those alternatives, which within the simulated objectivity (formed by a panel of methods) have the highest robustness (narrower range of possible ranks). Therefore, the prominent players defined by the most suitable method are with the minimised error of their role determination. Such an approach allowing the rigorousness and certainty of regional performance measurement seems to be suitable in the context of redistribution of funds.
Understandably, that the final choice of the MCDM method will not be absolutely objective and free from bias. Single method bias during the selection is going to be eliminated, but the bias attributed to the panel of methods (emulated reality) will remain because of the panel’s subjective construction. Despite this fact, we believe that single method bias coming from subjective choice is much dangerous and leads to grosser mistakes than the choice based on a comparison of a panel of methods under the pragmatic criterion. In fact, the methodological contribution is made in the direction of achieving robust evaluations, moving from “subjective objectivity” toward more “objective subjectivity” (Greco et al. 2017).

The main drawback of the presented robustness approach is that determination of the fittest perspectives significantly depends on a panel of methods playing the role of inputs. Thus, the formation of the panel should be made by some balancing principles keeping the panel heterogeneous without domination of any particular group of methods with specific features. It exposes the DM to control the process of the pre-selection step bringing some unavoidable degree of subjectivity into the selection process.

The suggested approach will be used for the selection of MCDM methods in section 3.2.2.

2.3.3 Approach to the construction of the method’s profile based on OWA operator

The presented approach to the profiling of MCDM methods accompanies the selection approaches presented in the two previous sections. The additional approach based on the OWA operator is suggested to understand what selected MCDM methods have in common and varying. In particular, all initially chosen and applied measurement perspectives represented by main MCDM methods are projected onto the sub-perspectives formed by the OWA operator. Therefore, two groups of methods have to be formed (fig. 2.18):

1. those, to which methods are compared or the basis for comparison, which is constant and further called as OWA sub-perspectives;

2. those, which are compared – constantly changing compared group also further called as main perspectives.

Firstly, taking the SAW method with equal weights (average – AV) and then generating its sub-perspectives according to the optimistic degrees implied by OWA operator we form the benchmarking basis. Eventually basic consist of AV (or equal weights) OWA sub-perspectives. The compared group is formed by the DM according to the measurement situation, specificities
of the methods taken or simply by subjective choice. It can be an inclusive panel with methods chosen arbitrary or exclusive panel when methods are pre-selected by some logic or criterion. Based on said above, the further analysis of each MCDM method requires the analysis of the correlation between main perspectives and OWA sub-perspectives to define the bias profile properties of each method.

fig. 2.18: MCDM methods comparison for profile construction

The distinction between initial aggregating MCDM perspectives is based on optimistic-pessimistic conditions (section 2.1.2.2, table 2.1) assumed by the OWA operator. By the OWA method mentioned conditions could be easily transformed into the sub-perspectives by the measurement of different variations of the basic MCDM method. Then ranks of initial MCDM method are projected onto ranks obtained by the AV OWA sub-perspectives. Projection implies the comparison between ranks of perspectives (main MCDM methods) and sub-perspectives (OWA derivatives) (fig. 2.18).

Such projection induces the following analysis of Pearson’s correlation between the ranks of initial MCDM perspectives and OWA sub-perspectives. To form the conclusion about the perspective’s characteristics, the precise properties need to be measured based on Pearson’s correlation coefficients structured in the following way (table 2.3).
To explore the features of initial MCDM methods, we suggest the straightforward approach built on the imitation of the frequency distribution curve. However, the curve is not a frequency curve itself, but the curve based on the correlation between perspective under consideration and benchmarking sub-perspectives originated from EW OWA (fig. 2.19, fig. B.12).

fig. 2.19: Skewness correlation curve MCDM method based on OWA sub-perspectives

All the properties of the projected perspectives apart from a peak are measured relatively, and their formulae are described below one by one: 1. the peak is presented as the max-defined correlation between the initial MCDM perspective and benchmarking sub-perspectives. It is expected to be greater than 0.70 to show a sufficient strength of the association between measurements. 2. the pseudo-kurtosis is perceived as a share of a relative spread between max and min correlation at a peak. The way it is calculated is relative to the Equal Weighs perspective.
It says about the variability of perspective in projection onto sub-perspectives giving to DM the understanding of the certainty or trust level regarding the defined bias. The higher value pseudo-kurtosis obtains the more credibility is given to the bias in case it is defined in the following way:

\[
p.kurt_i = \frac{slump_i \times \text{peak}_{EW}}{\text{peak}_i \times \text{slump}_{EW}},
\]

(2.99)

\[
slump_i = \text{corr}_i^{\text{max}} - \text{corr}_i^{\text{min}},
\]

(2.100)

where \( p.kurt \) – pseudo-kurtosis of \( l \)-th MCDM method, \( l = 1..q; \)

\( slump \) – the difference between max and min correlation;

\( peak \) – max correlation.

The bias of perspective is trusted and defined with sufficient certainty when the curve is considered to be leptokurtic with kurticity level higher than 0.70. Thus, if the kurticity is less than 0.70 and the following property (partial skewness) signalises about the bias, it cannot be accepted with sufficient certainty leading to the not defined bias profile.

3. The partial skewness (the relative difference between dichotomic correlations, in particular between pessimistic and optimistic ones). This property represents a sufficient condition for the bias determination, while two previous properties can be understood as important ones. The way to calculate the partial bias or skewness (\( skew \)) the given below:

\[
\text{skew}_{c} = \frac{d_{c}^{i}}{\text{slump}_{EW}} \times p.kurt_i, \; l = 1..q.
\]

(2.101)

\[
d_{c} = \text{corr}_{c}^{\text{optim}} - \text{corr}_{c}^{\text{pessim}},
\]

(2.102)

where \( c \) – a type of dichotomic optimistic-pessimistic conditions <fairly optimistic-pessimistic; optimistic-pessimistic; very optimistic-pessimistic>;

\( \text{skew}_{c} \) – partial skewness corresponding to the particular \( c \)-th condition;

\( d_{c} \) – difference between dichotomic correlations;

If the \( \text{skew}_{c} \) is more significant than 0.70, then the prominent bias is defined based on the corresponding \( c \)-th optimistic conditions. In the case of lower partial skewness bias is not defined, and the MCDM method is considered a neutral one. It is worth pointing that threshold 0.70 brings the subjectivity in decision-making, and this level can be different. Nevertheless, precisely, this threshold is taken as a typical cut off level for correlation analysis. Positive partial skewness
points out the optimistic bias, while negative – pessimistic one. Besides, the total level of skewness can be measured as a sum of absolute values of partial skewnesses:

$$skew_j = \sum_{\text{all } c} |skew^c_j|$$

(2.103)

All the mentioned properties rely on each other and are combined in the sequence of dependent steps offering one of the possible ways of MCDM methods’ profiling (fig. 2.20). This approach is simple and straightforward; thus, it was decided to use it for the MCDM method profiling. Admittedly, the degree of methods’ diversity influences the discriminating power of the Fitness function, making them less variant. Applying this approach, the choice of the MCDM method will become more supported by the identified difference between MCDM methods.

fig. 2.20: Algorithm for bias profile determination regarding optimistic/pessimistic conditions

Source: author

The suggested approach is applied to an inclusive panel of MCDM methods in section 3.2.3.

2.4 Alternative models for the optimisation of Structural funds' distribution

The Cohesion Policy plays a central role in the redistribution of ESI funds necessary for the harmonious regional development with a decrease of socio-economic disparities. It is generally
known that it is heavily dependent on the single GDP per capita criterion. The basic idea is the following: if the region is less developed (lagging), then it can get more financial support from the EU budget. The often-criticised methodology determines the distribution of funds within the Cohesion Policy between lagging regions for nowadays coming up from the Berlin formula established in the 1989 year (Wishlade, 1999). So far, this distribution formula has not been essentially reconsidered except some slight changes in parameters without any modifications in basic principles.

2.4.1 Variance minimisation optimisation model based on the monetary approach

This section aims to suggest the single-factor model for the optimisation of the distribution of the SF. This optimisation model is designed within the classic monetary (based on GDP) scenario (blocks 1.1-4.1) presented in fig. 1.17 and, in particular, belongs to block 4.1. In addition, based on the variance minimisation model and developed multi-attribute utility functions, the most effective allocation strategies will be found.

While redistributing SF regional policy-makers are interested commonly in the following targets to be reached. The population covered stands as the most obvious target as the redistribution. Therefore, the more people are to be influenced, the better and equal their living conditions become. Besides another goal is present – to make financial support for further development of regions basing on the fair platform embracing economic and political interests. The focus of the Cohesion policy pops up directly from its meaning. Literally, cohesion points out at the equality of the living conditions, thus the distribution of Funds has to be as well equally distributed. It is necessary to define the origin or the rational ground for the distribution equality analysis.

There are many analogous to GDP indicators, such as Regional Competitiveness Index (Annoni, Dijsktra, 2013; Aiginger, Vogel, 2015), Genuine Progress Indicator (Anielski, 1999), Human Development Index (UN Development Program 2015), etc. which are able to take into account the social, environmental and other dimensions. Although the GDP indicator has been frequently criticised because of its limited economic nature, it remains the main reference point.

We decided to proceed with this idea of stickiness to the GDP criterion and to suggest the new alternative way of distribution based on the optimisation model capable of eliminating some vague moments of the Berlin formula. For the analysis of inequality or disparities, while
applying the optimisation model, another criterion has to be involved, such as variance index, weighted variance, Theil index or Gini index, etc. In this research, the choice of the criteria is not prioritised, so the weighted variance was opted as more understandable.

The core of a new suggested methodology is the optimisation model based on the minimisation of GDP per capita variance between all NUTS 2 regions. This model helps define paying attention to the Regional Policy parameters the amount of funding in no direct way, finding the best values of the GDP/cap. for 276 regions, which eventually minimises the variance between their development level. In general, all necessary elements of modelling need to answer the stated research questions (fig. 2.21) at different steps of funds’ distribution modelling: “which regions are considered to be the donors and which to be funded as receivers?”; “how much resources can be funded to the receivers and taken out from the donors?”.

fig. 2.21: Research questions and steps of distribution modelling

3. Who is who?

Identification of parameters
- Gamma (eligibility rate)
- Beta (capping rate)
- Alpha (deduction rate)

4. How to redistribute optimally?

Nature of the optimization model
- Quadratic convex problem
- Minimization of Variance
- Optimized values of regional GDP/cap

5. What are the best rules (strategy) of the redistribution game?

Selection of the best strategy:
- Utility function
- Criteria of the distribution
- Simulation

Source: author

The first answer comes from the level of regional performance represented by the GDP per capita (PPS) and based on the eligibility threshold (γ). It varies from 75 % to 100 %, but in this research, only 90 % level is used. The second answer needs the introduction of the new general capping rate (β) based on the GDP per capita (PPS). It differs from 2% to 4 %, which were used
in practice for all previous periods. The third answer implies the usage of the deduction rate \((\alpha)\) – indicator as well based on the GDP per capita (PPS), letting define the amount of extractions. Graphically all essential parts of the new allocation mechanism are presented in the fig. 1.22.

The following steps are directed at the development of the optimisation model and analysis of its application:

1. to form the model of funds’ distribution based on the nonlinear quadratic optimisation with minimisation of variance as the objective function;
2. to develop the criteria for the distribution assessment, which could include not only variance criterion but as well population covered and amount of funds at the same time accounting consequences for the Member states and the EU in the whole;
3. to form a set of distributive strategies and to define the most optimal ones based on the optimised values of the parameters making rules of regional policy game:
   3.1 to define the optimal value of alpha \((\alpha)\) – incoming alpha rate) responsible for the amount of money deducted;
   3.2 to define the optimal value of beta \((\beta)\) – absorption beta rate) responsible for the maximum amount of money located to the regions;
   3.3 to define the optimal value of gamma \((\gamma)\) – threshold gamma rate) responsible for the regions’ selection eligible for the financing;
4. to distribute GDP Funds according to the best-defined parameters and to offer the correction coefficients for the current Funds distribution.

From now on, the process of model development (a second block from fig. 2.21) is given in detail. A linear optimisation model is used to find the best values, which minimise the variance of GDP/cap of 276 NUTS 2 EU regions paying attention to the parameters describing Regional Policy rules.

As we can see, there is no influence of national prosperity and the uniform approach to the LDR and TR is proposed based only on the prosperity of regions and remaining to regulate parameters \((\alpha, \beta, \gamma)\). Further, we need to define clearly all regulating parameters and implant them into the optimisation model. Blocks (A-F) of the model are presented below.

A. Input statistical data:

\[ R = \{r_i\} \] – set of Regions belonging to Member States \((R = \bigcup_{s \in S} s), i = 1…n;\]
S = \{ s_j \} – set of Member States (countries) belonging to European Union, j = 1…k;

Y_i^{t-1} – the actual average regional GDP of the i-th region for the reference period 2007-2009 years (article 90, No 1303/2013);

N_i – the actual average population of i-th region for the reference period 2007-2009 years (article 90, No 1303/2013).

B. Decision variable:

\[ x_i^{t-1} = \frac{Y_i^{t-1}}{N_i}, \quad (2.104) \]

where: \( x_i^{t-1} \) – actual average GDP per capita of the i-th region at the moment \( t-1 \) (the period before optimisation).

C. Objective function: the general form of an optimisation problem is to find some \( x^* \in X \) such that \( f(x^*) = \min \{ f(x) : x \in X \} \), for some feasible set \( X \in \mathbb{R}^n \) and objective function \( f(x) : \mathbb{R}^n \rightarrow R \).

\[ f(x) = \text{Var}'(X) = \sum_{i=1}^{n} (x_i - \bar{x})^2 \cdot n_i \rightarrow \min \quad (2.105) \]

D. Subject to constraints:

1. total budget \( F^\text{act.} = \sum_{i=1}^{n} F_i^\text{act.} = 0 \Rightarrow \sum_{i=1}^{n} Y_i^{t} = \sum_{i=1}^{n} Y_i^{t-1} ; \)

2. regional budget for lower and upper bounds \( x_i^{\alpha} \leq x_i^{t} \leq x_i^{\beta} \);

3. non-negativity \( x_i^{t} \geq 0 \), for \( i...N \).

Other additional formulas, control parameters and descriptions related to the presented model are given in Appendix B (Table B.4).

To proceed with the analysis of the distribution optimised by the developed variance minimisation model, we have to conclude the following set of criteria. Further, we will pay attention to the amount of funds redistributed and the population covered. The more money is involved in redistribution, the more powerful it becomes ceteris paribus. The more people obtained money, the influential the distribution is. To generalise, all the mentioned sub-indices are of benefits nature – the subject to be increased, the higher their value is, the more significant
influence the distribution has, and the greater impact can be under the effective usage of funds. The effective usage is out of the dissertation scope, and hereinafter we are going to be concentrated exceptionally on the optimality of the funds’ distribution.

To define the best redistributive strategy based on specific parameters and discussed the above criteria, the following complex criterion is proposed. It is a combination of the two aggregated sub-criteria, in particular, 1. the specific altruistic criterion; 2. the general impact criterion.

1. the first specific sub-criterion $g_1$ reflects an altruistic donor’s effect within a particular country of the EU. The date is taken on the regional level to measure the country and eventually to obtain the characteristic of the system (EU). The country is estimated from the regional perspective. All changes show whether a decreased country’s variance was caused by receiving or donating funds to the needy regions. If the reason for the declined variance is the donation, the index is being contributed by a positive value, while the recipient’s role makes negative value. The sum of such negative and positive values from each country constitutes the total value of the index. The more positive total value is, the more altruistic the distribution of Funds turns out to be. In fact, according to this criterion, the distribution is assumed to be effective even in the case of donor country;

2. the general index $g_2$ characterises a state of countries from the united point of view when all them perceived as one system (EU). Regional perspective is not counted here, however that data is taken from the country level and then aggregated to the system level. It is noticeable that all constituents of the index are the same as in the previous one, but the values are taken from the system perspective, not from its parts – regions or countries.

All the criteria and synthetic indices describing the distribution are presented in fig. 2.22. The rationale for the specific sub-criterion $g_1$ is based on the Kaldor – Hicks criterion that has a different logic from the Pareto efficiency principle. A reallocation of resources is a Pareto efficient if at least one subject is made better off and nobody is made worse off. However, in practice, it is well-nigh impossible to conduct economic policy, without making at least one object worse off. The regional policy actions related to the distribution of funds have specific paramount practical importance; since, socio-economic decisions should be made considering advantages, disadvantages, and their impact on different countries and regions. In fact, the Pareto
criterion is not capable of doing it as a guiding rule for making collective decisions. In this regard, the Kaldor-Hicks criterion is observed as a basis for making socio-economic decisions.

fig. 2.22: Multi-attribute determination of the best distribution strategy

<table>
<thead>
<tr>
<th>Multi-Attribute Utility function</th>
</tr>
</thead>
<tbody>
<tr>
<td>Distribution targets</td>
</tr>
<tr>
<td>Population covered</td>
</tr>
<tr>
<td>Member state’s property</td>
</tr>
<tr>
<td>ΔVar_i</td>
</tr>
<tr>
<td>Variance</td>
</tr>
<tr>
<td>ΔVar_j</td>
</tr>
<tr>
<td>Funds redistributed</td>
</tr>
<tr>
<td>ΔF_j</td>
</tr>
<tr>
<td>Source: author</td>
</tr>
</tbody>
</table>

The Kaldor-Hicks postulates that a decision is an efficient one since there is a net gain for the group of objects imposed on a decision made. The net gain is assumed to compensate potential losers in terms of other criteria taken into account. Therefore, this compensating principle can serve as a reliable platform for the analysis of the implications (advantages and disadvantages for participants) of policy actions. If \( g_1 \) takes positive value, it means that total conditions for the agents are improved. The higher the value of the indicator, the better distribution is. Of course, this criterion is just a rough approximation of policy implications; however, as an extra tool for the strategies differentiation, it is applicable.

Based on introduced criteria, the following objective function determines the optimal strategy. We examine here multi-attribute utility function (\( U(x)^{\alpha,\beta} \)) presented as a multiplicative function of two components, which include three necessary subcomponents (\( var, N, \Delta F \)) tending to be maximised during the distribution process. It should be mention that aggregating function can take any form; however, in this research, we limited the analysis to additive, multiplicative and weighted functions. Interconnection between all elements of strategy formulation and aggregating functions is given in fig. 2.22. The mathematical description of the problem to
determine the best distribution strategy considering all necessary criteria, indices and parameters take the following form.

\[ U(x)^{\alpha,\beta} = f(x^\prime, \alpha, \beta) = g_1(x^\prime, \alpha, \beta) \cdot g_2(x^\prime, \alpha, \beta) \rightarrow \max \text{ (multiplicative example)}; \]  

(2.106)

Additional formulas:

\[ g_1(x, \alpha, \beta) = \sum_{j=1}^{k} \Delta Var^j \cdot N_j \cdot \Delta F_j; \]  

(2.107)

\[ g_2(x, \alpha, \beta) = \Delta Var^\prime \cdot \sum_{i=1}^{n} F_i^{act,+} \cdot \sum_{i=1}^{n} N_i^{act,+}; \]  

(2.108)

\[ \Delta Var^j = \sum_{i=1}^{n} (x_i^{|j} - \bar{x}^j) \cdot n_j; \]  

(2.109)

\[ \Delta F_j = \sum_{i=1}^{n} F_i^{j,act,+} + \sum_{i=1}^{l} F_i^{j,act,-}; \]  

(2.110)

\[ \Delta Var^\prime = \sum_{i=1}^{n} (x_i^{\prime |-} - \bar{x}) \cdot n_i; \]  

(2.111)

\[ \sum_{i=1}^{n} F_i^{act,+} = F^{post} - \varepsilon = \sum_{i=1}^{n} Y_i^{t-1} \cdot \alpha - \varepsilon; \]  

(2.112)

where: 

\[ g_1(x^\prime, \alpha, \beta) \] – internal sub-utility function showing the summation of Member states’ features of the redistributive process;

\[ g_2(x^\prime, \alpha, \beta) \] – general sub-utility function showing regions’ features of the redistributive process at general EU level;

\[ \Delta Var^j \] – delta variance in the \( j \)-th Member state at the optimised moment \( t \);

\[ N_j \] – the average population of the \( j \)-th Member state for three years;

\[ \Delta F_j \] – net \( j \)-th country Funds defining is as donor or recipient;

\[ \sum_{i=1}^{n} F_i^{j,act,+}, \sum_{i=1}^{l} F_i^{j,act,-} \] – a sum of \( j \)-th Member state optimised incomings or out comings respectively;

\[ N_i^{act,+} \] – the average population of the financed \( i \)-th region (or population covered by GDP Funds);

\[ x_i^{t,j} \] – GDP per capita of \( i \)-th regions at the moment \( t \) after a redistribution within \( j \)-th Member state;

\[ \bar{x}^j \] – the average GDP per capita within \( j \)-th Member state;
$n'^j$ – population weight coefficient within $j$-th Member state.

Determination of the difference between optimised and current allocation of Funds (comparison with the existing practice) is realised due to the application of the steps presented in Appendix B (Table B.5).

Nevertheless, the question about multi-attribute utility ranking remains not formalised in the presented picture, as the choice of it is a subjective matter. Therefore, three of the most essential and suitable functions are included in the consideration without giving priority to any of them. The final choice of the strategy is going to be made due to the solution of a simple MCDM problem using average operator processing the results from all utility functions. A certain rank will be assigned to every distribution strategy according to an average value.

The limitation of the proposed model is the way the capping rate has been established. Due to the specificities and simplicity of the model, it was assigned to the regional level duplicating the rate for a national level (Regulation EU No 1303/2013). The assigning different capping rates for each region can significantly influence the optimisation process and correspondingly the distribution itself. However, the determination of the regional capping rate remains not discussed both in the literature and in this research.

The application of the minimum variance single factor optimisation model is presented in section 3.3.1.

### 2.4.2 Multi-variable MCDM based optimisation model

The second MCDM based model is a multi-variable one with embodied linear regression, including all variables influencing the result of optimisation. As opposed to the previous model, this model belongs to the multi-dimensional scenario (blocks 1.2-4.2 in fig. 1.17) of regional performance measurement (block 4.2).

The multi-variable model is based on the utility values produced by the MCDM method. Consequently, a variance minimisation is focused in this case on the utility values as opposed to the previous approach where the GDP criterion was in focus. Within this approach, two optimisation models will be applied, in particular, 1. with the consideration of classification factor and 2. without. The results of the model application will refer to the analysis of the clustering solution and consideration of regional status. Depending on the status, certain regions can be allowed or prevented from the funding flows.
Let us establish the objective function, the constraints for the multi-variable optimisation model. All formulae below just complement the analogous ones from the previous section.

Decision variable:

\[ v_i = \beta_0 + \beta_i x_i + ... + \beta_p x_p + \varepsilon_i, \quad i = 1, ..., n. \]  

(2.113)

Assuming that some variables can be fixed, the regression model in a vector is:

\[ v = \tilde{X} \beta + X \beta + \varepsilon. \]  

(2.114)

where: \( v \) – vector of utility values (endogenous variables or regressands) produced by the MCDM method before the optimisation;

\( \tilde{X} \) – the constant part of the design matrix including repressors or exogenous variables which do not take an active part in the optimisation;

\( X \) – varying part of the design matrix including repressors or exogenous variables which take an active part in the optimisation;

\( \varepsilon \) – error term.

The constant part plays the role of one factor in the optimisation process, while the varying part is responsible for the second factor, which is the subject for the changes during the optimisation.

Objective function: the general form of an optimisation problem is to find some optimal \( \tilde{x}^o \in X \) such that \( f(x^o) = \min \{ f(x) : x \in X \} \), for some feasible set \( X \in R^n \) and objective function \( f(x) : R^n \rightarrow R \).

\[ f(x) = Var(v) = \sum_{i=1}^{n} (v_i^o - \bar{v})^2 \cdot n_i \rightarrow \min \]  

(2.115)

Subject to constraints:

1. Total budget constraint \( F^{act} = \sum_{i=1}^{n} F_i^{act} = 0 \Rightarrow \sum_{i=1}^{n} Y_i^o = \sum_{i=1}^{n} Y_i \);

2. Country budget constraints for the lower and upper bounds: \( Y_{j_{min}}^o \leq Y_j^o \leq Y_{j_{max}}^\beta \);

3. Regional budget constraints for the lower and upper bounds: \( x_{i_{min}}^o \leq x_i^o \leq x_{i_{max}}^\beta \);

Additional formulas (also rely on formulae from Table B.4, Appendix B):

without classification factor \( x_{i_{min}}^o = \frac{Y_i \cdot (1 - \alpha / 100)}{n_i} \),

(2.116)
with classification \( x^a_{i_{\text{min}}} \) = \[
\begin{cases}
  \text{if } i \in \text{I cluster} & \Rightarrow \frac{Y_i \cdot (1 - \alpha / 100)}{n_i}, \\
  \text{if others} & \Rightarrow x_i.
\end{cases}
\]

without classification factor \( x^\beta_{i_{\text{max}}} = \frac{Y_i \cdot (1 + \beta / 100)}{n_i} \);

with classification \( x^\beta_{i_{\text{max}}} \) = \[
\begin{cases}
  \text{if } i \in \text{III cluster} & \Rightarrow \frac{Y_i \cdot (1 + \beta / 100)}{n_i}, \\
  \text{if others} & \Rightarrow x_i.
\end{cases}
\]

The application of the introduced model is presented in section 2.4.2.

### 2.4.3 Markowitz mean-variance optimisation model for the selection of the best portfolio based on effectiveness measurement and concept of fairness

The third optimisation model falls into the unorthodox scenario (blocks 1.3-4.2 in fig. 1.17) of regional performance measurement (block 4.3). As opposed to two previous models, it is based on the use of non-conventional methodologies, such as MCDM method for the effectiveness measurement and mean-variance portfolio optimisation model.

Dealing with the GDP or any other criterion mirroring the level of regional performance, we tend to decrease the variance of criterion between all regions, giving preference to the worst lagging regions and allocating funds to them. Such an approach is considered to be a cohesion policy approach playing exclusively supporting function. How to deal with disparities based on single a GDP factor approach coupled with the minimum variance optimisation model was suggested in the previous sub-chapter 2.4.1. However, this approach is capable of producing the free-ride problem, unless the financed regions are also rewarded based on different, antagonistic as a rule, criteria.

Simply put, to prevent a free-ride for lagging regions and drive them out from stagnation, other more prosperous regions should also get rewarded for their better (i.e. more effective) performance. Eventually, the priority should be given partly to ineffective regions considered as less developed and partly to the regions that are relatively effective among them. In this case, the door to the solution is opened. It appears that while minimisation of variance is responsible for the supportive Cohesion policy factor favouring free-ride problem, the opposite stimulating factor oriented on the maximisation of total utility tends to counterbalance the mentioned problem.
This more sophisticated understanding of the distribution goes along with two other sub-goals pretending on equity and equality of SF allocations between all regions. These two extra sub-goals give rise for another comprehensive conception of optimisation with the more general and complex term “fairness”. However, implementation of this in practice is a highly complex process and involves many contentious choices related to the optimisation of the SF redistribution. The suggested approach to fair redistribution of SF in the form of steps’ sequence is presented in fig. 2.23.

fig. 2.23: Approach to a portfolio optimisation of fair distribution based on effectiveness

| 1. Conceptual basics  | 1.1 fairness sub-factors: equality, equity, equitability;  
| 1.2 approaches to analysis  | 1.2.1 ability (needs) based approach;  
| 1.2.2 equality based approach  | 1.2.3 merit-based approach.  |
| 2. Methodological foundation  | 2.1 stimulation (rewarding) based on merits;  
| 2.2 optimization framework  | 2.1.2 supporting based on needs and equality;  
| 2.2 Markowitz portfolio theory (M-V model).  |
| 3. Modeling aspects  | 3.1 max of expected utility of fair effectiveness;  
| 3.2 tuning up the parameters  | 3.2 setting up the importance of unfairness sub-factors.  |
| 4. Practical aspects  | 4.1 min of relative unfairness / max Sharp ratio;  
| 4.2 behavioral analysis  | 4.2.1 relationships between sub-factors of fairness;  
| 4.2.2 correlation between distribution and effectiveness or GDP.  |

Source: author

One should notice that the presented sequence of steps is not aimed at the analysis of social fairness or general economic distribution as any conclusions on this topic would be too debatable, and within the scope of the current research, the problem is almost unsolved. In fact, the discussion here is about the fairness of exclusively financial distribution in the context of government assistance embodied in redistributive Cohesion Policy, thus about just redistribution of SF among regions.

Concerning the fairness of funds’ distribution, some papers were found concerning the efficiency-equity trade-off. The efficiency-equity trade-off discussion was started by Kuznets (1955), Myrdal (1957), et al., and has been deepened recently by contemporary scientists such as
Martin (1999, 2001), Puga (2002), Midelfart (2004), Meyer (2005), which rely on the combined platform of new economic geography and the theory of endogenous growth. However, their research does not touch the sociological and philosophical aspects of fairness but focuses only on efficiency-equity trade-off within the context of spatial agglomeration of economic activities.

Nevertheless, being guided by logic and common sense, we highlighted three following approaches relating to how funds can be redistributed. These approaches are worth examination to form the basis for the fair distribution concept.

1. The ability (needs) based supportive approach. This approach pretends to be the most profound and justified because of its straightforwardness and simplicity. John Rowls (1971): “Any inequality that exists in a social system should favour the least well off because this levels the playing field of society or “just society rules tend to work to the maximum advantage of the least well of classes”.

The foundation for this approach can be either effectiveness or GDP, or any other benefit criterion describing the regional performance. For example, taking GDP as a monetary criterion, it is easy to identify the needs of the regions based on the variance minimisation function (as in section 2.4.1). Thus, the regions with the lowest GDP per capita appear to be the best candidates to be supported by cohesion allocations. The essence of this approach is supportive, meaning that the most is given to those who the most in need.

2. The equality-based approach is another supportive approach. The core of this approach is the principle of the same treatment. It implies that all regions that have been identified as lagging ones in terms of effectiveness or any other performance criterion are subject to be supported by SF in equal proportion regardless of the value of performance criterion. However, that treatment would be very questionable in practice. It does not mean that support equality as a characteristic feature and conceptual basis of the approach is totally rejected; it just does not seem adequate and fair enough to apply it in the full extent.

3. The merit-based stimulating approach, this is opposite to the two first approaches. A regional contribution expressed by any performance criterion turns out to be the benefit (the more, the better) determinant for the funds’ allocation. It can show how much is required to keep up the level of current performance. In other words, this view forms a stimulating foundation, which is a great complement to the two previous approaches. Those approaches include intrinsic flaws leading to the free ride problem, which means that backwardness in performance can be
favoured creating free riders. To cope with this drawback current approach does the opposite thing, in particular, it stimulates performance that is more successful by rewarding it with higher allocations.

At this step of conceptual and theoretical analysis, the well-timed question arises about the meaning of fair distribution. It is not stated precisely, that fairness includes equality with the equality-based approach or it needs equity stemmed from a merit-based approach, or it is enough just to count needs and according to this to decrease disparities between regions as was done in section 2.4.1. Fairness is a complex philosophical concept precise measurement of which seems to be debatable enough in terms of methodology and theory not saying about the subjective side of the question. However, controlling some aspects of the problem and applying suitable methodology the results in the form of insights and policy recommendations are still possible and valuable in the context of the Cohesion policy.

The first ability-based approach has been considered in its full extent within the single-factor variance minimisation model earlier. Therefore, here, two other approaches to distribution are taken into account and will be incorporated into the proposed portfolio optimisation model.

A selected MCDM method provides for the DMr utility values assigned for each region under the evaluation. If the benchmark is done for the competitiveness analysis (single GDP criterion approach is included), then the distribution typically has the target to support lagging regions. The opposed situation comes alive when the benchmarking is based on the effectiveness of regional performance. This case implies policy-makers to stimulate regions for their high level of effectiveness, considering them as attractive assets. Effectiveness plays the role of return to be maximised what allows us to pick up the best and most promising regions among the lagging ones and to stimulate (reward) them for their effective performance.

The presence of regional disparities complemented with effectiveness measurement and fair funds redistribution together form the promising conceptual basis for the application of the optimisation process based on modern portfolio theory. The idea of SF portfolio optimisation is similar to investment diversification in part that allocation of funds to different regions is more balanced or less risky than the allocation to one region. Effectiveness and risk are not assessed by itself, but how they contribute to the portfolio’s effectiveness and risk. It assumes and allows the maximisation of the portfolio’s effectiveness for a given level of risk (unfairness).
Within regional cohesion, the risk criterion measured as variance of the portfolio is interpreted as a chance that the combination of regions for allocations of SF fails to meet or to cover all cohesion objectives expressed in effectiveness sub-utilities. Each allocation carries its own risk that not all criteria of effectiveness are satisfied, meaning that the effectiveness of the portfolio is not balanced or equitable. This risk gets higher with the higher effectiveness of the portfolio. This risk of not balanced (equitable) effectiveness can be eliminated by efficient diversification. The optimal portfolio of SF is assembled under the effectiveness maximisation for a given level of fairness expressed by its sub-factors.

The main element of this section’s originality is the fair effectiveness serving as the basis for the portfolio optimisation of SF redistribution. Eventually, the whole process of SF optimisation is shadowed not only by the portfolio’s risk (variance). Besides, within the context of cohesion policy, other features of fairness or risks of distribution can be imposed on portfolio optimisation, such as equity and equality.

The optimised portfolio based on fair effectiveness distribution is the alternative way of how to redistribute SF considering the effectiveness of regional performance and different aspects of fairness, such as equality, equity and equitability of allocation. Fairness combined with effectiveness represents a fair, effective distribution based on the two main principles corresponding to identify approaches: 1. stimulation (rewarding) of the most effective regions regarding their effectiveness level within the merit-based approach; 2. support to lagging regions with regard to needs-based principle within equality and needs-based approach. The former plays a stimulating role, and the latest is responsible for the support of those who are most in need. As well, such fairness approach to the optimisation allows avoiding a free-rider problem when less developed regions take advantage of their lagging position and keep their low level of performance (unchanged) because of benefits from funding.

To better grasp the difference between this Markowitz mean-variance model and presented earlier variance minimisation model, the conceptual basis of both models is given in fig. B.13. (Appendix B). As opposed to variance minimisation model, the Markowitz mean-variance optimisation model considers both supporting and stimulating influences and based on measurement of effectiveness. Due to this, it is able to deal with a free-rider problem when lagging regions keep their low socio-economic status as long as possible for getting funds.
Eventually, this model allows fair distribution considering equity, equality and equitability properties.

To optimise the portfolio of SF, the max distribution function should be constructed in the following manner: effectiveness maximisation (stimulating factor) with the corrective minimisation factor (supportive correction factor). This factor can relate to effectiveness as a risk factor. The higher this factor is, the fairer and more supportive strategy becomes. One should mention that usually equality and equity appear in economics concerning taxation or welfare economics and might specifically refer to identity-free equal life chances, supply all citizens with a necessary and equal income minimum, goods, services, and funds redistributed. Commonly, equity targets at the distribution of capital, services’ access, or only GDP and is measured by Gini index, variance, etc. One should notice that even though equity is quite often understood as a synonym to equality, in the overall evaluation of social welfare, it is a way different from equality and economic efficiency. One prominent moral disagreement is the opposition between equality and equity. We use the term “equality” to refer to equal payoffs and the term “equity” to refer to pay-offs proportional to inputs (Adams, 1965; Walster, Walster, Berscheid, 1978).

These two components can generate a handy conflict serving as a conceptual basis for the further portfolio optimisation following the idea of fair effectiveness distribution. In the currents research, it has different meaning and plays the role of the additional counterpart or, saying differently, the second criterion in yielding an optimised distribution of SF.

During the portfolio optimisation, fairness components play the role of correction factors which nature is opposed to the effectiveness maximisation. Therefore, the sub-factors reduce the total portfolio utility of the distribution in the form of deductions responsible for specific characteristics of fair distribution. Sub-factors as equitability, equality and equity are measured respectively as a variance of inputs, outputs and outcomes describing aspects of the redistribution process. According to the suggested application of Modern Portfolio Theory the overall "fairness" of distribution is judged by comparing regional distributional inputs, outputs and outcomes with an internally derived standard or optimal point pointing at the optimal portfolio.

Inputs are represented as initial regional effectiveness contribution of each region to the regional performance giving the reason for the further funds' allocation. In other words, regions with their effectiveness level play the role of assets and classified as "relevant inputs" – inputs that legitimately endow the contributor with certain rewards expressed in the number of SF.
Outputs are defined as a reward (support) in the form of SF that regions obtain having a certain level of inputs (effectiveness). Simply saying, the reward is given at maximum to the lagging regions with the highest effectiveness. Outcomes are the possible results of invested SF into the region considering its initial regional effectiveness contribution.

For the sake of clarity and systematic description all variables and parameters of the further presented objective function are mentioned in table 2.4 below for different aspects of modelling, which give a more comprehensive understanding of the whole modelling process.

table 2.4: Key aspects of distribution modelling

<table>
<thead>
<tr>
<th>Aspects of the modelling</th>
<th>Initial contribution (E)</th>
<th>Reward / support (W)</th>
<th>Final result (R)</th>
</tr>
</thead>
<tbody>
<tr>
<td>basic concept</td>
<td>effectiveness</td>
<td>portfolio’s shares (weights)</td>
<td>result</td>
</tr>
<tr>
<td>input</td>
<td>output</td>
<td>equality</td>
<td>equity</td>
</tr>
<tr>
<td>distribution property</td>
<td>–</td>
<td>equitability</td>
<td>tight fairness</td>
</tr>
<tr>
<td>variance (unipode of fairness)</td>
<td>–</td>
<td>var ( W (\sigma^2_w) ) – shares variance sub-factor</td>
<td>var ( R (\sigma^2_r) ) – results variance sub-factor</td>
</tr>
<tr>
<td></td>
<td></td>
<td>var ( P (\sigma^2_p) ) – portfolio variance sub-factor</td>
<td>var ( T (\sum \text{var}) ) – total variance factor</td>
</tr>
<tr>
<td>corresponding attitude / coefficients</td>
<td>–</td>
<td>( k^W )</td>
<td>( k^R )</td>
</tr>
</tbody>
</table>

Source: author

Regional portfolio due to the sub-factors describing different aspects of fairness can be compared with those of others, and then flaws of fairness are addressed to be eliminated through the optimisation caused by changes in allocation shares outputs (W).

When the ratio of regional outputs to inputs is close to the similar ratio assigned to other regions, such distribution is considered as efficient in terms of fair equality. Equality relates more to providing equal playing field by assigning equal support (allocated SF marked as outputs). Equality-sation of rewards decreases the portfolio effectiveness because more effective regions are not favoured so intensively. The consequence of it is the slowed down regional performance, however with reduced disparities on the other side. Equity matters as an end–tendency to evenly satisfy different needs (outcomes) expressed as a product of effectiveness efforts and support. Such equivalence of outcomes leads to fairness of portfolio when support is given according to equality of outcome. Equity-sation of outcomes makes as well a decrease of portfolio
effectiveness, as more effective regions are less favoured. The consequence is slowing down the system’s regional performance with reduced disparities.

In mathematical terms, the problem of selecting the optimal regional portfolio is formulated as a stochastic one with random parameters within the objective quadratic utility function reflecting the level of regional performance. From a theoretical point of view, the objective utility function is the most developed and allow us to include results obtained from previous steps related to the MCDM methods application. In particular, the utility values describing regional effectiveness are going to be used for portfolio optimisation. As utility values are assumed to be normally distributed, the probability distribution can be described using two parameters, such as mean value and variance. The former will express the expected regional effectiveness and the latter – different features of the distribution. Features of the distribution to be explored with the help of variance will be introduced and discussed below.

A SF portfolio that is possessed at the amount of \( W = \{ w_i | i = 1..n \} \) should be allocated to regions \( R = \{ r_i | i = 1..n \} \). The portfolio is selected due to the optimisation based on the expected utility criterion \( E[U(W)] \) based on regional effectiveness \( e = \{ e_i | i = 1..n \} \) with the coefficients of attitude \( k^W \), \( k^R \), \( k^P \) to the distribution qualities, such as equality \( (\text{var}_W) \), equity \( (\text{var}_R) \), equitability \( (\text{var}_P) \) correspondingly. \( k^W \sigma^2_w \), \( k^R \sigma^2_r \), \( k^P \sigma^2_p \).

By the objective function, the maximisation of the expected effectiveness utility is expressed. In general, the optimising process is completed by the consideration of two basic factors, namely effectiveness and fairness. As a result, all fairness sub-factors add a penalty to the total distribution utility function.

Further, the focus will be made on the type of mean-variance model, namely on the Markowitz model, assuming just allocation of funds or, saying in financial terms, investments into risky assets. To present an efficient set graphically (fig. 3.19) three following problems (A, B, C) have to be mathematically formulated and solved. Different objective functions make the main difference.

A. sub-problem of maximum expected portfolio’s effectiveness.

Objective function:

\[
E[U(W)] = E(W) - Unf^{W.R,P} \rightarrow \text{max.}
\]  

(2.118)
Constraint:

\[ \sum_{i=1}^{n} w_i = W \mid w_i \geq 0 \text{ for } \forall i. \]  
C1  (2.119)

\[ \sum_{i=1}^{n} x_i = 1000 \mid w_i = x_i \geq 0 \text{ for } \forall i. \]  
C2  (2.120)

while \( E(W) = \sum w_i \cdot E(e_i) \) alternatively, \( E(W) = \vec{w} \cdot E(\vec{e}) \),
E1  (2.121)

\[ Unf^{W,R,P} = (k^W \cdot \sigma_w^2 + k^R \cdot \sigma_r^2 + k^P \cdot \sigma_p^2) \]
E2  (2.122)

\[ \sigma^2_p = \sum_{i} \sum_{j} w_i \cdot \sigma_{ij} \cdot w_j \text{ or } \sigma^2_p = \vec{w}^T \cdot C \cdot \vec{w}, \]
E3  (2.123)

\[ \sigma_y = \sigma_{y} \cdot \rho_{y} \cdot \sigma_{y} \text{ and } i, j = 1,2,...N, \]
E4  (2.124)

\[ \sigma^2_w = \sum_{i=1}^{n} \frac{(w_i - \bar{w})^2}{n-1}, \]
E5  (2.125)

\[ \sigma^2_r = \sum_{i=1}^{n} \frac{(r_i - \bar{r})^2}{n-1}, \]
E6  (2.126)

\[ r_i = w_i \cdot E(e_i); \]
E7  (2.127)

where \( E[U(W)] \) – expected utility of fair effectiveness,

\( E(W) \) – mean of the portfolio’s effectiveness,

\( Unf^{W,R,P} \) – total unfairness (variance) of the distribution (supportive or risk factor),

\( w_i \) – shares of funds to be allocated into region \( i \)-th,

\( E(e_i) \) – expected effectiveness of \( i \)-th region,

\( k^W, k^R, k^P \) – attitude to equality, equity, equitability correspondingly,

\( \sigma^2_w, \sigma^2_r, \sigma^2_p \) – respectively variance of distribution shares (outputs),

of results (outcomes), of a portfolio,

\( \sigma_y, \rho_{y} \) – the covariance and correlation between \( i \) and \( j \) regions,

\( r_i \) – result representing the outcome from the allocation,

\( \vec{w}, E(\vec{e}) \) – vector form of expected regional shares and effectiveness, respectively.
According to the constraint (C1) the total amount of allocated funds, which are positive or equal to 0, must be equal to the amount at the initial disposal. The constraint (C2) ascribes a certain number to the amount of allocated funds making possible the determination of shares (W) as the unknown (X) variable. Equations (2.121)-(2.126) present how the portfolio’s characteristics are calculated. The solution to A problem is the upper rightmost point on the efficient set with the max expected effectiveness equal to $E_{\text{max}}[U(W_A)]$ and unfairness $Unf_A$.

B. sub-problem of total variance (unfairness) minimisation

Objective function:

$$Unf^{w,R,p} \rightarrow \min.$$  (2.128)

Constraints:

$$\sum_{i=1}^{n} x_i = 1000 \mid w_i = x_i \geq 0 \text{ for } \forall i.$$  (2.129)

All other equations and descriptions are adopted from problem A.

According to the objective function, the optimal portfolio is that with a minimum of distributional unfairness or a total variance. The $X$ as the solution to problem B defines the portfolio as the leftmost point B on the efficient frontier with the minimal unfairness ($Unf_B$) and expected effectiveness $E[U(W_B)]$.

C. sub-problem of interior points’ determination.

Objective function:

$$Unf^{w,R,p} \rightarrow \min.$$  (2.130)

Constraints:

$$\sum_{i=1}^{n} x_i = 1000 \mid$$  (2.131)

$$w_i = x_i \geq 0 \text{ for } \forall i,$$

$$E[U(X)] = E_{\text{gen}}[U(X)],$$  (2.132)

while

$$E_{j\text{req}}[U(X)] = E_{j-1\text{req}}[U(X)] + \frac{E[U(W_A)] - E[U(W_B)]}{m},$$

where $E_{j\text{req}}[U(X)]$ – equidistant initially specified requested expected effectiveness.

All other equations and descriptions are adopted from problem A.

The presented problem finds the minimum possible distributional unfairness for the particular level of expected portfolio’s utility ($E_{\text{gen}}[U(X)]$) of fair effectiveness. The $X$ as the
solution to problem C defines the portfolios as the equidistant intermediary points on the efficient frontier between the extreme points found from problems A and B.

The attitude coefficients play an important role in portfolio optimisation, and their choice is a subjective matter. That is why the coefficients’ fitting is the step requiring the choice of guiding selection principle. It was decided to pick up the attitude coefficients on the separated basis providing the reduced forms of problem A, dealing with the only unfairness sub-factor. First, the coefficients are searched under the maximisation of the expected portfolio’s effectiveness and second, the greatest unfairness intolerance is favoured. Put it differently, the unfairness sub-factor has to be maximum. The steps for the determination of coefficients are presented as problem D in Appendix B (Table B.5). The first step allows finding the max expected effectiveness \( E_j^{w,f} [U(W)] \) respecting just one particular unfairness sub-factor \( \sigma_{s,f}^2 \) and related to the particular \( j \)-th attitude coefficient. In the second step, the optimal attitude coefficient is found as the one providing the maximum of unfairness \( E_j^{w,f} [U(W)] \) respecting just one particular sub-factor \( \sigma_{s,f}^2 \) and related to the particular \( j \)-th attitude coefficient.

Having constructed the efficiency set presented as the upper part of the efficient frontier, it is possible to find the optimal portfolio and reach the maximal ratio of the expected effectiveness and the level of unfairness. This portfolio commonly is referred to as the tangency portfolio. Tangency characteristics come from the graphical way of finding the optimal point – by drawing the tangent line touching the Markowitz bullet obtained by solving the problems A, B, C. The two following models with identical but different objective functions give the mathematical formulation of the problem below.

E.1 sub-problem of optimal tangency portfolio.
Objective function:

\[
\frac{E(W)}{U_{nf}^{w,r,p}} \to \text{max.}
\]  

(2.133)

All other constraints, equations and descriptions are adopted from problem A

The solution gives shares of distribution providing the best ratio between two contradictory characteristics of the distribution, namely between expected effectiveness and unfairness. Saying figuratively, the ratio finds the portfolio. Meantime, the mentioned ratio also points to the fairest distribution. It can be easily checked out by the unfairness ratio making the minimising objective
function of the identical sub-problem allowing getting the same result but from the slightly different angle.

E.2 sub-problem of the minimum unfairness portfolio.

Objective function:

$$\frac{\text{Unf}_{W,R,P}}{E[U(W)]} \rightarrow \min.$$  \[2.134\]

All other constraints, equations and descriptions are adopted from problem A.

This objective function shows at the portfolio with the minimum level of unfairness calculated as the ratio between expected effectiveness and unfairness.

The application part of the presented model is given in section 3.3.3.

**Conclusions to chapter 2**

1. The main research task of the sub-chapter 2.1 is not merely the discussion of existent and applicable in the Cohesion policy MCDM methods, but also the development of more suited and adjusted for the specific needs approaches and methods. Therefore relying on the basic multi-criteria decision-making methods given in the sections 2.1.2, 2.1.3, 2.1.4 the methodological foundation was proposed in sub-chapter 2.2 for the developed methods and approaches filling in the gap in existent practice of regional performance measurement.

   Newly developed methods allow measurement of the following aspects: the risk attitude differently considered by the hybridized compromise MCDM methods (sec. 2.2.1), data-driven synergy interaction between criteria based on correlation (sec. 2.2.2), effectiveness (“doing the right thing”) of regional performance (sec. 2.2.3) and extensive and intensive aspects at both hierarchical NUTS 1 and NUTS 2 levels (sec. 2.2.4).

2. The sub-chapter 2.3 is based on the discussed prerequisites for the IMC, in particular, pseudo-objectiveness, exhaustiveness, unanimity, context relevancy and sequential consistency. With regard to this, the two practical criteria were suggested for the selection of MCDM methods. Every criterion rises from the essence of the practical problem to be solved. It makes suggested selection approach to be pragmatic and suited to the further specific sub-problems underlying the final distribution of SF.

   The first problem of the genuine regional classification is suggested to be solved based on the quality of the clustering structure identified by the set of 15 validating indices. Depending on
the quality of the clustering structure, the MCDM methods are classified according to their clustering power. The last defines which method is more suited for clustering purpose. It is assumed that the genuine classification of regions requires the significant and the most frequently identified clustering structure proved by the majority of validating indices. Such an approach helps avoid subjective thresholds (presented in sub-chapter 1.1) for the identification of the economic status of the region and correspondingly its eligibility for receiving the funds.

The second criterion comes from the other aspect of MCDM application, in particular, the distribution of funds. It is evident that the distribution of funds is based on the properly-identified roles of regions, namely recipients or donors. Therefore, the proper measurement of regional performance is of high importance and needs to be verified by the results obtained from the set of applicable MCDM methods. If the ranking of the critical distribution players (sure lagging or weak regions – the least developed, sure donors – the most developed regions) is in compliance with the majority of MCDM methods applied (the conformism principle) then this method pretends to have the highest robustness and to be the most suitable for the ranking. Saying differently, the ranking of the particular MCDM method is expected to be robust, when the regions with low variability in ranks obtained by the panel of methods, have been placed at the edging position of key players. The robustness of ranks is measure by fitness function representing the level of the measurement error, which has to be minimised or centered.

In addition, the approach to profiling and comparison of applied MCDM method was offered. The profile is built of the defined distinctions of the MCDM methods from the so-called basic sub-perspectives formed by the OWA operator. Such a comparison can serve as the additional tool for a better understanding of the MCDM method’s philosophy and its aggregating function in the light of prevailing optimistic conditions. Thus, eventually, it can be understood which aggregating strategy stands behind the application of a particular MCDM method.

3. The main contribution of the sub-chapter 2.4 was to provide the set of alternative ways of the SF distribution. According to the gaps found in the literature, there is no research focused on the improvement of the current funds’ distribution mechanism based on GDP indicator incorporated by the Berlin formula.

The models suggested for the distribution of SF are newly developed and have a strong connection with actual parameters of distribution guided by the current Berlin formula. Therefore,
all distribution models can be perceived as alternative ways of distribution and mathematically verified improvements of the current practice.

Three types of models have been presented. The first type of the optimisation model (2.4.1) is considered as an improvement of the Berlin formula based on the variance minimisation optimisation model. Besides the complex criterion was suggested to define the best distribution strategy. The second type of optimisation model (section 2.4.2) is the extension of the first type but with the consideration of multi-dimensional measurement made with the help of MCDM methods. Thus, this model considers the utility values produced by MCDM and incorporates them due to the regression model built into the optimisation model. It is necessary to notice that the multi-variable MCDM based optimisation model is the first in its kind model connecting the results of MCDM application with the distribution of funds. Before this research, the application of MCDM methods in Cohesion policy has been characterised by the methodological gap between the measurement and optimisation aspects of the distribution problem.

The third type of model (section 2.4.3) is based on the Markowitz mean-variance portfolio theory. It helps avoid the free-ride problem that originated from lagging regions reluctant to improve their status because of losing the needed allocations of SF. After all, the optimal portfolio allows obtaining the fair distribution based on the regional effectiveness and complemented by such properties as equality, equity and equitability playing the role of risk factors.
3. APPLICATION OF SUGGESTED METHODS, MODELS AND APPROACHES

This chapter, according to the introduced in the previous chapter methods, models and approaches will present the results of their application. For the calculations to the real data was retrieved from official Ukrainian and EU statistical websites. The data used to describe the regional socio-economic performance was selected based on the GDP complementing or adjusting approach when other criteria except income are taken into account for the more comprehensive measurement. The replacing approach, when income component is one amongst others equally important, is avoided. The data slightly differs depending on the number of analysed regions and correspondingly its availability (limited reachability) in the Eurostat database. The regional performance has been measured by the help of different MCDM methods and measurement approaches presented in sub-chapter 2.1 and sub-chapter 2.2, respectively. The results of the regional performance measurement will be verified due to the pragmatic approaches based on analysis of clustering structures (sec. 2.3.1) and methods’ robustness (sec. 2.3.2). Besides the measurement bias of applied MCDM methods will be revealed by offered OWA based approach to profile construction (sec. 2.3.3). This will eventually help select the most suitable MCDM method for the final problem of distribution optimisation, which will be solved by the three proposed models (sec. 2.4.1, 2.4.2, 2.4.3).

3.1 Multi-dimensional measurement of different aspects of regional performance

Speaking of the IMC approach, two scenarios from fig. 1.17 are followed, in particular, the scenario of mainstream (block 2.2) and unorthodox (block 2.3) multi-dimensional measurement. Within the first scenario, both regional competitiveness and regional performance were measured with the help of existent MCDM methods. Concerning unorthodox measurement, such non-traditional for the regional studies aspects were measured, as efficiency and effectiveness.
3.1.1 Determination of lagging regions concerning risk attitude based on two-factor outranking approach (example of 35 Visegrad NUTS 2 regions)

In this section, the two-factor outranking approach is applied to the identification of lagging regions with regard to the risk attitude. This approach has been introduced in section 2.2.1 and follows the multi-dimensional measurement scenario (blocks 1.2, 2.2 in fig. 1.17).

The initial list of 10 essential indicators being used for the analysis of the performance of 35 NUTS 2 regions from the Visegrad group (Czech Republic, Hungary, Poland, Slovakia) countries is given in table 3.1. The logic underpinning the selection of the indicators is determined by the consideration of the most important economic, social and innovative factors influencing the regional performance and competitiveness in the Eastern European countries. As well, it is limited by the availability of the data on the “Eurostat database”.

table 3.1: Indicators describing the socio-economic development of NUTS 2 regions from Visegrad group in the 2013 year

<table>
<thead>
<tr>
<th>#</th>
<th>Abbrev.</th>
<th>Indicators</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>DI</td>
<td>Disposable Income (net) of households by NUTS 2 regions, in purchasing power standard based on final consumption per inhabitant, PPS/inhab.</td>
</tr>
</tbody>
</table>
| 2  | EAR    | Economic Activity Rates by sex, age (from 15 to 64 years) and NUTS 2 regions, %.
| 3  | ER     | Employment Rates by sex, age (from 15 to 64 years) and NUTS 2 regions, %.
| 4  | TE     | Tertiary Education (levels 5-8), %.
| 5  | UN     | Total Unemployment (%), %.
| 6  | PROD   | Regional productivity measured as the ratio between Gross Value Added at basic prices and the number of persons employed, euro/pers. |
| 7  | GFC    | Gross Fixed Capital formation by NUTS 2 regions, euro/per. |
| 8  | TRD    | Total intramural R&D expenditure (GERD) by sectors of performance and NUTS 2 regions (Percentage of gross domestic product (GDP), %). |
| 9  | JVR    | Job Vacancy Rate activities (except activities of households as employers and as own use producers; activities of extra-territorial organisations and bodies), %.
| 10 | BRD    | Total intramural R&D expenditure by the business enterprise sector, %.

Source: Eurostat base (available from http://ec.europa.eu/eurostat)

The commonly used input-output (outcome) dividing approach to the data set is not used here, as following it the data can be divided in a very flexible way depending on the analyst’s point of view. All indicators are previously transformed to become relative and scale-free what makes the adequate benchmarking. The hierarchical structure of criteria needed to obtain the composite index (utility value) is the 1 type strategy assuming single MCDM method and 1 level of aggregation with no pillars, but the mixed panel of presented above criteria (fig. A.7).

The entire indicators are benefit ones apart from the UN (cost), meaning that its decrease makes the level of regional performance better off. The number of indicators suffices the

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appropriate number to be used for the MCDM methods; however, the space reduction is going to be conducted. This procedure, in consequence, will specify the results of the MCDM application. Besides, it will not be superfluous to check the suitability of the data sample for the regional performance measurement by the usage of the Kaiser-Meyer-Olkin indicator and Bartlett's test. According to the test shows that the chosen indicators are suitable (KMO is more significant than 0.6; sig. < 0.05) for the further space reduction and obtaining the regional performance factors measured by principal components (Table C.1, Appendix C). Despite the satisfactory results of the test we still have to check the variance coefficient and the correlation between indicators to be sure that indicators cause the conflict between alternatives and do not replicate each other (Table C.2, Appendix C).

The high correlation has been found between the ER and EAR. Having considered the fact that the variance coefficient of these indicators is below 10 %, both of them appeared to be not essential. Pulling it together, we have the ground for the exclusion of EAR as the redundant indicator because of its high correlation with ER (0.94) and the lowest variance coefficient (6 %). Thus from 10 initial indicators, the 9 essential ones are left for further analysis.

The next step is to use the multivariate explorative technique called Principal Component Analysis (PCA) (Morrison, 2005) for the determination of the latent factors or main dimensions by which the level of regional performance can be described. These dimensions initially are not explicitly defined, but after the space reduction by PCA all primary \( n \) indicators \( (C_1, C_2, \ldots, C_n) \) are reduced to the number of \( k \) components, when \( k \ll n \).

From the Table C.3, (Appendix C) we see that two components with the Eigenvalues higher than one were extracted by the Varimax rotation Method with Kaiser Normalization. In general, they explain 73 % of the variation, which seems to be sufficient to accept the result.

Ideally, each component should consist of a unique and most relevant variability associated with the full set of indicators. In our case, we see that \( ER \) (0.462) and \( UN \) (-0.358) do have some connection with the 1st components, but we are going to neglect it because the absolute value is lower than 0.5 (table 3.2). It is worth mentioning that we were able to define the components logically before the PCA, but what we are more interested in is the values of the principal components (Appendix C, Table C.4) against which the clustering of lagging regions will be done below.
Table 3.2: Rotated Component Matrix

<table>
<thead>
<tr>
<th>Indicators</th>
<th>Component 1 (economic)</th>
<th>Component 2 (social-innovative)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.GFC</td>
<td>.926</td>
<td>.235</td>
</tr>
<tr>
<td>2.PROD</td>
<td>.897</td>
<td>.021</td>
</tr>
<tr>
<td>3.TE</td>
<td>.823</td>
<td>.132</td>
</tr>
<tr>
<td>4.DI</td>
<td>.760</td>
<td>.321</td>
</tr>
<tr>
<td>5.BRD</td>
<td>.019</td>
<td>.891</td>
</tr>
<tr>
<td>6.TRD</td>
<td>.281</td>
<td>.867</td>
</tr>
<tr>
<td>7.JVR</td>
<td>.005</td>
<td>.751</td>
</tr>
<tr>
<td>8.ER</td>
<td>.462</td>
<td>.717</td>
</tr>
<tr>
<td>9.UN</td>
<td>-.358</td>
<td>-.713</td>
</tr>
</tbody>
</table>

Source: author

To sum up shortly the results of preliminary analysis, we decided to use for the application of MCDM methods 9 essential indicators describing the regional performance in two directions specified by the PCA method, in particular economic (1st component) and social-innovative (2nd component).

Having applied the selected distance-based MCDM methods (sec. 2.1.3), in particular, Hellwig’s, TOPSIS, VIKOR and their hybrid modification we obtained the six rank orders for 35 NUTS 2 regions from Visegrad countries (Appendix C, Table C.5). The relatively high degree of consistency is present for many regions being considered as robust relating to the MCDM methods applied. Nevertheless, there are some regions, which ranks mismatch with the difference in some cases equal to 10 positions. For example, region PL41 by most methods gets 18th rank, when by VIKOR (or Hybrid VIKOR) it has a much better 8th rank. A similar situation arises with many regions having essential deference in ranks, especially compared to the mentioned latest methods. It makes the reason for the correlation analysis between ranks produced by selected and hybrid methods.

Looking at the ranks from the hybrid methods, we can notice that in the frame of the VH method, the decision-making process is less sensitive, making by this some alternatives incomparable and sharing the same rank. In relation to Regional Cohesion policy, it can be considered as an advantage, as in such case small differences in criteria will not lead to the distinction in ranks of regions. Thus, basing on this, we conclude that hybridisation is empowered
to decrease a compensatory effect of original MAUT MCDM methods by introducing into them new elements from the outranking group of MCDM.

To measure the correspondence between the initial ranking and the hybrid ranking, Kendall's Tau correlation coefficient was chosen (table 3.3). Preference was given to this coefficient putting aside the Spearman’s one because the latest does not pay attention to the concordance and discordance among all possible pair wise events and thereby it would increase the correlation between methods.

Table 3.3: Correlation between methods (Kendall's Tau, two-sided)

<table>
<thead>
<tr>
<th>Methods</th>
<th>H</th>
<th>HH</th>
<th>T</th>
<th>TH</th>
<th>V</th>
<th>VH</th>
</tr>
</thead>
<tbody>
<tr>
<td>H (Hellwig's)</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HH (Hellwig’s Hybrid)</td>
<td>0.899</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>T (TOPSIS)</td>
<td>0.919</td>
<td>0.845</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TH (TOPSIS Hybrid)</td>
<td>0.950</td>
<td>0.872</td>
<td>0.967</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>V (VIKOR)</td>
<td>0.708</td>
<td>0.720</td>
<td>0.647</td>
<td>0.666</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>VH (VIKOR Hybrid)</td>
<td>0.712</td>
<td>0.718</td>
<td>0.655</td>
<td>0.672</td>
<td>0.965</td>
<td>1</td>
</tr>
<tr>
<td>average correl.</td>
<td>0.838</td>
<td>0.811</td>
<td>0.807</td>
<td>0.825</td>
<td>0.741</td>
<td>0.744</td>
</tr>
</tbody>
</table>

Source: author

A high value of Kendall's Tau can be interpreted as the degree to which k methods ranked N alternatives similarly. In the case of similarity, the coefficient is closer to one, and the H0 about the independence of rank orders is rejected. Looking at table 3.3, we note that there is a high correlation (>0.89) between the original rankings and hybrid versions. It says that the difference in ranks is almost missing; however, one should mention that the H method is the most influenced by the TFO approach.

In contrast, the T method is the less influenced method (0.967). It means that TFO works similar to the initial aggregating function (distance to the ideal and negative) applied in the T method, and in a slightly different way to the H method based just on a distance to the positive ideal point. The most significant difference (0.647) in the ranks within the original methods is found between V and T methods; similar can be said about their hybrid versions (0.672). The most significant similarity (0.919) is defined between T and H methods; the same is said about their hybrid versions (0.872).

Relying on the average correlation measured within all methods, the most conformal method is H, which correlation is the highest (0.838); among the hybrid methods – TH (0.825) method. The most distinctive is V (0.7141), while the VH method behaves differently to the rest methods having the lowest compare to other hybrid modifications average correlation (0.744).
We can infer that within these data set and panel of methods the V method appeared to be “different animal”. Through that, the H0 that TFO approach will provide different ranks is rejected owing to the high correlation between original and hybrid ranks. Meantime the revealed nonconformity of VH method provides another positive effect in the making attempt to define the cluster of the lagging regions.

The following step is to use the advantage of the TFO approach for the lagging regions’ determination. It can be done in a straightforward way, just looking at the net flow (eq. (2.44), Appendix C, Table C.5). If the net flow takes negative value, it means that this region is mostly dominated by the rest of the regions. This fact relates the region to the category of lagging regions (3rd cluster). Having provided that, it is necessary to choose among three hybrid methods the most effective one using some criteria of cluster’s quality. For this purpose, we propose the criterion corresponding to the results of the PCA method in the view of the earlier obtained scores of two principal components. Thus, to verify obtained lagging clusters, they should be explored against the two principal components, in particular, economic and socio-innovative development (fig. 3.1).

Implementation of three Hybrid methods and overlapping their results to the PCA makes a choice of the lagging regions more precise in an ad-hoc fashion and easy to be interpreted. The MCDM methods itself, including their Hybrid version with net flows, do not provide a sufficient basis for lagging clusters determination. The combination of MCDM with the multivariate PCA method is of particular interest because overlaying the cluster on the two components the level of regional performance attributed to countries can be better defined and analysed.

Projecting the obtained by the Hybrid methods lagging clusters on the two principal components defined by PCA, we have found that TH and HH methods mix enough regions from different clusters (fig. 3.1a, b). It leads to the strong Pareto violations between 3rd and 2nd clusters assigned to neighbouring regions being compared from the left-down quadrants. The VH method, in contrast, gives the most appropriate and easy to interpret the placement of the lagging cluster. In this relation, it has been confirmed before that the ranks from the V and HV methods have the lowest correlation, which makes these methods the least conformal with other MCDM methods. Lagging regions defined by the VH are scattered in the homogeneous left-down quadrant, which is smaller compared to the rest Hybrid methods. The range is approximately limited by (-1; 0) for economic comp. 1 and (-1;1) for socio-innovative comp. 2. Compare to
others, this method defines lagging regions in the most concentrated way, hardly mixing them with more developed regions (CZ07, CZ08).

fig. 3.1: Analysis of lagging NUTS 2 regions cluster for Visegrad group, 2013 year

a. Lagging regions by Hellwig’s Hybrid (HH) method

b. Lagging regions by TOPSIS Hybrid (TH) method

c. Lagging regions by VIKOR Hybrid (VH) method

d. Additional country aspect to fig. 2 (c), VH method

Source: author

Thus, the VH method is occurred to be giving the best-defined cluster with clear interpretation relating to the PCA results. Basing on it, the lagging regions are characterised by the negative level of economic development, when a socio-innovative component can reach in
this cluster even to the average level. Besides, from the fig. 3.1 (c, d), we can state that the socio-innovative component is not the most critical factor in the regional clustering, because there are a lot of more developed regions falling into the value lower than 0 within the second component. The same does not relate towards the first economic component, which 0 level divides almost all regions into lagging and more developed. It appeared to be that improvements in the socio-innovative direction are not so efficient to change the cluster. Such a situation can be quite beneficial to lagging regions supporting innovative and social development, as these activities will not necessarily change the cluster of the region or will do it much slower keeping the “funding faucet” open. To such regions, mostly we can relate regions from the Czech Republic and Hungary.

Moving further in this way, we can state that there are some patterns attributed to the development of each country. Regions from Poland are distinctly characterised by the economic way of development what makes these regions more efficient compare to regions from the other countries paying more attention to social-innovative direction. On the other hand, Polish regions being efficient might be suffering from a high level of unemployment and the necessity to be improved technologically by providing innovations. Relying mostly on a level of innovativeness and a low level of unemployment does not mean necessarily the high level of regional performance. This can be referred to as the Czech Republic regions except CZ01 being at 1st cluster.

Beyond said above, it is visible from the graphs that regional performance in Visegrad countries is not balanced; only some lagging regions from the 3rd cluster (CZ4, PL32) seem to be equally close to the origin from the negative side, giving some signs of balanced development. It is obvious that the shortest way to switch the cluster is the balanced development, but it belongs to highly developed regions from the 1st cluster, in particular, SK01, CZ01 and HU01.

From the methodological point of view, the application of the TFO approach allows revealing new perspectives (clusters determination) for the MCDM methods, left behind the curtains of their initial formulation. In this way, aggregating function in the view of the TFO approach happened to be more advantageous in the light of the lagging regions determination complemented by PCA. The compensating effect of original MCDM methods was decreased slightly by the introduction of the Regret factor in the outranking comprehensive model based on the binary relationships, pseudo-criteria and thresholds. Such a new extension to the selected
methods helps identify the lagging regions based on dominated alternatives defined by the negative net flow indicator utilising cardinal properties coming from the ordinal ones.

From the practical point of view, the fruitful combination of the PCA and hybridised compromise MCDM methods is of particular interest relating to the lagging regions’ determination and analysis of the regional performance. Using the panel of compromise methods complemented by the developed TFO approach, the lagging regions’ cluster was defined. Analysing the placement of the lagging regions, the hybrid version of the VIKOR method appeared to be the most effective relating to the clustering based on the current data sample. The lagging cluster obtained by this method is clearly structured and easily interpreted. It is characterised by the lowest economic and medium socio-innovative aspects of regional performance.

It was found that the transition to the 2nd and 1st clusters (fig. 3.1d) is determined to a greater extent by the economic factor of the development, not by socio-innovative factor. Thus, the economic factor is more important for the cluster’s affiliation. The example of it is socially deprived Polish regions taking the minimum socio-innovative vector of the development, but being closer to the more developed 2nd and 1st clusters. In contrast, the patterns of the Czech Republic and Hungary show that they prefer the way of the socio-innovative development giving them a slower transition to the second more developed cluster and more extended stay under the Regional Cohesion funding. The balanced development is more attributed to the highly developed regions from Hungary, Slovakia and the Czech Republic presenting the capital cities. It worth noting that the problem of the lagging region's determination can be referred to as the ad-hoc problem, where among the panel of MCDM methods the best one giving the rational and transparent interpretation can be chosen.

3.1.2 Measurement of regional effectiveness based on ratio weighting method (example of 35 Visegrad NUTS 2 regions)

To measure effectiveness as unprecedented in regional practice aspect of regional performance, we applied the RAW method suggested in section 2.2.3. This approach follows the unorthodox multi-dimensional measurement scenario (blocks 1.3-2.3 in fig. 1.17).

It is based on the decomposition of an original set (eq. (2.70), Appendix B., fig. B.5) to obtain an extended set of sub-criteria for the subsequent measurement of ratio sub-utilities. The
RAW method based on eq. (2.70)-(2.79) was applied to the data describing the performance of 35 Visegrad NUTS 2 regions in the 2013 year.

The set of criteria consists of the following original 7 indicators and their weights reflecting the preferences in the following development pattern: gross domestic product (PPS) ($w_7 = 0.25$); unemployment (persons) ($w_6 = 0.21$); employment (persons) ($w_5 = 0.18$); human resources in science and technology (persons with tertiary education and/or employed in science and technology) ($w_4 = 0.14$); total intramural R&D expenditure (euro) ($w_3 = 0.11$); gross fixed capital formation (euro) ($w_2 = 0.07$); economically active population (persons) ($w_1 = 0.04$).

The hierarchical structure of criteria needed to obtain the composite index (utility value) is the 1 type strategy assuming single MCDM method and 1 level of aggregation with no pillars, but a mixed panel of presented above criteria (fig. A.7).

Weights of criteria were established using the ordering method considering the ranks of criteria (eq. (2.71)). Due to the decomposition, seven original indicators have been extended to the 21 ratio sub-criteria. All newly obtained sub-criteria are treated as independent benefit ones contributing to the total utility function. This data was chosen for the effectiveness measurement because it is the most complex and latest data available from the Eurostat database. Uniformity aspect (2.79) is taken into account on the regional level as all targets have to be achieved evenly, and the high level of compensation is not acceptable. Therefore, the coefficient of variation will influence negatively the performance effectiveness of some regions in case the reach targets in the not balanced. For the representation of effectiveness measurement, we have chosen two-dimensional space (fig. 3.2, fig. 3.3), which includes Productivity on axis Y (measured as a ratio of Gross Value Added / working hours) and Effectiveness on axis X.

This space presented as Productivity-Effectiveness matrix describes regional performance in four main quadrants. In our case, some quadrants were mixed because of the presence of outliers (PL12, PL22, HU10) in the data. They have high productivity and high effectiveness, which makes them leaders within the Visegrad group with balanced performance. As well, we highlighted two mixed areas showing regions marked as “dying-wasting” and “surviving-thrilling”. Regions under the “dying-wasting” mark are considered as highly productive but not effective. In comparison to “surviving-thrilling”, their resources are not used to a full extent and targets need to be re-established according to the development pattern reflected in the weights of initial criteria. Thus, “surviving-thrilling” regions reach the “right targets”, and they are quite
successful in it what is proved by the relatively high productivity. Particular attention should be
given to regions falling to the opposite “dying slowly” sector as they do not possess enough
resources and spend them in a not effective way. Meanwhile, the more promising “surviving”
regions take a better place in the matrix due to their higher level of effectiveness stressing the
right path of development but still low level of resources reflected in low productivity.

fig. 3.2: Productivity-Effectiveness matrix, (2013 year)

Analysis of the 2015 year (fig. 3.3) shows in general similar but still a slightly different
situation. It is necessary to mention that in both years the most occupied quadrants are the
“surviving” and “dying slowly” which can refer to the cluster of lagging regions. The best path to
move will be surely from the low left corner to the right upper one passing by “dying wastefully”
and “surviving” areas. However, amongst negative regularities, it is worth mentioning that Polish
regions in both 2013 and 2015 years show peculiar stability in placing the “dying wastefully”
quadrant. These regions are considered as quite productive, but targets they pursue seem to be
established not in the best way in terms of effectiveness. The “capital” regions, such as CZ01, SK
01, HU10, PL12 stick to the same quadrants (“thrilling outliers” and “surviving thrillingly”), with
the only distinction. It is about the opposite tendencies in the 2015 year of outliers: HU10 and
PL12 are losing the level of effectiveness and “surviving-thrillingly” CZ01, SK 01 are moving
towards better targets fulfilment increasing effectiveness.
Another methodological benefit of this application is the analysis of the treatment of interacting criteria based on their correlation (method from section 2.2.2). Incorporation of interaction between criteria (eq. (2.49), (2.56) - (2.61)) allows their proper treatment considering positive and negative synergies resulting from complements and substitutes, respectively. Such treatment, after all, can decrease or increase effectiveness scores. For interacting criteria consideration, the fuzzy measures and theory of capacities (sec. 2.2.2) have been addressed, allowing the evaluation of new weights of criteria.

The consideration of criteria interaction has proven to be not influential and without a considerable impact on regional performance. New weights have slightly changed the original effectiveness ranks in the 2015 year. Saying more, there are no regions changing their quadrant under the interaction influence. On average relative rank change for countries is the following: -0.9 for the Czech Republic, -1.25 for Hungary, 0.5 for Poland and 2.2 for Slovakia. The worst impact was made on the measurement of the Slovakian regional effectiveness, while the most benevolent on Hungarian followed by Czech regions. It is also necessary to notice that for different quadrants, slight changes in effectiveness levels are different. In particular, all Slovakian regions changed their better effectiveness positions to worse; the majority of Polish regions obtained the same or worse positions, excluding two regions which situation turned for better; a
half of eight Hungarian regions improved their situation, while others stayed the same; a half of Czech regions displayed better ranks (Table C.6, Appendix C).

One should mention that it is unlikely the case when effectiveness is the only focus of the analysis. The effectiveness investigation just complements and enriches the classical analysis of regional performance measured by traditional indices, such as efficiency, competitiveness etc. The concept of effectiveness plays the role of a source, giving additional information and broadening the modelled picture of the reality as it was pictured on the example of the performance of Visegrad regions.

Further analysis needs to account the effect being made by different normalisation procedures, as each of them will differently treat outsiders and by this display alternative in a better or worse way. This will allow their proper treatment considering positive and negative synergies resulting from complements and substitutes, respectively. There is a hope that expressed in this research initiative of the unorthodox aspect’s analysis would motivate other research to reveal new sound aspects of the regional performance. Similar close attention to so far not studied aspects and disregarded MCDM methods could bring new insights into a regional analysis and make regional policy more comprehensive, grounded and effective.

3.1.3 Measurement of regional competitiveness with regards to hierarchical levels based on resonance approach (example of 26 Ukrainian NUTS 2 regions)

This section leads us to practical results obtained from the application of the described methods (sec. 2.1.3.1, 2.1.4 2.2.3) and the resonance approach (sec. 2.2.4) allowing the determination of policy interventions based on competitiveness measurement. This measurement approach follows the unorthodox multi-dimensional measurement scenario (blocks 1.3-2.3 in fig. 1.17) with the fourth type of hierarchical structure (fig. A.7). This structure needs to obtain the composite index assumes the application of multiple MCDM methods and data divided by multi-pillars.

The proposed resonance approach is applied for the Ukrainian regions’ data from the 2013 year – the last year before the escalation of the armed conflict with Russia and the separation of the Crimea, Donecky and Lugansky regions.

In Appendix C (Table C.7) we present the Ukrainian NUTS division suggested by Różańska-Putek J., Jappens M., et al. (2009), which we assume to be functional and acceptable in
terms of EU standards to NUTS classification. In this list, Kyiv, the capital city, is presented, as it has a special status and will thus be included in benchmarking.

The list of 27 indicators used for technical efficiency and effectiveness measurement is given in the context of input/output three-group division (Appendix C, Table C.8). The logic underpinning such a division is quite flexible. Based on an output-oriented model, we try to increase outputs using no more than the given inputs. For instance, holding such initial inputs for a business group such as employed aged 15–70, staff engaged in R&D, total expenditure by innovation activity direction and capital investment, we expect such outputs as sold industrial product, innovation products output, gross value added, agricultural output and activity of enterprises operating in services sphere to be increased.

The list of 12 relative input indices (Appendix C, Table C.9) is used for the other perspective uncovering the extensive dimension through Hellwig’s method. This set of indices with the same group structure is intended to give the opposite managerial point of view with a tendency to increase input factors under the condition that the efficiency of their use is already on a relatively high level. The indicators characterising the resource component have the nature of its relative index; e.g., we use a share of innovatively active industry enterprises among all industry enterprises, but not just the dominator of the index. From this side, an improvement in the business resource level can be achieved with an increase in the level of employment rate, personnel engaged in research and development activities, innovative expenditures and investments per 1 business unit. Both sharply different output and input increasing perspectives are provided to extend and complement the tools of competitiveness management.

The whole structure of criteria used for the competitiveness measurement is shown in (Appendix C, Table C.8, Table C.9). Before space reduction, we check the suitability of the samples on each of the groups of competitiveness by using the Kaiser-Meyer-Olkin indicator and Bartlett's test. The test showed that the chosen indicators are suitable (KMO for all groups > 0.6; Sig. for all groups < 0.05) for further space reduction and obtaining the competitiveness factors measured by sub-indicators of competitiveness (Appendix C, Table C.10).

To estimate structural effectiveness, normative relationships between the growth rates of different basic indices must be established. Structural effectiveness (the L index) is not considered during the clustering process because it is a kind of combination of both
aforementioned dimensions and it will serve later as an additional dimension for the final decision-making process linked to resonance effect identification.

The first preliminary space reduction step is merely the application of the Hellwig’s, DEA and RAW methods described in sections respectively (2.1.3.1, 2.1.4, 2.2.3). This leads to the estimation of 9 variables representing the composite sub-indicators of RC based on 3 aspects and 3 dimensions (table 3.4).

table 3.4: Components of the RC in the light of aspects and dimensions

<table>
<thead>
<tr>
<th>Composite indices (variables)</th>
<th>Groups (aspects or pillars)</th>
<th>Human capital (H)</th>
<th>Business (B)</th>
<th>Meso-level (M)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Resource level (R)</td>
<td></td>
<td>RH</td>
<td>RB</td>
<td>RM</td>
</tr>
<tr>
<td>Technical efficiency (E)</td>
<td></td>
<td>EH</td>
<td>EB</td>
<td>EM</td>
</tr>
<tr>
<td>Structural effectiveness (St.)</td>
<td></td>
<td>St.H</td>
<td>St.B</td>
<td>St.M</td>
</tr>
</tbody>
</table>

Source: author

The second step is a clustering procedure focused on defining the latent variables, namely clusters that have been extracted based only on 6 values (RH, EH, RB, EB, RM, EM). Having used agglomerative hierarchical procedure (section 2.3.1), in particular Ward’s Method (minimum variance), the regions are divided into 3 clusters: regions with the highest level of development – “engines” (I cluster); “outsiders,” or lagging regions – “brakes” of a country’s economy (III cluster); “middle link” – without prominent advantages and disadvantages (II cluster) (Appendix C, Table C.12). The results of the clustering analysis show that in 2013, Ukraine did not have many prominent regions with the best characteristics. In particular, there are only 3 (11.5 %) driving “engines”: Kyiv city, Donecky and Dnipropetovsky. Thus, the lion’s share (53 %), including 14 “lagging” regions, is considered to be entitled to policy interventions as they create negative multiplicative effects in regional performance and inhibit sustainable development of the country. This means that they require regional interventions for future perspective transformations leading them out from the position of outsiders. Subsequently, more than half of the regions need to undergo an essential developing regulative intervention. The remaining 34 % (9 regions) is referred to as the II middle cluster, where regions do not have an urgent need to be recipients of interventions.

The next part of the section focuses on benchmarking of NUTS 2 regions based on the composite indicators. The aggregating function could take on various forms such as additive or multiplicative functions leading to the compensatory effect. In this research, the compensatory effect is demonstrated through an additive function providing a relatively high degree of
variability of ranks. To compute CI, we aggregate RH, EH, RB, EB, RM, EM. Due to the limited scope of this research, the weights of sub-indicators are considered the only factor of uncertainty.

Having checked the correlation between composite $CI$, $GDP$ and sub-indicators, we determined the correlation between $RM$ and other indicators to be $<0.5$ and not statistically significant. This means that this sub-indicator is the subject of exclusion. Then we once again formed the 51 sets of weights for all 5 remaining sub-indicators, in total we obtained $5 \times 51$ sets of weights and possible sets of ranks. With this number of sub-indicators, the correlation appeared to be relatively high and significant at the 5 % level (Appendix C, Table C.11).

We can now thus conclude that the way the index is constructed is sound. Due to the exclusion of the $RM$ component, the level of max-min robustness increased from 49.7 % to 62.28 %, and the $\sigma$ robustness changed slightly from 80.42% to 82.61% (fig. 3.4).

fig. 3.4: Variability of CI ranks of NUTS 2

Even though we decreased the level of CI variability, on average, there are still 2.26 ranks per 1 region (fig. 3.4), and the presence of the high max-min ranks’ variability is at 38 %, which represents quite a negative precondition for forming precise regional policy interventions. Thus, a sufficiently high variability level indicates the main limitation and drawback of the CI composite. That is why, to avoid the compensatory effect and high sensitivity of the ranks, resonance approach is applied as follows.

The ranks of regions are presented (Appendix C, Table C.12) in the context of two NUTS levels ($G$ – general index for NUTS 1 regions, $S$ – specific index in charge of the NUTS 2 level)
and one additional local intra-level L used for structural effectiveness (St.). The content of this table is the foundation for determining the direction of each region’s improvement.

According to the resonance approach, the components of competitiveness are already composite indicators, and they are not subject to the further total aggregation leading to a single aggregated competitiveness index. Taking this position, we state that the more complex the system we investigate, the more differential the approach to its characteristics should be applied. This means that further during target determination, each component is treated individually without any aggregation. For this purpose, we proposed the concept of dominant resonance index-combination to define the focus of policy interventions. Following the steps listed in subsection 2.2.4, we arrived at resonance combinations for the NUTS 2 lagging regions from the “weakest” cluster III (table 3.5).

table 3.5: Determination of the dominating combinations for the “weakest” cluster III

<table>
<thead>
<tr>
<th>Region</th>
<th>Weaknesses in the 3 dimensions: (worst rank), B-business, H-human, M-meso-level</th>
<th>Dominating combination</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Resource level (R)</td>
<td>Efficiency (E)</td>
</tr>
<tr>
<td>1</td>
<td>NUTS 1 (G)</td>
<td>NUTS 2 (S)</td>
</tr>
<tr>
<td>1</td>
<td>(6) B</td>
<td>(14) M</td>
</tr>
<tr>
<td>3</td>
<td>(10) B</td>
<td>(19) B</td>
</tr>
<tr>
<td>6</td>
<td>(9) H</td>
<td>(22) B</td>
</tr>
<tr>
<td>9</td>
<td>(9) M</td>
<td>(25) B</td>
</tr>
<tr>
<td>11</td>
<td>(7) B</td>
<td>(20) B</td>
</tr>
<tr>
<td>17</td>
<td>(10) B</td>
<td>(23) B</td>
</tr>
<tr>
<td>18</td>
<td>(4) H</td>
<td>(8) H</td>
</tr>
<tr>
<td>22</td>
<td>(10) B</td>
<td>(25) H</td>
</tr>
</tbody>
</table>

Source: author

These regions are the first ones standing in the queue for interventions among all regions being compared. The ranking process for the lagging regions from the 3rd cluster is shown in table 3.6. In the case of the EM(GSL) combination of the 24th region, we see the importance of interventions for the meso-level group (M) directed toward the improvement of technical
efficiency (E) for three levels (G, S, L); the RM(GS) combination shows the necessity of interventions of two levels for M focused on increasing the resource level (R).

Table 3.6: Ranking regions in lagging cluster III based on the urgency of interventions

<table>
<thead>
<tr>
<th>Preferences of combinations’ (1- the most urgent)</th>
<th>Region</th>
<th>Resonance combination</th>
<th>Rank of G index</th>
<th>Rank of S index</th>
<th>Final intervention ranking</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>24</td>
<td>EM(GSL)</td>
<td>11</td>
<td>26</td>
<td>1</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>EB(GSL)</td>
<td>11</td>
<td>20</td>
<td>2</td>
</tr>
<tr>
<td>1</td>
<td>21</td>
<td>RH(GSL)</td>
<td>11</td>
<td>19</td>
<td>3</td>
</tr>
<tr>
<td>1</td>
<td>14</td>
<td>RH (GSL)</td>
<td>11</td>
<td>11</td>
<td>4</td>
</tr>
<tr>
<td>1</td>
<td>3</td>
<td>EB(GSL)</td>
<td>10</td>
<td>11</td>
<td>5</td>
</tr>
<tr>
<td>1</td>
<td>18</td>
<td>EM(GSL)</td>
<td>8</td>
<td>6</td>
<td>6</td>
</tr>
<tr>
<td>1</td>
<td>6</td>
<td>EB (GSL)</td>
<td>7</td>
<td>7</td>
<td>7</td>
</tr>
<tr>
<td>2</td>
<td>7</td>
<td>RM(GS)</td>
<td>10</td>
<td>25</td>
<td>8</td>
</tr>
<tr>
<td>2</td>
<td>17</td>
<td>EB(GS)</td>
<td>10</td>
<td>24</td>
<td>9</td>
</tr>
<tr>
<td>2</td>
<td>25</td>
<td>RH (G)</td>
<td>9</td>
<td>10</td>
<td>10</td>
</tr>
<tr>
<td>2</td>
<td>9</td>
<td>EB(GS)</td>
<td>8</td>
<td>11</td>
<td>11</td>
</tr>
<tr>
<td>2</td>
<td>11</td>
<td>RB(GS)</td>
<td>7</td>
<td>12</td>
<td>12</td>
</tr>
<tr>
<td>3</td>
<td>22</td>
<td>EB(GL)</td>
<td>10</td>
<td>13</td>
<td>13</td>
</tr>
<tr>
<td>3</td>
<td>19</td>
<td>EB(GL)</td>
<td>8</td>
<td>14</td>
<td>14</td>
</tr>
</tbody>
</table>

Source: author

The data is sorted according to the preferences (importance) of combinations (GSL>GS>GL). For instance, for region 24 with a triple match of G, S, L indices, the first step is to define the rank of a region on the G index. The rank of this region is 11th according to EM. A complication arises in that, in the GSL group, a similar rank is observed in regions ranked 1st, 14th, 21st and 24th. This causes a transition to the succeeding S index level, where we have to compare new ranks of the mentioned peer regions. All newly received ranks are different, which implies it is not necessary to proceed to the L index level. After being ranked, the worst regions have the highest priority for intervention. Region 24 has the worst rank (26) on the S index level and is thereby ranked 1st for RI.

Next, we begin testing the hypotheses outlined in the sec. 2.2.4. The first one is whether there is a correlation between RI and the level of CI or its components using data for lagging regions. As we see from table 3.7, corr (RI, CI) and corr (RI, GDP) are extremely low, and the alternative hypothesis H1 (A) cannot be accepted. This means that the algorithm based on resonance weaknesses with respect to lagging regions does not correspond with the economic or competitiveness level. However, we can accept the hypothesis Halt. (B) and assume that there is sufficient correlation between RI and RB (0.723).
table 3.7: Correlation between the RI, CI and its components

<table>
<thead>
<tr>
<th>Variables</th>
<th>RH</th>
<th>EH</th>
<th>RB</th>
<th>EB</th>
<th>RM</th>
<th>EM</th>
<th>CI</th>
<th>GDP</th>
</tr>
</thead>
<tbody>
<tr>
<td>RI rank</td>
<td>Spearm. rho</td>
<td>0.160</td>
<td>-0.279</td>
<td>0.723**</td>
<td>-0.176</td>
<td>0.064</td>
<td>0.134</td>
<td>0.073</td>
</tr>
<tr>
<td>Sig. (2-tailed)</td>
<td>0.584</td>
<td>0.333</td>
<td>0.003</td>
<td>0.547</td>
<td>0.829</td>
<td>0.648</td>
<td>0.805</td>
<td>0.887</td>
</tr>
</tbody>
</table>

**. Correlation is significant at the 0.01 level (2-tailed).

Source: author

Next, C and D hypothesis types are tested visually with a map (fig. 3.5). All NUTS 1 regions on the map are marked with their pattern, and three different colours of patterns signify the level of general competitiveness described by cluster number (the best, lightest is cluster I, the worst, darkest is cluster III). Results from the Ukrainian regional map illustrate the aggregated parts of competitiveness and localisation of RI stirring up synergetic activities in the region. For instance, we can observe a group of regions in the West with the lowest competitiveness. The type of economic activities these regions concentrate on can explain their low competitiveness. In particular, these are western regions mostly focused on agricultural activity and southern regions focused on fishing and shipbuilding sectors. Both groups of regions suffer from a low level of life quality caused by the character of their economic activities.

fig. 3.5: Clustering of Ukrainian regions in 2013

Source: author

The next step is to test hypothesis C and find neighbouring regions with a coincidence of targets on both NUTS 1 and 2 levels. For western regions, the set of business efficiency (EB)
interventions turned out to be a necessity for the 3<sup>rd</sup>, 6<sup>th</sup>, 9<sup>th</sup>, 17<sup>th</sup>, 19<sup>th</sup>, and 22<sup>nd</sup> region. Relying on such an agglomeration of lagging regions with contiguous homogeneous regions, we can reject H<sub>0</sub> (C) and state that there is the area homogeneous with corresponding RI targeted at neighbouring NUTS 2 regions. In this case, it would be advisable to utilise any policy instruments directed at business efficiency development within regions infrastructure investments, innovative programs, subsidies to business, etc. Concerning H<sub>0</sub> (D), we are unable to reject it, as the mentioned regions do not follow each other in a series (one by one) in the final intervention order (table 3.6).

Such synchronised interventions will trigger the resonance effect, initiating synergetic activities. What is more, it will provide for the rise of both country economic growth and regional equity. Attention should be paid to the absence of the strong region from cluster I – otherwise, all interventions could increase the overflow of businesses from the poor regions in cluster III to the closest cluster I “reach” region, only creating more significant disparities between them.

The regional interventions based on competitiveness can be more objective and lead to a more effective decrease in regional inequality. To provide such a result, the approach to competitiveness interventions should adequately consider the systemic and specific features of competitiveness, such as its “magnetic” essence, dimensions and resonance effect of weaknesses coinciding from both hierarchical and spatial aspects.

The attractiveness of regions has been regarded as a key property of competitiveness, since attractive regions are capable of boosting the concentration of business activities and, as a result, providing sufficient labour conditions. The higher the RC, the more factors of growth it possesses and consequently, the better conditions it has for leaving. Thus, according to the concept of area attractiveness, competitiveness is measured in the context of three groups of “consumers” - human capital, business and mixed meso-level groups.

Having analysed the structure of competitiveness, two of its dimensions were chosen to be explored using Hellwig’s indicator and DEA methods. Brought together, these methods go in line with methodological pluralism and complement competitiveness measurement practice by introducing extensive and intensive aspects revealed by a resource (Hellwig’s indicator) and technical efficiency (DEA) components correspondingly.

Policy interventions for lagging regions from the weakest cluster are based on the coincidence between weaknesses of NUTS 1 and included NUTS 2 regions, which represent
hierarchical weakness resonance. Speaking systemically, the element (NUTS 2 region) can influence the system the most effective if the former’s changes are in coincidence with desirable changes for the latter.

Concerning practical results, we have found no correlation between regional RI and RC or economic development levels. It means that neither of these commonly used aggregate characteristics corresponds to the interventions based on the resonance approach. However, sufficient correlation was found with the resource level of the business group (RB), meaning that low level of employment rate, personnel engaged in research and development activities, innovative expenditures and investments appeared to be the most defining factor in the necessity of RI. Meanwhile, the set of homogeneous RI based on hierarchical and spatial coincidence was determined in western Ukraine. It targets six NUTS 2 regions (3rd, 6th, 9th, 17th, 19th, 22nd). All these regions with a dominant agricultural sector of the economy needing interventions focused on increasing business attractiveness through the improvement of their efficiency conditions leading to both regional economic growth and equity.

As regards further developments, it should be stated that the resonance approach could be applied on three managerial levels, such as NUTS 2, NUTS 1 and country-level, bringing an even higher effect in the light of bigger scale resonance target synchronisation. It should be mentioned that the main drawback of resonance approach is the assumption of equality between, from one formal side, the NUTS 1 division and, from the other practical side, true functional groups consisting of the most spatially correlated NUTS 2 regions. This possible difference has to be minimised what determines the direction for the future research of actual (authentic) NUTS 1 functional regions. Another limitation of the obtained results is that priorities for the policy interventions are determined due to the non-compensatory resonance approach in the ordinal fashion, saying nothing about the intensity of the needed interventions. Therefore, further research needs to be directed on the determination of other utility values assigned to every region or some other intensity value.

3.2 Verification of multi-criteria decision-making methods based on practical criteria

This sub-chapter demonstrates the proposed in sub-chapter 2.3 selection approaches to the verification of measurement results obtained by MCDM methods. The idea of verification is
based on the selection procedure, which allows choosing the most appropriate method for the problem at hand. Besides, in section 3.2.3, the results of profile construction will be presented. All subsequent sections will solve the selection model in the fashion of multi-dimensional measurement scenario, in particular, block 3.3 in fig. 1.17.

3.2.1 Selection of the most suitable method from the exclusive panel based on the search for the genuine regional classification (example of 273 EU NUTS 2 regions)

The proposed in section 2.3.1 selective approach provides the results following the multi-dimensional measurement scenario (blocks 1.2-4.2, fig. 1.17). This approach belongs to block 3.2, responsible for the selection of the most suitable method from the panel of applied MCDM methods. The main task here is the selection of the most suitable pair of MCDM and clustering methods for the regional classification. The quality of the clustering structure will help identify at the same time them both. Additional originality of this section comes from the application of hybrids distance-based MCDM methods measuring regional performance with respect to different aggregating strategies representing the different attitude to risk. Disparities are measured due to the application of MCDM methods that allows obtaining the aggregated value of regional performance. MCDM methods themselves represent the different schemes of aggregating when each of them follows different risk considerations strategy. The applied MCDM methods (sec. 2.1.3), such as Hellwig’s, VIKOR and TOPSIS are selected based on their aggregating strategy. Hellwig’s method represents the risk-loving strategy of aggregations with the highest compensating effect. The other two methods share the risk-averse strategy to a different extent. The TOPSIS method is the most penalising MCDM method as it counts positive and negative ideals (fig. 2.3), while VIKOR apart from positive ideal considers minimum regret criteria or the worst criteria describing the performance of the region. Having constructed the set of MCDM methods, the utility values are produced, compared due to the outranking principles and laid into the basis for the classification of regions.

Clustering methods are used to obtain genuine and properly validated classification of regions, which is compared with existent static GDP based classification. The main feature is that the clustering solution consists of the true lagging regions in terms of considering more than 1 single GDP indicators. Moreover, based on the produced utility values, the genuine classification
was found and objectively verified by the 15 validating indices that count two characteristics, such as separation and compactness of clusters.

The GDP criterion is used to be the one that determines the level of regional performance in the current practice of Cohesion policy. The object of the research is the EU Regional Policy providing the SF distribution, which is, unfortunately, still based on the GDP indicator. It happens even despite the fact that Simon Kuznets – the father of GDP, the Nobel Prize winner warned that it does not reflect the wellbeing and living standards; thus, it just cannot be used to define the lagging regions. That is why the classification of NUTS 2 regions will be obtained on a multi-dimensional basis. The diversity of applicable MCDM methods in regional studies is essential what is even evidenced by the range of methods reviewed in sec. 2.1.2, 2.1.3 and 2.1.4. Nevertheless, according to our knowledge, there is no research on how to define the best MCDM method for the ranking or clustering goal. Besides, there is no research in regional studies that would find the genuine classification of regions based on the optimal and validated clustering solution.

The initial set of indices has been formed using the Eurostat source and consists of the following indicators (table 3.8). The choice of criteria is underlined by the availability of the Eurostat data and by its relevance to describe the socio-economic performance of NUTS 2 regions. NUTS 2 level has been chosen for the analysis as the most appropriate for the elaboration of EU Regional Policy recommendation and the one according to which the distribution of EU Structural Funds is conducted. Besides, it is necessary to mention that the complementary logic was followed, when the purpose is just to enrich the data set by adding other most important criteria to the founding GDP.

<table>
<thead>
<tr>
<th>#</th>
<th>Abbrev.</th>
<th>Indicators</th>
<th>direction</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>ear</td>
<td>economically active rate of population, %</td>
<td>benefit</td>
</tr>
<tr>
<td>2</td>
<td>tert</td>
<td>share of employed personnel with tertiary education in economically active population, %</td>
<td>benefit</td>
</tr>
<tr>
<td>3</td>
<td>hrst</td>
<td>share of persons employed in science and technology with tertiary education in employed personnel, %</td>
<td>benefit</td>
</tr>
<tr>
<td>4</td>
<td>empl</td>
<td>employment rate, %</td>
<td>benefit</td>
</tr>
<tr>
<td>5</td>
<td>unempl</td>
<td>unemployment rate, %</td>
<td>cost</td>
</tr>
<tr>
<td>6</td>
<td>gdp_av</td>
<td>euro per inhabitant in the percentage of the EU average, %</td>
<td>benefit</td>
</tr>
</tbody>
</table>

Source: Eurostat base available from: http://ec.europa.eu/eurostat

To neutralise the effect of scale, all presented indicators are relative ones. The mentioned criteria describe the performance of the 273 NUTS 2 regions constituting 27 EU countries. Due
to the missing data, Ireland (regions IE01, IE02) and one region from Finland (FI20) are excluded from the data sample giving a total of 273 NUTS 2 regions. One should mention that almost all indicators are benefit ones, except for the unemployment rate, which was transformed into its reversal value (unempl_r) to work with it easier afterwards.

The following step may be the reduction of dimensions by means of the exploratory factor analysis directed on the extraction of principal components. However, the KMO value 0.56 obtained from the Kaiser-Meyer-Olkin indicator and Bartlett's test indicates that sampling is not suitable (<0.7) for the data reduction and that remedial action should be taken. It means that highly correlated criteria have to be omitted as they duplicate others. In this case, the threshold for the unacceptable correlation is set up subjectively at 0.75. Afterwards, we have to sort out the essential criteria from redundant ones, which are not highly correlated and which present each dimension themselves. It will be done relying on the analysis of variance coefficient and bivariate correlation analysis. The correlation analysis (Table C.14, Appendix C) gives the warning in relation to the three pairs of indicators, namely (hrst, tert), (empl, ear) and (empl, unempl_r). Based on this, some of the mentioned indicators are the subject for further exclusion to avoid the duplication of the information. Speaking of the first pair, the tert has to be omitted as considering the lagging regions, especially in the eastern part of the EU, this indicator is not able to describe the level of socio-economic development adequately. It happens because tertiary education in this area is more available, the matter of image and supposed to be the necessity for most youth.

Saying about other pair (empl, ear) of highly correlated indicators, we need to have a look at the descriptive statistics, in particular at the variance coefficient. If the criterion has VC less than 10%, it is the subject for the exclusion as it does not vary enough to bring the difference to the benchmark of regions. From Table C.15 (Appendix C) we observe that ear has very low variance less than 10%, based on what it is the first candidate to be excluded from the analysis as being low varied among the regions and highly correlated. The empl is a subject to deletion as well, as its variance coefficient is close to the threshold (13.5%) and highly correlates (0.79) with the unempl_r.

Next step is the testing and transformation of the data for the normality relying on the level of distribution skewness (Annoni, Kozovska, 2010), measured as (Helsel and Hirsch, 2002):

\[ k = \frac{n}{(n-1)(n-2)} \sum_{i=1}^{n} \frac{(x_i - \bar{x})^3}{s^3}, \]  

(3.1)

where n – number of observed values,
\[ \bar{x} - \text{arithmetic means}, \]
\[ s - \text{the standard deviation}. \]

To preserve necessary information characterising the disparities in regional socio-economic performance the threshold is chosen to be relatively high at level of |1|. In this way, the outliers are decided to be counted in the research as the genuine and realistic classification of regions, which we are looking for, has to include it at an acceptable maximum. Paying attention to the skewness (Table C.15, Appendix C), we can state that just one indicator \( gdp\_av \) (4,68) is not normally distributed. Logically the following step is the transformation of data for having it linear, symmetric and with relatively constant variance. The possible way to normalize data is through the Box-Cox transformation (Zani, 2000) or other simpler way as log transformation.

Before doing this, let us specify the constraint about the weight of criteria. As the task of regions’ classification is going wider than single GDP criteria for the purpose of classification, nevertheless this criterion has to have always a dominant position supported by higher weight, while others should be just complementary giving additional new dimensions. That is why applying the objective Entropy method (section 2.1.2.1) of weights determination, we can test if the normality data transformation is appropriate. For instance, having normalized GDP, its importance among all other criteria can become the lowest, which is not realistic. This possibility can justify holding the original data and keeping the prominent outliers.

Provided that and being left with the set of three indicators, such as \( gdp\_av, unempl\_r, hrst \), there would be no opportunity to obtain for it the maximal importance, if the \( gdp\_av \) is normalized. Thus, it was decided to keep values original without any transformation. As a result, the following weights were obtained by the Entropy method: \( w_1 \ (gdp\_av) = 45,41\%, \ w_2 \ (unempl\_r) = 43,77\%, \ w_3 \ (hrst) = 10,81\% \).

Having applied all listed indices, the optimal choice was made between two clustering methods (k-means and agglomerative hierarchical), possible numbers of clusters varying from 2 to 10 and 3 aggregating MCDM strategies. The structure is optimal when the majority of validating indicators defines a certain number of clusters.

The summarized results from the analysis of the most frequently identified clustering structures are given in table 3.9. Results obtained based on 15 validating criteria (Table B.3, Appendix B) and eq. (2.88). We can see that the expected 3 clusters’ structure is found to be the most frequent and optimal for the Hellwig’s and VIKOR MCDM methods applying both hierarchical and k-means methods.
Table 3.9: Summary of the optimal clustering solutions

<table>
<thead>
<tr>
<th>Clustering method</th>
<th>MCDM strategy</th>
<th>most frequent optimal number of clusters ($n_{opt}^{*}$)</th>
<th>number of times ($f_{opt}^{*}$)</th>
<th>frequency ($f_{opt}$, %)</th>
<th>$D$, %</th>
</tr>
</thead>
<tbody>
<tr>
<td>hierarchical (average linkage)</td>
<td>Hellwig's</td>
<td>3</td>
<td>5</td>
<td>33%</td>
<td>55%</td>
</tr>
<tr>
<td></td>
<td>VIKOR</td>
<td>3</td>
<td>7</td>
<td>47%</td>
<td>51%</td>
</tr>
<tr>
<td></td>
<td>TOPSIS</td>
<td>2</td>
<td>4</td>
<td>27%</td>
<td>53%</td>
</tr>
<tr>
<td>k-means</td>
<td>Hellwig's</td>
<td>3</td>
<td>8</td>
<td>53%</td>
<td>58%</td>
</tr>
<tr>
<td></td>
<td>VIKOR</td>
<td>3</td>
<td>5</td>
<td>33%</td>
<td>58%</td>
</tr>
<tr>
<td></td>
<td>TOPSIS</td>
<td>10</td>
<td>6</td>
<td>40%</td>
<td>59%</td>
</tr>
</tbody>
</table>

Source: author

For instance, according to the majority rule for the VIKOR method, the 3 clusters structure is defined 4 times applying the hierarchical method. It is not the most frequent structure (47% frequency), but on average VIKOR strategy combined with hierarchical gives the lowest discriminating power (51%) proving that this combination or way of clustering tends to decrease the number of clusters. In contrast to this, the TOPSIS method within k-means clustering tends to create more clusters, and 10 clusters appear to be the optimal number, which also has been proven by the maximum discriminating power (59%). In addition to table 3.9, the other optimal solutions are presented in more detail in table 3.10. It shows that 3 clusters are indeed the dominant optimal solution verified by 15 validation indices most often.

Table 3.10: Frequency of optimal clusters by hierarchical (average linkage)

<table>
<thead>
<tr>
<th>MCDM method</th>
<th>N of clusters in the structure</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1</td>
</tr>
<tr>
<td>H</td>
<td>n of valid. indices</td>
</tr>
<tr>
<td>V</td>
<td>0</td>
</tr>
<tr>
<td>T</td>
<td>0</td>
</tr>
</tbody>
</table>

Source: author

Besides, the presented way of analysis helps define the MCDM method, which is either more suitable for the clustering purpose (lowest discriminating power) or the ranking (highest discriminating power). At this stage, the focus moves directly to the clustering structure extracted based on the hierarchical average linkage method. The correction of regions’ placement has to be done based on the Silhouette indicator before we proceed to the statistical analysis of clustering structures. According to this correction, certain regions from the 2nd cluster have to move to the 1st cluster (Table C.16, Appendix C). Considering new corrected clustering solution, one-way ANOWA analysis shows that means of variables (values from the MCDM) are statistically
different between clusters proving that the clustering structure is significant (Table C.17, Appendix C).

The description of the clustering solution is presented in table 3.11. Means of variables are consistently growing from the 3rd to the 1st cluster showing the increase of the socio-economic development level through all clusters. In addition, one should mention that all variables within 1st cluster change gradually, as the skewness is less than 1 and the distribution of data can be considered relatively normal. The 2nd cluster has outliers in terms of the unempl_r variable, while the 3rd cluster consists of outliers in terms of gdp_av and hrst variables, demonstrating highly developed regions. From this, it can be concluded that the more developed cluster is less homogeneous.

<table>
<thead>
<tr>
<th>cluster / variables</th>
<th>N of regions / %</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Mean</th>
<th>Std. Deviation</th>
<th>Skewness</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>hrst</td>
<td>102/37,4</td>
<td>.13</td>
<td>.47</td>
<td>.2407</td>
<td>.06451</td>
</tr>
<tr>
<td></td>
<td>unempl_r</td>
<td></td>
<td>.09</td>
<td>.40</td>
<td>.2203</td>
<td>.06997</td>
</tr>
<tr>
<td></td>
<td>gdp_av</td>
<td></td>
<td>88,00</td>
<td>737</td>
<td>142,5686</td>
<td>67,90828</td>
</tr>
<tr>
<td>2</td>
<td>hrst</td>
<td>88/32,2</td>
<td>.09</td>
<td>.36</td>
<td>.2136</td>
<td>.05367</td>
</tr>
<tr>
<td></td>
<td>unempl_r</td>
<td></td>
<td>.05</td>
<td>.29</td>
<td>.1272</td>
<td>.05106</td>
</tr>
<tr>
<td></td>
<td>gdp_av</td>
<td></td>
<td>17</td>
<td>219</td>
<td>91,5455</td>
<td>25,87899</td>
</tr>
<tr>
<td>3</td>
<td>hrst</td>
<td>83/30,4</td>
<td>.10</td>
<td>.30</td>
<td>.1828</td>
<td>.03874</td>
</tr>
<tr>
<td></td>
<td>unempl_r</td>
<td></td>
<td>.03</td>
<td>.19</td>
<td>.0822</td>
<td>.04061</td>
</tr>
<tr>
<td></td>
<td>gdp_av</td>
<td></td>
<td>13</td>
<td>77</td>
<td>45,3614</td>
<td>17,18804</td>
</tr>
</tbody>
</table>

Source: author

The results of the comparison of two clustering solutions are presented in table 3.12 below.

<table>
<thead>
<tr>
<th>cluster / variables</th>
<th>N of regions / %</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Mean</th>
<th>Std. Deviation</th>
<th>Skewness</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>hrst</td>
<td>154/56,4</td>
<td>.12</td>
<td>.47</td>
<td>.2342</td>
<td>.06099</td>
</tr>
<tr>
<td></td>
<td>unempl_r</td>
<td></td>
<td>.05</td>
<td>.40</td>
<td>.1836</td>
<td>.07745</td>
</tr>
<tr>
<td></td>
<td>gdp_av</td>
<td></td>
<td>91</td>
<td>737</td>
<td>130,1558</td>
<td>58,84478</td>
</tr>
<tr>
<td>2</td>
<td>hrst</td>
<td>25/9,2</td>
<td>.14</td>
<td>.31</td>
<td>.216</td>
<td>.04564</td>
</tr>
<tr>
<td></td>
<td>unempl_r</td>
<td></td>
<td>.04</td>
<td>.29</td>
<td>.1004</td>
<td>.05373</td>
</tr>
<tr>
<td></td>
<td>gdp_av</td>
<td></td>
<td>75</td>
<td>90</td>
<td>84,16</td>
<td>4,26888</td>
</tr>
<tr>
<td>3</td>
<td>hrst</td>
<td>94/34,4</td>
<td>.09</td>
<td>.31</td>
<td>.1814</td>
<td>.04216</td>
</tr>
<tr>
<td></td>
<td>unempl_r</td>
<td></td>
<td>.03</td>
<td>.29</td>
<td>.1031</td>
<td>.06210</td>
</tr>
<tr>
<td></td>
<td>gdp_av</td>
<td></td>
<td>13</td>
<td>74</td>
<td>44,8404</td>
<td>16,26878</td>
</tr>
</tbody>
</table>

Source: author

The clustering structure based on GDP contains more (34.4 %) less developed regions from the 3rd cluster, and this cluster already includes outliers in terms of unempl_r variable. Outliers are even more prominent in the 2nd cluster, which compared to the previous MCDM based
solution possess only 9.2 % of transitive regions with $gdp_{av}$ less than 90 and more than 75. Besides means of $unempl_r$ in 1st and 2nd clusters are almost equal, showing us that GDP based clustering does not differentiate regions properly in terms of this variable. The visual demonstration is given below by the 3-dimensional graph (fig. 3.6) presented by the input variables.

Summing the results of clustering solutions, the analysis of regional performance can be conducted focusing on the aggregated characteristics of 27 countries. The ranking of countries is formed based on the analysis of their aggregated regional performance in the light of regional structural division. For example according to the MCDM based classification Czech Republic has 12.5 % of more developed regions (1st cluster), 62.5 % of transitive regions (2nd cluster) and 25% of less developed regions (3rd cluster). Relying on such structural division and using the decisive domination rule, this country obtains the status of the transitive country having the 2nd cluster as a dominating one.

fig. 3.6: Visual representation of the optimal clustering solution

![Visual representation of the optimal clustering solution](image)

*Source: author*

The classification made from GDP indicator endues the Czech Republic with the status of a less developed country with a dominating 3rd cluster, which includes 87.5 % of regions. The summarising characteristic of two different classifications concerning the structural division of the data sample, including 27 EU countries, is provided in table 3.13.
table 3.13: Structural division of regions and countries

<table>
<thead>
<tr>
<th>level of development/status</th>
<th>based on MCDM classification</th>
<th>based on GDP classification</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>regional level</td>
<td>country level</td>
</tr>
<tr>
<td></td>
<td>number</td>
<td>%</td>
</tr>
<tr>
<td>more developed (1st cl.)</td>
<td>102</td>
<td>37.4%</td>
</tr>
<tr>
<td>transitive (2nd cl.)</td>
<td>88</td>
<td>32.2%</td>
</tr>
<tr>
<td>less developed (3rd cl.)</td>
<td>83</td>
<td>30.4%</td>
</tr>
<tr>
<td>Total</td>
<td>273</td>
<td>100.0%</td>
</tr>
</tbody>
</table>

Source: author

According to the GDP classification, there is no such country with the dominating transitive type of regions and correspondingly with the status of the transitive country. In total, there is 41% of countries where regions are more developed and 59% of countries with less developed regions. By GDP classification, the transitive element as the regional policy target is missing on the country level and at a small degree present on the regional level (9.2% or 25 regions). The MCDM based classification proposes a more balanced classification with 22% of countries with the transitive status. Speaking of the 3rd cluster, there is no significant difference between two classifications in the light of regional (33.4% and 34.4%) and country (48% and 59%) division. However, the GDP based classification includes outliers within the third cluster in terms of unempl_r variable, while MCDM based classification does not. Two rankings of 27 EU countries in terms of regional structural division based on two classifications is presented thereinafter on the histograms (fig. 3.7, fig. 3.8). The abbreviations of countries’ names are given in Table C.18 (Appendix C).

fig. 3.7: Ranking of countries based on multi-dimensional MCDM classification

Source: author
For instance, Czech Republic according to the MCDM classification takes 10\textsuperscript{th} priority (rank) for the funding, while according to the GDP classification – 3\textsuperscript{rd} priority considering the possibility of the same place sharing by several countries.

It is worth noticing that the status of an absolute less developed country is shared between 6 countries within MCDM classification (fig. 3.7) and between 10 within GDP classification (fig. 3.8). A similar situation is observed for the countries with opposite status of more developed countries having the least priority for funding shared between six countries compared to two countries from the MCDM classification. It is also visible from the number of differentiated positions (ranks), in particular, 20 positions from MCDM based classification and 13 – from GDP classification.

fig. 3.8: Ranking of countries based on single GDP criterion

![Bar Graph

Source: author

Provided analysis proves that the regional classification based on the paired application of MCDM and clustering methods is statistically significant and more grounded as it is based on more comprehensive multi-dimensional measurement. In addition, MCDM based classification is more balanced compared to the traditional GDP based classification as it has 22 \% of countries with the transitive status. However, the more significant share of transitive countries leads to the cutting of active players in redistribution game, as transitive regions more likely will be excluded from the redistribution and by this make the decrease in the regional disparities lesser. Thus, on the one hand, we have a more balanced classification deprived of subjective thresholds, but on the other hand – less effective Cohesion policy and less influential funds distribution. It leaves
the choice of the classification approach with a trade-off component worth further consideration but beyond the area of MCDM application.

Speaking of the limitations, without any doubts, the panel of clustering methods is not an exhausted one as it considers only two methods. More clustering methods could be applied to determine the genuine classification of regions, such as PAM and hierarchical k-means methods. However, the main task was not finding the most verified clustering structure in terms of exhaustiveness of methods used, but to introduce the verification approach due to which the MCDM methods could be further selected.

3.2.2 Selection of the most suitable method from the inclusive panel based on robustness analysis (example of 273 EU NUTS 2 regions)

The results obtained from the presented in sec. 2.3.2 selective approach are placed within the scenario of multi-dimensional measurement presented in sec. 1.3.1 (blocks 1.2-4.2, fig. 1.17). In particular, this section functionally belongs to block 3.2, responsible for the selection of the most suitable method from the inclusive panel of applied MCDM methods.

In this section, the eight MCDM methods as the inclusive panel have been applied to the data of 273 EU regions of NUTS 2 level. All methods applied, such as Hellwig’s (H), TOPSIS (T), VIKOR (V), Simple additive weighting sum (W), Choquet (CH), equal weights or average weighting (AV), DP-2 (DP), RAW method for effectiveness (E) constitute the inclusive panel of MCDM perspective. One should mention that in previous section 3.2.1, compromise MCDM methods were combined into an exclusive panel with regard to a risk attitude. After all, MCDM methods have been compared with the sub-perspectives generated from the basic EW method projected through the OWA operator. In total, considering separate criteria (table 3.14), we obtained an inclusive panel of 37 measurement perspectives on regions to be compared.

<table>
<thead>
<tr>
<th>#</th>
<th>Abbrev.</th>
<th>Indicators</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>EAR</td>
<td>economically activity population;</td>
</tr>
<tr>
<td>2</td>
<td>TRET</td>
<td>persons with tertiary education (levels 5-8);</td>
</tr>
<tr>
<td>3</td>
<td>Unempl</td>
<td>total unemployment, pers.;</td>
</tr>
<tr>
<td>4</td>
<td>prod</td>
<td>regional productivity measured as the ratio between Gross Value Added at basic prices and the number of the persons employed, euro/pers.</td>
</tr>
<tr>
<td>5</td>
<td>HRST</td>
<td>persons employed in science and technology with tertiary education;</td>
</tr>
<tr>
<td>6</td>
<td>Empl pers</td>
<td>persons employed;</td>
</tr>
<tr>
<td>7</td>
<td>GDP</td>
<td>Gross domestic product measured in purchasing power parities (PPS).</td>
</tr>
</tbody>
</table>

Source: Eurostat base available from http://ec.europa.eu/eurostat

200
To show the necessity of the methods’ selection, two illustrative examples of regional performance measurement will be considered. Both examples demonstrate the results obtained from the application of a pair of methods, such as the RAW method for the measurement of effectiveness and another complementing method (SAW or DP-2). Having combined the results from RAW (effectiveness) and SAW methods we can witness from fig. C.1 (Appendix C) the evident supremacy of Czech regions compare to other Visegrad regions. The majority of Czech regions fall into the better outliers’ quadrant. However, if we exclude the duplicated information by the application of the Pena's method (DP-2) presented in sec. 2.1.2.4, many Czech regions move from thrilling to surviving and measurement picture changes considerably. Thus, even our not comprehensive application of only eight listed above MCDM methods is embarrassing enough to decide resolutely which method is the most trusted. The degree of differences between rankings produced by applied methods can be analysed by the presented correlation table in Appendix C (Table C.22). Relying on the significant difference between rankings it is very important to state that application of any MCDM method is worthless unless the problem of methods’ selection is solved and the use of methods is verified to prove that one method is more applicable than others.

The comparison and selection of MCDM methods is made by the presented in section 2.3.2 approach based on robustness analysis and fitness score. The idea of fitness implies a specific ranking of alternatives (regions) that allows defining leaders (more developed regions) and lagging regions in a more precise way. It means that the measurement robustness of key regions is relatively higher compared with other mediocre regions less involved in the redistribution process. In other words, a highly fit ranking assumes high measurement invariability of regions defined as leaders or lagging regions. It allows relative certainty about the determination of regions as active participants of the distribution process.

It is worth noticing that fitness function calculated by the eq. (2.98) for the sake of convenience can be min-max normalised to obtain scaled values varying from 0 to 1. The MCDM method possessing the highest value 1 is considered the most suitable for the optimisation problem. To measure the fitness score, the $\lambda$ parameter has to be calculated. Having used the eq. (2.94)-(2.97) the optimal value of $\lambda$ parameter equal to 0.96 was obtained, which also satisfies the maximisation condition: the sum of importance coefficients tends to be 1, while the sum of the differences of standing together weights tends to be 0. We can see the defined
weight coefficients for the 136 transformed ranks and their accumulated value on the graph (fig. C.6, Appendix C).

Having done the robustness analysis by eq. (2.89)-(2.98) it was defined that the most suitable aggregating method is the Fairly Pessimistic sub-perspective of Equal Weights OWA operator. The closest to 1 are the following ones: V3 (VIKOR with 3 criteria), V7 (VIKOR with 7 criteria), W7 (SAW method with 7 criteria), Ch7 (Choquet with 7 criteria). These aggregating perspectives have the same fitness score equal to 0.92. The histogram presents all normalised $F_1$ values in fig. 3.9. The derived OWA sub-perspectives are marked by white colour, while single criteria additionally presented for the comparison purpose – by light grey colour. Dark grey colour represents the fitness values of MCDM methods being compared and composing the core of an inclusive selected panel. The methods’ correlation is in Table C.22 (Appendix C). The average correlation is able to show the most conforming method (Ch7), but not the most robust.

fig. 3.9: Normalized values of fitness function measuring applicability of MCDM methods

The higher the value of fitness function, the better the MCDM method suits the optimisation problem. Therefore, the active players of the distribution measured by the most robust or the most suitable for ranking MCDM method are with the minimised (centred) measurement error of their distribution roles (ranks). The distribution of measurement errors for several measurement perspectives (MCDM methods) is given in (fig. C.7, Appendix C).
On the graphs below (fig. 3.10) special attention is paid to the transformed by eq. (2.93) (flipped as in lower left part of fig. 1.20) ranks exceeding the 100th, what on the importance axis is higher than 0.01.

fig. 3.10: Placement of pseudo-objective regional robustness within the MCDM method

a. Fairly pessimistic (score 1)

b. VIKOR 3 (score 0.92)

c. VIKOR 7 (score 0.92)

e. Hellwig’s 7 (score 0.67)

f. Effectiveness 7 (score 0.67)

g. TOPSIS 7 (score 0.43)
Thus, all regions falling righter than 0.01 represent the most likely “key players” (certain recipients and donors) in the distribution game. Having highlighted the focus of our attention, it is worth adding that all dots on the right show on the higher robustness and by this, the error of distribution model outcome is minimised (centred). In the fig. 3.10 (a) fairly pessimistic aggregating perspective has the highest fitness values equal to 1. All dots with importance exceeding 0.01 draw clear right up-rising pattern. Other leading aggregating perspectives, such as VIKOR 3, VIKOR 7, Weighted sum (7) and Choquet (7) have the value 0.92 and take the second place among the fittest MCDM methods. For the comparison purpose other lagging in terms of fitness function perspectives (Hellwig’s 7, TOPSIS 7, Effectiveness 7 and Random) are having uncongested alignment with the right and sparse placement.

Admittedly, the degree of considered methods’ diversity influences the discriminating power of the fitness function converging methods in the panel and making them less distinctive. Applying this approach the choice becomes more grounded due to the usage of the fitness function, but now the question can be put on conditions (exhaustiveness of methods included) under which this function has been calculated.

More distinguishing features of compared MCDM methods are presented and explained in detail in the following 3.2.3 section devoted to the method’s profile construction.

**3.2.3 Identification of the method’s profile based on OWA operator (example of 273 EU NUTS 2 regions)**

For the understanding of what the selected methods have in common and what varying, the suggested in section 2.3.3 approach to profile construction is applied to an inclusive panel of
MCDM methods. This section is the logical continuation of the robustness analysis partly performed in previous section 3.2.2. An applied approach to profile construction exploits the OWA operator together with the Equal Weighted method and considers different optimistic degrees of the latter one. In particular, all applied perspectives representing applied MCDM methods are projected (compared with) onto the sub-perspectives formed by the Equal Weighted method and OWA operator. Further analysis requires the analysis of the correlation between perspectives and OWA sub-perspectives to define the bias profile properties of each method.

All MCDM perspectives under consideration obtained on seven (table 3.14) and three criteria extension basis (GDP, Unempl, HRST) are characterised by corresponding correlations with the chosen benchmarking equal weighting OWA sub-perspectives. These correlation coefficients are given below in table 3.15 and table 3.16, according to table 2.3, fig. B.12 (Appendix B) and fig. 2.18. In the tables coefficients processed by eq. (2.99)-(2.103), serve as inputs for the further features calculations necessary for the bias profile determination (see the algorithm in fig. 2.20).

**table 3.15: Bias projection onto three criteria OWA sub-perspectives**

<table>
<thead>
<tr>
<th>Attributes</th>
<th>MCDM main perspectives</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>H3</td>
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<tr>
<td>Correlation coefficients</td>
<td></td>
</tr>
<tr>
<td>Optimist conditions</td>
<td>0.01 – FO</td>
</tr>
<tr>
<td></td>
<td>0.1 – O</td>
</tr>
<tr>
<td></td>
<td>0.5 – VP</td>
</tr>
<tr>
<td>Neutral</td>
<td>1 – N</td>
</tr>
<tr>
<td>Pessimist</td>
<td>2 – FP</td>
</tr>
<tr>
<td></td>
<td>10 – P</td>
</tr>
<tr>
<td></td>
<td>100 – VP</td>
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<td></td>
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<tr>
<td>peak (max)</td>
<td>0.877</td>
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<td>dominant feature, &gt; 0.7</td>
<td>P</td>
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<td>kurt slump / variability</td>
<td>0.342</td>
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<tr>
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<td>99%</td>
</tr>
<tr>
<td>Skewness</td>
<td>FP-FO</td>
</tr>
<tr>
<td></td>
<td>P-O</td>
</tr>
<tr>
<td></td>
<td>VP-VO</td>
</tr>
<tr>
<td>bias type, with peak &gt; 0.7</td>
<td>VP</td>
</tr>
<tr>
<td>absolute bias sum</td>
<td>202%</td>
</tr>
</tbody>
</table>

Source: author
If a peak is high, then the perspective (MCDM) resembles the corresponding basic EW OWA strategy. The higher, the more resemblance is defined. If the peak is low, then the perspective is referred to as the different one from the EW OWA origin. As a result, we can see the degree of resemblance and conclude that EF does not fall into the EW OWA benchmarking group and all in all it cannot be compared with other MCDM as it is entirely different. The only thing that we can state about EF is that it is considered to be pessimistically (VP or FP) skewed. The bigger the kurtosis slump (range between max and min correlation) of the MCDM perspective, the better it is projected by OWA operator and therefore can be better described by its range of sub-perspectives. According to the established kurticity trust level, the conclusion is made about the significance of the defined bias. For instance, all MCDM perspectives except the DP-2 method are sensitive enough to OWA sub-perspectives and potentially can have some bias. However, as the skewness of the DP-2 3 method is not greater than 0.7, it does not have any bias.

Results show that the effectiveness method (E7) does not satisfy the level of min correlation (0.7) allowing the comparison with OWA sub-perspectives. That is why the profile of this method cannot be defined. Even if the correlation appears satisfactory, bias is not registered as skewness lower that |0.7|. Just two methods, such as Hellwig’s (H7) and TOPSIS (T7) occurred to be with very pessimistic (VP) bias (table 3.16).

<table>
<thead>
<tr>
<th>Attributes</th>
<th>MCDM main perspectives</th>
<th>H7</th>
<th>T7</th>
<th>V7</th>
<th>W7</th>
<th>Ch7</th>
<th>EW7</th>
<th>DP-2</th>
<th>E7</th>
<th>best 2/3</th>
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<tr>
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<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Optimist conditions</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>0.01 – FO</td>
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<td>0.491</td>
<td>0.577</td>
<td>0.589</td>
<td>0.590</td>
<td>0.656</td>
<td>0.662</td>
<td>0.441</td>
<td>0.580</td>
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<tr>
<td>0.1 - O</td>
<td>0.566</td>
<td>0.541</td>
<td>0.618</td>
<td>0.637</td>
<td>0.638</td>
<td>0.715</td>
<td>0.717</td>
<td>0.474</td>
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<tr>
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<td>0.679</td>
<td>0.701</td>
<td>0.754</td>
<td>0.752</td>
<td>0.893</td>
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<td>0.549</td>
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<td>0.760</td>
<td>0.711</td>
<td>0.780</td>
<td>0.776</td>
<td>1</td>
<td>0.909</td>
<td>0.565</td>
<td>0.823</td>
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<td></td>
<td></td>
<td></td>
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<td></td>
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<td></td>
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<tr>
<td>2 – FP</td>
<td>0.775</td>
<td>0.843</td>
<td>0.689</td>
<td>0.772</td>
<td>0.775</td>
<td>0.890</td>
<td>0.882</td>
<td>0.589</td>
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<tr>
<td>10 – P</td>
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<td>0.792</td>
<td>0.566</td>
<td>0.626</td>
<td>0.645</td>
<td>0.653</td>
<td>0.710</td>
<td>0.633</td>
<td>0.688</td>
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<tr>
<td>100 – VP</td>
<td>0.875</td>
<td>0.773</td>
<td>0.556</td>
<td>0.613</td>
<td>0.633</td>
<td>0.643</td>
<td>0.702</td>
<td>0.622</td>
<td>0.673</td>
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<td>peak (max)</td>
<td>0.892</td>
<td>0.843</td>
<td>0.711</td>
<td>0.780</td>
<td>0.776</td>
<td>1.000</td>
<td>0.909</td>
<td>0.633</td>
<td>0.840</td>
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<tr>
<td>dominant feature, &gt; 0.7</td>
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<tr>
<td>kurt slump / variability</td>
<td>0.367</td>
<td>0.352</td>
<td>0.155</td>
<td>0.191</td>
<td>0.186</td>
<td>0.357</td>
<td>0.247</td>
<td>0.192</td>
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<tr>
<td>kurticity / trust, &gt;70</td>
<td>115%</td>
<td>117%</td>
<td>61%</td>
<td>69%</td>
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<td>100%</td>
<td>76%</td>
<td>85%</td>
<td>87%</td>
<td></td>
</tr>
<tr>
<td>FP-FO</td>
<td>-36%</td>
<td>-54%</td>
<td>2%</td>
<td>-3%</td>
<td>-4%</td>
<td>1%</td>
<td>-3%</td>
<td>-10%</td>
<td>-17%</td>
<td></td>
</tr>
<tr>
<td>P-O</td>
<td>-105%</td>
<td>-82%</td>
<td>9%</td>
<td>-2%</td>
<td>-1%</td>
<td>18%</td>
<td>2%</td>
<td>-38%</td>
<td>-13%</td>
<td></td>
</tr>
<tr>
<td>VP-VO</td>
<td>-113%</td>
<td>-92%</td>
<td>4%</td>
<td>-5%</td>
<td>-8%</td>
<td>4%</td>
<td>-9%</td>
<td>-43%</td>
<td>-23%</td>
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</tr>
<tr>
<td>bias type, with peak &gt; 0.7</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>absolute bias sum</td>
<td>254%</td>
<td>229%</td>
<td>14%</td>
<td>10%</td>
<td>14%</td>
<td>22%</td>
<td>13%</td>
<td>91%</td>
<td>53%</td>
<td></td>
</tr>
</tbody>
</table>

Source: author
Considering the three criteria extension, the situation is almost similar. Effectiveness appears beyond the condition of the bias determination. Hellwig’s method again placed itself at the very pessimistically (VP) oriented perspective that moved him back after the rest of the MCDM perspectives.

From the fig. 3.9 we see that OWA sub-perspectives except Neutral, Fairly optimistic, Fairly pessimistic are taking the last positions of the fitness function. The best fitness function is referred to as the fairly-pessimistic sub-perspective. A similar picture is drawn with the applied for seven criteria extension; however, the difference between mentioned leading sub-perspectives is not so prominent what says about lower sensitivity to a bias of more extensive seven criteria extension.

The general inference about the MCDM methods’ application is drawn from the analysis of the bias type in correspondence with a fitness score. It can be concluded that the stronger the bias of MCDM perspectives, the lower their fitness scores are in the current application. For example, H3 has VP bias and takes the last fitness place among all three-extension MCDM methods (table 3.15); H7 and T7 are also exposed by the VP bias that pushes them back from leading positions (table 3.16). The optimal point is the fairly pessimistic bias attributed to the corresponding 2/3 OWA sub-perspective. All MCDM perspectives close to it are considered to be highly fit in terms of the developed fitness function. The biggest fitness score within the three criteria extension is provided by the MCDM method marked with the fairly pessimistic bias, such as best 2/3 (FP OWA) or without bias at all. This characteristic refers to relatively symmetric MCDM methods, such as T3, V3, W3, Ch3, EW3 and DP-2 3.

Thus to be fit the MCDM perspective within the three criteria extension has to possess a slight fairly pessimistic bias in relation to benchmarking OWA sub-perspectives. As for symmetric (not biased) MCDM perspectives, their fitness score or robustness would be lower, while perspectives with a strong pessimistic bias find themselves at the very periphery of the ranking. Within the extension of seven criteria, perspectives with bright pessimistic bias are in a backwards ranking, while symmetric perspectives without a bias take leading positions.

Summing up, three criteria extension is characterised by a higher sensitivity to a bias (table 3.15, fig. 3.11a,b); however, MCDM perspectives are not very differentiated in terms of fitness level. On the contrary, seven criteria extension provides less sensitive background for the OWA sub-perspectives (table 3.16, fig. 3.11c,d), but higher differentiation between MCDM
perspectives (fig. 3.9). The abstract prototype for the fig. 3.11 is introduced in section 2.3.3 and presented in fig. 2.19.

The suggested for the measurement of regional performance MCDM candidates with the further purpose of funds’ distribution are the following: highest score 1 is given to the fairly pessimistic OWA sub-perspective, which is followed by equally fit perspectives with score 0.92, such as V3, V7, W7, CH7. Undoubtedly, all of them produce a slightly different ranking. All these MCDM methods allow approaching optimisation problem deliberately considering the robustness of ranking obtained from the inclusive panel of MCDM method. Therefore, the optimal choice of the most appropriate MCDM method fell on the fairly pessimistic perspective of the Equal Weighting (EW) method. In the case of fitness score equality, the final choice amongst the most robust MCDM perspectives is still left to subjective considerations.

**fig. 3.11:** Graphical OWA bias profile of MCDM methods (ranks’ correlation)

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**Source:** author

---

a. Projection onto three criteria OWA  
b. Projection onto three criteria OWA  
c. Projection onto seven criteria OWA  
d. Projection onto seven criteria OWA
More extensive 7 criteria extension has been recognised as reflecting the essence of the MCDM perspective more correctly. For example, AV3 is purely defined as symmetric (while being projected on three criteria extension it is not purely symmetric one what is not correct), the same is said about H3 and V3. However, H3 has the most prominent tendency to be pessimistically biased, which makes it less fit. Considering kurtosis, almost all methods defined as symmetric because the kurtosis is relatively small to signify their bias. So all MCDM methods with 3 criteria extension are defined as symmetric ones except H3 and Effectiveness, which cannot be analysed due to the low correlation with all EW OWA benchmarking perspectives.

In terms of OWA 7 benchmarking almost all methods except two compromise ones, such as Hellwig’s and TOPSIS, are considered to fall into a group of neutral, unbiased MCDM methods, which aggregation mechanism is equalised to the mechanism of equal weighting (EW) method. Narrow extension with three criteria produces slightly different results, placing even TOPSIS into the neutral, unbiased group. However, the most suitable Fairly pessimistic three criteria perspective being projected on the OWA7 (7 criteria) is defined to be neutral.

It is worth mentioning that nevertheless, fitness function finds methods suitability connected to some degree to neutrality, the most neutral methods, such as V7, W7, Ch7 and DP2 7 are not the fittest ones. Thus, neutrality itself does not guaranty the maximum fitness function concerning the applied data set.

Another conclusion is about the nature of a particular MCDM method. For example, the DP-2 method (section 2.1.2.4), designed to pick up the unique variance of indicators, is marked according to profile as the most neutral one having very low skewness. Besides, the application of more extensive criteria range makes no clear advantage to the DP-2 method, which has higher neutrality than other methods (VIKOR7, Weighted 7, Choquet 7, Equal weighting 7). Thus DP-2 method, according to its design, claims to count unique variance as opposed to equal weighting (EW) method blending the information from all criteria. By this, it is expected to obtain from DP-2 method different ranking and some pessimistic or optimistic bias. However, on the contrary, it appears to be even more neutral (without bias) then the equal weighting method (EW). This type of inferences is quite counterintuitive, which makes the application of the proposed approach to profile construction useful in case of the panel methods consideration or selection problem.

As all methods are centred against the average or the Equal weights method. It can be stated that the Effectiveness method (RAW) is an entirely different one with the orientation on the
pessimistic bias. However, this bias, according to the proposed approach, is not significant. It means that the nature of this method is principally different, and further research can be focused on the investigation of its compensation effect.

### 3.3 Analysis of the alternative ways of Structural funds redistribution

In the current section, the alternative distribution models will be presented in the order of increasing conceptual complexity. The application starts from the first optimisation model, which is characterised as an improvement of the Berlin formula, which drawbacks were highlighted in sec. 1.3.3. The following model is an extended version of the previous one amended by the usage of the multi-variable regression model. Both two models are based on variance minimisation objective function and provide the identification of the best parameters of the distribution. The third model is principally different and based on the Markowitz mean-variance optimisation model provides the optimal and fair distribution of funds allowing the minimisation of the free-ride problem. All subsequent sections will solve the optimisation problem in the fashion of three scenarios (blocks 4.1, 4.2, 4.3 in fig. 1.17), in particular, monetary single GDP approach (sec. 3.3.1), multi-dimensional (sec. 3.3.2) and unorthodox measurement (sec. 3.3.3).

#### 3.3.1 Search for the best distribution strategy based on GDP criterion (example of 276 EU NUTS 2 regions)

This section shows the results obtained from the application of the single-factor minimum variance optimisation model within the GDP based classic monetary scenario (block 4.1) presented in fig. 1.17.

According to the Blue Guide for ESI funds (2015), 217552,9 million EUR allocated to LDR (182171,8 million EUR) and to TR (35381,1 million EUR). To extract an amount of SF based on GDP per capita from mentioned above allocations we have to subtract the calculated Unemployment Premium (573.517 million EUR in accord to annex VII, No 1303/2013) and to receive 30505,47 million EUR. This is precisely the amount of potential SF ($F_{pot}$) based on the GDP/cap., which will be redistributed for 1 year period by optimisation model. Derived $F_{pot}$ represents the GDP based share ($S_{GDP}$) equal to 60.6 % of Regional Policy Funds or 20 % of the EU budget (ec.europa.eu, 2016). The next step is to estimate the adjusted deduction and capping rates.
Having obtained basic numbers describing the importance and amount of funds redistributed by the suggested model, we finally turn to the results from the optimal redistribution of GDP based SF performed by the add-in EXCEL package called “Premium Solver 2016”, allowing to process more than 50 variables for the optimisation purpose. In our case, we worked with 276 EU regions. Optimisation model (sec. 2.4.1, eq. (2.104)-(2.105)) produces the new optimal values of regional GDP per capita \( \chi' \), which are used for the determination of difference \( (\Delta F_j^\text{opt}) \) between optimised \( F_j^\text{opt} \) and actual which is corrected by Unemployment Premium GDP based Funds \( F_j^{t-1} \). In fig. 3.12 the optimised results are shown with the benchmark point based on the \( \alpha=0.241\% \), \( \beta=1.52\% \) and \( \gamma=90\% \) corresponding to the basic control parameters coming from the Cohesion Policy 2014-2020 rules, such as \( \alpha^*=1.23\% \), \( \beta^*=2.5\% \), \( \gamma=90\% \). Abbreviations of the Member States are given in Table C.18 (Appendix C).

On the graph (fig. 3.12) three values are displayed, namely, the total difference of SF in mln. Euro, optimised (by eq. (2.105)) and current (taken from Blue guide for ESI funds, 2015) distribution measured in euro per capita. The Member States are laid out according to the GNI/person to see the distribution in the connection to the level of prosperity of the country. Referring to this indicator, for convenience, we roughly identify countries as the poorest (from BG to HU), medium (from EE to ITC) and rich ones (from FR to LU).

fig. 3.12: Optimal 2.5 % capping rate distribution VS current one (2.5 %)

![Image of graph showing distribution of funds among Member States](source: author)
According to the eq. (b.14) (Appendix B, Table B.4), the optimality level of the current distribution compared to the optimised with capping rate 2.5 % is 86.8 %, which is relatively close but still, significant differences are present. Grounding on the 2.5 % optimal distribution, we can state that the poorest Member States are mostly underfunded (the exceptions are overfunded PL and HU). Herein we can notice that capping rate works tougher for poor countries, funding them less. Most of the following medium countries with better average economic conditions, such as SK, PT, MT, CZ, SI, EL are treated much better than it might have been done by the optimisation (the exception is underfunded CY). The rich Member States, such as ITC, FR, UKC, DK are underfunded, which is saying that national coefficients from the Berlin formula cut funds at a lower level than the optimisation does it. Meanwhile some of the rich Member States, in particular, BE and DE are in fact oversupplied.

The optimality level of the current distribution compared to the 2 % optimised one is 85.5 %. According to the results obtained from the next sec. 3.3.2 this distribution strategy (capping rate 2 %) happened to be the most optimal. Surprisingly, even such negligible difference in 0.5 % between current and optimised capping rate the overfunding and underfunding is significant (fig. 3.13). In this funds’ redistribution mostly all left part of Member States is overfunded when the right one is vice versa. This mismatch happens because of subjectively defined thresholds (GNI related coefficients from fig. 1.21), causing not equal treatment of lagging regions depending on the national prosperity. However, some poor countries are underfunded as well, such as Bulgaria, Romania and Croatia what can be explained by the political trading involved in the process.

Therefore, the comparison of the current distribution with 2 % optimisation shows an obvious pattern. Poorer countries get more funds, while the right side of Member States lacks funding. The exception is only oversupplied DE from the rich side and underfunded BG, RO, HR from the poor side (fig. 3.13).

To analyse the basic difference in funding, let us look in fig. 3.14 at absolute values per country (mln. Euros). The level of funds deficiency and abundance is provided in (Appendix C, table C.19) as a mismatch. The countries are aligned according to the mentioned mismatch in funding from the highly overfunded (left) to the most underfunded (right). From the left, we can find less developed countries, which are overfunded, including one developed country Germany and from the right – the undefended countries.
fig. 3.13: Optimal 2 % capping rate distribution VS current one (2.5 % capping rate)

Source: author

Thus arranging the countries according to the shortfall of funds, surprisingly we find that lagging German regions are overfunded while regions from other also donating countries located at the right, such as France, Belgium, UK, Italy, Spain are underfunded. For this phenomenon, the explanation has not been found except political influence and voting power of countries.

fig. 3.14: Optimal 2 % capping rate distribution VS current 2.5 % (aligned mismatch)

Source: author
The question arises about the selected optimised redistribution, which can be perceived as a paragon to compare it with and correct the current distribution of GDP based SF. As we have seen, the small difference in 0.5 % of β creates essential deviations in the funds’ allocations. That is why the next step is to compare the most likely possible redistributions (fig. 3.15).

As one can see from the fig. 3.15, the higher capping rate is more beneficial for the poorer Member States, which is proved by the peak on the graph attributed to the HR. The BG, as the exception, is out of the mentioned dependency. The opposite in this regard can be said to the lower capping rate (2 %), which favours the regions from the richer Member States. As well, we can define the most profitable redistributions for a group of member states. For example, at beta equal to 4 % the poorest countries from BG to HU will benefit considerably, at the same time ITC, EE, CZ, EL will lose maximum compare to the rest of distributions. Vice versa, the latest countries will benefit most of all from 2 % capping rate.

fig. 3.15: Comparison of redistributive strategies

Besides, controlling the capping rate, the choice of the maximum possible amount of funds for the Member States becomes possible. For example, at 3 % capping rate EE gets maximum funded or the most favourable capping rate for the CZ, SI, EL, ES and BE is 2 %, while for the poor countries such as RO, PL, LV, LT, HR, HU it occurs to be the least attractive. For the ITC the capping rate 2.5 % gives a maximum and 3 % for the EE, CZ, EL and ITC is the least beneficial.
Moreover, analysing the picture of distributions, we see that 2 % allows reaching the most uniform distribution of GDP based Structural Finds. We can conclude that variation (VAR) of funds per capita positively correlates with the capping rate of the distribution and negatively with the variance of regional performance represented by the delta VAR decreased (table 3.17).

<table>
<thead>
<tr>
<th>capping rate, %</th>
<th>delta VAR, %</th>
<th>VAR of Funds/cap</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>1.60</td>
<td>524.24</td>
</tr>
<tr>
<td>2.5</td>
<td>1.67</td>
<td>676.58</td>
</tr>
<tr>
<td>3</td>
<td>1.73</td>
<td>889.01</td>
</tr>
<tr>
<td>3.5</td>
<td>1.78</td>
<td>948.45</td>
</tr>
<tr>
<td>4</td>
<td>1.81</td>
<td>1193</td>
</tr>
</tbody>
</table>

*Source: author*

The higher the capping rate, the higher the variance of funds per capita is, but, what is as well very important, – the lower regional variance considered as the main target of the Cohesion Policy. However, the contradiction is obvious and from the fig. 3.12, fig. 3.13 we cannot see the whole picture of donor-recipients trade-off. Therefore, donors’ conditions such as variance within rich Member States are the subject to the usage of additional indicators for the best strategy choice.

The choice of the best strategy requires the conduct of a simulation procedure implying the creation of all possible strategies according to the acceptable parameters. The formed strategies are subject to a comparison based on established $g_1$ specific altruistic and $g_2$ general impact criteria (fig. 2.22, eq. (2.107)-(2.108)). The dynamics of normalized criteria values calculated with the current in the practice alpha 0.6 are presented respectively on the graphs in fig. 3.16 and fig. C.3, fig. C.4 (Appendix C). It is important to notice that all other strategies except 0.6 alpha simply repeat identified patterns with minor differences. Thus, the only set of strategies with alpha 0.6 is going to be analysed further. The complex aggregated criterion reflecting the total utility of the strategy is measured by the multiplicative weighted function (fig. 3.16). The combination of 0.9 (gamma) and 2 % (beta) appeared to be optimal.

Weights are determined based on the amount of each criterion variance. The higher the variance of the criterion, the greater in proportional terms its weight is. From the utility dynamics, we see that the best strategy is that with gamma 0.9 and beta 2. According to this strategy, the optimal capping rate is 2 %, and the threshold for regions recipients is 90 % of the
average EU GDP. However, all other strategies are worth considering as well as other aggregating functions that have to be implied.

fig. 3.16: Utility values of strategies by multiplicative weighted function

Table C.20 (Appendix C) shows the generated variety of all possible combinations of parameters representing 83 strategies, while 5 from them do not have the optimal solution. Therefore, in the basement of 78 strategies, the following conclusions are arising. Speaking of the best strategy, it is one with the alpha parameter 1, meaning that with this maximum parameter, absolutely all ESI funds are redistributed based on the GDP criterion what is not the real case. In fact, only around 60 % (0.6 alpha) of ESI are redistributed based on GDP criterion as SF. Surprisingly the following best strategy originates from the group related to the 0.6 alpha parameter what is actually used in the current practice. Relying on this, we can state that this strategy obtaining the highest utility value from all aggregating function applied, is considered the absolute leader among the 78 combinations. Besides, what is more surprising is that the difference between the defined best strategy and current strategy in practice is negligible and consists of 0.5 % of the beta parameter (2.5 against best 2.0).

To understand better the pushing up competitors of the best strategy, let us see the possible clusters built for the different strategies depending on aggregating function (fig. C.5, Appendix C). It is obvious that the best 2/0.9 (beta/gamma) strategy always belongs to the best I cluster and from four cases related to four aggregating functions shares it only ones with the strategy 3/0.9. This strategy also belongs to the I cluster formed by the additive function.
However, it is not enough to conclude for sure that this strategy takes the second place, all the more not saying about the certainty of other strategies’ ranks. To get the ranking of all strategies belonging at least one alpha level, in our case it is 0.6, we can count average ranks of strategies within every group of functions (all functions together, just weighted and not weighted). Therefore, due to the aggregation of average rankings, the final ranks of each strategy is identified and presented in table 3.18 with regard to all 4 types of utility functions (fig. 2.22).

The obtained results are quite unambiguous. The second place is taken by the strategy 3.5/0.75, while the strategy 3/0.9, which was under the question, falls at third place with the gap in 3 ranks. The best place for the strategy with 1 gamma threshold strategy is the 8th place, which shows its lowest distributional effectiveness compare to 0.9 and 0.75. Thus, medium gamma threshold 0.9 and minimum acceptable beta capping rate 2 is the combination producing the most effective distributional strategy with the 0.6 deduction alpha rate.

The suggested alternative distribution underlying the distribution of SF is underpinned by the optimisation model with the objective function oriented on the variance minimisation of GDP per capita between regions. The capping and deductive rates bind the optimisation process. The latest one defines the amount of SF, and the former one is the subject to optimal tuning from 2 % to 4 %. The capping rate influences the way of funds’ distribution, and itself is the parameter to be regulated according to the political, social and economic preferences.

table 3.18: Average ranking of distributional strategies

<table>
<thead>
<tr>
<th>strategy</th>
<th>average rank by functions</th>
<th>sum of ranks</th>
<th>rank</th>
<th>cluster</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>all &amp; weighted only &amp; not weighted</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2/0.9</td>
<td>1 &amp; 1 &amp; 1</td>
<td>3</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>3.5/0.75</td>
<td>2,5 &amp; 2 &amp; 2</td>
<td>6,5</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td>3/0.9</td>
<td>2.75 &amp; 3.5 &amp; 3</td>
<td>9.25</td>
<td>3</td>
<td>1</td>
</tr>
<tr>
<td>4/0.75</td>
<td>4.25 &amp; 3.5 &amp; 4</td>
<td>11.75</td>
<td>4</td>
<td>1</td>
</tr>
<tr>
<td>3.5/0.9</td>
<td>4.75 &amp; 5.5 &amp; 5</td>
<td>15.25</td>
<td>5</td>
<td>2</td>
</tr>
<tr>
<td>2.5/0.9</td>
<td>5.75 &amp; 5.5 &amp; 6</td>
<td>17.25</td>
<td>6</td>
<td>2</td>
</tr>
<tr>
<td>4/0.9</td>
<td>7.25 &amp; 7.5 &amp; 7</td>
<td>21.75</td>
<td>7</td>
<td>2</td>
</tr>
<tr>
<td>2.5/1.0</td>
<td>8.75 &amp; 9 &amp; 8.5</td>
<td>26.25</td>
<td>8</td>
<td>3</td>
</tr>
<tr>
<td>2/1.0</td>
<td>9.25 &amp; 9 &amp; 9.5</td>
<td>27.75</td>
<td>9</td>
<td>3</td>
</tr>
<tr>
<td>3/0.75</td>
<td>10 &amp; 9.5 &amp; 10</td>
<td>29.5</td>
<td>10</td>
<td>3</td>
</tr>
<tr>
<td>3/1.0</td>
<td>10.25 &amp; 10.5 &amp; 10.5</td>
<td>31.25</td>
<td>11</td>
<td>3</td>
</tr>
<tr>
<td>3.5/1.0</td>
<td>11.5 &amp; 11.5 &amp; 11.5</td>
<td>34.5</td>
<td>12</td>
<td>4</td>
</tr>
<tr>
<td>4/1.0</td>
<td>12.5 &amp; 12.5 &amp; 12.5</td>
<td>37.5</td>
<td>13</td>
<td>4</td>
</tr>
</tbody>
</table>

Source: author
The new suggested GDP based optimisation method is free from subjective coefficients and provides a uniform approach to all regions in need regardless of the level of national prosperity. The functional distinction between limiting Berlin formula and capping rate influencing differently poor and reach the Member States is excluded in the new model by the introducing capping rate based on the regional GDP level and by the optimisation process selecting the proper candidates defined as the lagging regions which are most in need. The optimisation is easily realised by the EXCEL’s add-in “Premium Solver 2016” package.

The suggested optimisation model is based on the traditional GDP per capita indicator and provides the distribution of approximately 60 % of ESI Funds. The optimisation model is free of national dependency optimised distribution and legally can be perceived as transparent due to the mathematical model oriented on the minimisation of variance of EU regional GDP per capita level. In particular, the targets of objectivity and mathematical rigorousness as should be considered the priority of Cohesion Policy. However, in fact, the matters stans differently because of negotiating political components interrupting the analytical decision-making process.

The results have shown different treatment of Member States depending on the capping rate. It is found that the lowest capping rate (2 %) is favourable for the lagging regions from rich countries and the highest rate (4 %) benefits LDR from the poor countries. There are as well some specific win and loss relations between the level of capping rate and particular country. For example, CZ gets more funds under the 2 % capping rate, when HU gets minimum at such conditions. Such Member States as RO, PL, LV, LT, HR gain maximum with 4 %, while CZ, EE, EL, ITC are least favourable with it.

The lowest variance of SF per person is found to be at the level of 2 %. Nevertheless, the choice of capping rate is not defined only by the variance funds redistributed, but also by political, social and other economic factors.

The choice of capping rate needs an additional analysis and the tested simulation of the set of possible distribution strategies. For this purpose, criteria of the distribution describing its degree of altruism and distribution impact were developed what helped according to suggested Utility function find the best (effective) strategy of the funds’ allocation attributed with specific parameters.

The set of possible strategies was formed and clusterized. It was found that the difference in strategies’ effectiveness is more prominent with the larger amount of SF at the disposal. The
relatively stable pattern of the simulated strategies was identified with deferent incoming alpha rates. According to table 3.18 only 3 strategies were recognized as best working strategies reaching distinct targets, in particular 2% / 0.9, 3.5 % / 0.75 and 2.5 % / 1.

In particular, it was found that the current 2.5 % of capping rate does not lead to the optimal distribution and the best (effective) one will be at 2 % for the allocation between regions with GDP/cap less than 90% of aver. EU 27 (strategy 2% / 0.9).

The distribution of funds was made according to the defined optimal strategy. The difference in the distribution consists of 14.6 % from the optimal one. The essential part of the difference (table C.19, Appendix C) between actual and optimised distributions can be explained due to overfunded countries with lower GNI/cap (PL, LV, LT, HU, EE, SK, PT, MT) and underfunded less developed and transitive regions from countries like SL, EL, ES, ITC, FR, UKC, BE with higher GNI/cap. Exceptions are BG, RO (underfunded) and DE (overfunded).

3.3.2 Optimisation of distribution considering MCDM utility values (example of 49 Eastern Europe NUTS 2 regions)

This section shows the results from the application of the MCDM based optimisation model suggested in sec. 2.4.2 and thematically belonging to the multi-dimensional scenario (block 4.2 in fig. 1.17). Hereinafter the multi-factor variance MCDM based optimisation model will be tested on the example of EU regions. However, for simplicity sake, the fictitious union of eastern European countries was made which includes only such countries as Bulgaria (BG), Czech Republic (CZ), Hungary (HU), Poland (PL), Romania (RO), Slovakia (SK). This sample of six Eastern Europe countries, including 49 NUTS 2 regions shows the implications of the offered model.

The first step is the construction of the regression model consisting of endogenous variable – utility value produced by the VIKOR method and four exogenous variables, such as $gdp$, $hrst$, $unempl_r$ (from table 3.8), and one new variable $v_clust$ representing the cluster of a region. After the selection of possible models, the choice was given to the regression model (table 3.19, table 3.20) for three clusters, including all variables plus a new classification variable.

The model and all included variables are considered statistically significant. The Adjusted R square is high (0.956), however, in terms of ranks, there is a noticeable difference between original and modelled ranks of regions. To investigate if the difference between ranks within each
cluster is statistically significant, the Wilcoxon test is applied (Table C.21, Appendix C). Having
analysed the results of the Wilcoxon test, it can be said that medians of ranks are equal, and the
difference is not statistically significant. Thus, the presented regression model will be used in the
optimisation part.

table 3.19: Summary of the regression model for all clusters

<table>
<thead>
<tr>
<th>R</th>
<th>R Square</th>
<th>Adjusted R Square</th>
<th>Std. Error of the Estimate</th>
<th>Change Statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td>.978</td>
<td>.956</td>
<td>.956</td>
<td>.08671</td>
<td>.956</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>1475.052</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>4</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>269</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>.000</td>
</tr>
</tbody>
</table>

Predictors: hrst, v_clust, unempl_r, gdp

Regression with no-intercept model

Dependent Variable: v

Source: author

The optimisation results obtained by eq. (2.113)-(2.117) are demonstrated in fig. 3.17.

fig. 3.17: The distribution of funds by three optimisation models

Source: author

From the figure, we see different optimisation results of two approaches, while the MCDM based approach is also differentiated in terms of classification factor consideration. It means that
the distribution of funds within the MCDM approach is realised to a full extent when there are no limitations about the flow between donors and recipients; to a limited extent when there are limitations on potential donors (with classification). Potential donors are the regions, with higher GDP per capita. Considering the classification factor, the regions with higher GDP per capita will not provide funds unless they have the status of donors assigned based on MCDM based clustering solution. Without the classification factor, the distribution of funds is more effective and sensible to the differences in utility values.

Comparing two distributions within the approach based on MCDM, the classification factor considered in the optimisation model appears to be decisive. Having the same variance optimisation basis – MCDM utility value, the distribution is done between all regions when the classification is not included. In the opposite case, of counted classification, the fewer regions become donors, and consequently, fewer funds are redistributed. As a result, not all lagging regions are covered by funding umbrella. For example, with no classification, HU becomes the recipient, as there are other regions, which have a better level of development and can play the role of donors in this scheme of the full distribution.

Comparing the GDP and MCDM approaches, as was stated above, the main difference is caused by a different basis for the optimisation – presented by the GDP/cap or aggregating utility value. The single-variable optimisation is appropriate when just one factor is considered to be essential and self-sufficient; multi-variable – when several factors seem to be essential and complementing essentially another dominating one (i.e. GDP). Thus, we can observe the situation when relying on the single GDP, SK is donor and RO is recipient, while the MCDM basis assigns the roles oppositely, namely, RO becomes the donor and SK a recipient. It means that two other indicators counted by the MCDM approach influenced the status of regions and changed the role of the country as a result. In particular, SK compared to RO has higher on average GDP / cap, but performs worse in terms of other criteria, which made SK less developed and more funded.

Concerning the limitations, even though the suggested regression model has a high Adjusted R Square, there are still differences between real and modelled utility values. These small differences can significantly distort the optimisation process based on variance minimisation. Therefore, either regression model provides a perfect match between modelled and original utility values, or it should be improved finding other ways of more precise multi-variable
optimisation. In the rest cases, it can be used for the simulation purpose to analyse some aspects and tendencies of funds distribution roughly.

3.3.3 Portfolio optimisation based on the concept of fair distribution and effectiveness measurement (example of 35 Visegrad NUTS 2 regions)

This section demonstrates the results obtained from the application of non-usual for regional studies mean-variance portfolio optimisation offered in sec. 2.4.3. The conclusions will be made within the unorthodox measurement scenario (blocks 1.3-4.2 in fig. 1.17) utilising, in this case, the results from effectiveness measurement (block 2.3) and portfolio optimisation (block 4.3) concerning the fairness of distribution.

The first step of the application of the Markowitz mean-variance model is the tuning of the parameters, which is done based on the principle of maximum variance produced by sub-factors. All sub-factors and their rationale are presented in section 2.4.3. Eventually, the tuning turns out to provide roughly equal maximal variances. These maximal relatively equal variances allow counting all three sub-factors (equality, equity and equitability) with relatively the same intensity not favouring any of them. From fig. C.8 (Appendix C) on Y-axis variance of sub-factors is presented, reflecting their maximal possible influence being treated in a singular, isolated manner. All identified peaks have their corresponding parameters presented on the axis X. All parameters eventually are chosen to equalise the absolute influence of unfairness caused by sub-factors separately considered.

It is quite intuitive that the portfolio’s fairness decreases with the rise of effectiveness. It happens because more effective regions are funded more while lagging regions are left out. The same dependency works for all sub-factors of fairness (fig. 3.18). A mean-variance model allocates funds based on the trade-off between unfairness and effectiveness when the improvement on one side leads to the worsening on the other.

This triviality ends when the question arises concerning the optimal ratio between effectiveness and unfairness expressed by variance. In one way, this problem can be solved due to the construction of concave "Markowitz bullet" and Sharp Ratio adopted from finance according to optimisation models consisted of eq. (2.118)-(2.122), (2.128)-(2.132).
A positive frontier represents different trade-offs between maximised effectiveness and variance made by correction sub-factors. The efficient frontier represents a set of portfolios with expected effectiveness, which is higher than any other portfolio with equal or even greater unfairness. Thus, the optimal portfolio is found based on the constructed efficient frontier, which considers together all unfairness sub-factors. The tangent point to the efficient frontier represents the maximum ratio of the portfolio effectiveness and unfairness measured by total variance (fig. 3.19). To calculate the tangent point, we estimated the Sharp ratio with risk-free asset equal to zero effectiveness.

Concisely, the Sharpe ratio describes in finance the reward-to-variability ratio measuring the excess return (or risk premium) per unit of deviation in an investment asset (Sharpe, 1966).
To put it simply, it characterises how well the return of an asset compensates the investor for the risk taken. When comparing two portfolios (assets), the one with a higher Sharpe ratio gives a better return for the same risk. Within the Cohesion policy context, the Sharp ration describes the effectiveness-to-variability ratio or put it differently, it characterises how well the supported and simulated by SF regional effectiveness will compensate the preserved or/and caused unfairness of the distribution. Thus, this criterion appears to be a very suitable tool in the pursuit of the effectiveness-fairness balance pointing eventually at the optimal portfolio.

Another insightful way of investigation of a positive frontier is a behavioural analysis targeted at relations between unfairness sub-factors (distribution properties) and effectiveness. Of particular interest are shares of unfairness sub-factors within the feasible region of the optimal portfolio. Analysis of unfairness behaviour (fig. 3.20) reveals the degree of each sub-factor contributing its portion of unfairness in the optimal portfolio. In addition, it can be understood what kind of policy actions should be implemented for a specific level of effectiveness.

**fig. 3.20: Unfairness and its sub-factors behaviour**

It is clear that all sub-factors have inverse relationships with their respective relative variance. A higher relative variance leads to lower fairness. At the same time, the lowest variance share points at a maximum of fairness sub-factors (table 3.21). It leads to the conclusion that the optimal portfolio should have a min relative total variance demonstrating the highest fairness.
table 3.21: Behavioural characteristics of the fair-effective distribution

<table>
<thead>
<tr>
<th>types of distribution</th>
<th>type of influence</th>
<th>variance of subfactors, %</th>
<th>total unfairness (var_T), %</th>
<th>Sharpe measure (S)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>supportive</td>
<td>stimulating</td>
<td>equality / (var_W)</td>
<td>equity / (var_R)</td>
</tr>
<tr>
<td>Cohesive (supportive)</td>
<td>high</td>
<td>low</td>
<td>high / low</td>
<td>low / high</td>
</tr>
<tr>
<td>Optimised</td>
<td>medium</td>
<td>medium</td>
<td>medium</td>
<td>medium</td>
</tr>
<tr>
<td>Effective (stimulating)</td>
<td>low</td>
<td>high</td>
<td>low / high</td>
<td>high / low</td>
</tr>
</tbody>
</table>

Source: author

From the table above, we see that optimised portfolio shows the balanced portfolio in terms of supportive and stimulating influences providing the maximum of relative fairness of the distribution. Interestingly, a relative minimum of the total variance (maximum of relative fairness) turns out to be an optimal compromising point finding the balance between two conflicting virtues of fairness. Thus, at this point, equality and equity contribute the minimum mutual relative variance into a total utility of portfolio. In addition, this optimal point lies in the efficient frontier that is proved by the maximum of Sharp ratio. Having analysed the relations presented in the previous graph, the schematic abstraction is given on the fig. 3.21 below.

fig. 3.21: Schematic relations between fairness sub-factors and effectiveness

Source: author
From fig. 3.21, it can be concluded that fairness before the optimal point at the cohesive (under stimulated) part of the distribution is made mostly by high equality changing later into rising equity and stimulating greater effectiveness at the over effective part. Policy implications obtained from the behavioural analysis are the following. Before the optimal point at the over supported stage, the equity effectiveness approach should be followed by which more effective regions have to be stimulated. After the optimal point, the equality support approach should be followed, and less effective regions have to be supported; this will decrease the effectiveness and increase fairness.

The portfolios from the efficient frontier are presented on the graph (fig. 3.22). Set of efficient portfolios demonstrates that with the increase of portfolio’s effectiveness, regions that are more effective are better funded. However, after the optimal point (8.06), as we see from the correlation curve (fig. 3.23), the correlation between funds and effectiveness drastically slows down, meaning that further stimulation is not so required.

The difference in portfolios is determined by the type of influence made by allocated SF. It is quite trivial that within the portfolio based on effectiveness, the shares assigned for more effective regions (located at the ascending order) are on average higher. However, when the level of stimulation gets higher (> 8), the shares’ alignment becomes bumpy, hindering the growth of correlation between shares and effectiveness. This situation reflects the second stage of the correlation dependency displayed by the S-shape function (fig. 3.23).

fig. 3.22: Set of efficient distributions depending on the level of portfolio’s effectiveness

Source: author
The shares of over-stimulated distributions (10, 13, 18) with the getting higher upper parts do not repeat the dynamic of effectiveness presented by smoothly increasing bars. All of the distributions have hanging down right tales showing that more effective regions are not funded at maximum. It happens because of the influence of fairness sub-factors which is in compliance with the equality and merit-based approaches mentioned in sec. 2.4.3. Also, it points to the lack of correlation between shares and effectiveness. Such increasing unevenness of over-stimulated portfolio shares is explained by nothing but equitability measured by the portfolio’s variance. Thus, the variance of the portfolio increases with the stimulation effect of funds distribution. It is explained even on the level of regional effectiveness, where its variance grows with higher effectiveness (fig. 2, Appendix C). Therefore, to decrease the portfolio’s variance, fewer effective regions are financed more than other more effective ones reaching the optimal distribution. The allocation made according to such distribution appears to be more equitable and with better stimulated regions which are less effective.

Correlation between shares or weights of distribution portfolio takes a particular interest in behavioural analysis. The two main correlations are to be investigated, namely the correlation of the portfolio’s shares with GDP per capita and effectiveness (fig. 3.23).

fig. 3.23: Dependency of the portfolio’s effectiveness from GDP or regional effectiveness

![Correlation Graph](image)

*Source: author*

The presented figure shows the correlation between weights and effectiveness (or GDP). It can be described with the Logistic function, but the attention is focused only on the upper-right efficient part representing the Markowitz “bullet”.
In particular, three main stages of the right part may be identified. The first one corresponds to the gradual increase of fair portfolio’s effectiveness caused by intensive growth of dependency between regional shares (W) and effectiveness (E) (fig. 3.23), during which the losses in equality are considerable; the second one corresponds to the fast take-off of portfolio’s effectiveness at small costs of correlation grows. In the third stage of slow growth, slight changes in preferences towards more effective regions creates a drastic increase in the portfolio’s effectiveness.

The main conclusion is that a high correlation between shares of portfolio and regional effectiveness is found in the over stimulated funds’ distribution characterised by low equality and high equity. Therefore, overstimulation relies on high equity and high correlation with regional effectiveness. Low shares/effectiveness correlation, on the contrary, is attributed to over supportive (under-stimulated) distribution characterised by high equality and low equity.

The quite high correlation (0.8) between the portfolio’s shares and effectiveness is attributed to the level of optimal distribution. It says that regional effectiveness is the strong enough determinant for constructing the optimal portfolio of SF by the mean-variance optimisation model. For the comparative purpose, a similar S-shape graph is presented for the GDP criterion dependency. From that, we conclude that GDP per capita does not play an important role as the correlation reaches 0.3 at optimal distribution; however, this criterion was not defined as such as opposed to dominant Effectiveness. This makes a significant difference, and added value for the approach based on effectiveness, which works noticeably in a different way compare to the GDP criterion and previously used variance minimisation model (sec. 3.3.1.

The main drawback of the current model is that it considers such subtle aspects of the distribution as equality, equity and equitability. Mentioned distribution aspects are taken here to show the full methodological power of the model as enriching additional factors without preliminary deep philosophical, economic and sociological justification and sound references on them. Thus, all these aspects of regional performance and funds distribution are new, quite controversial and need further deepening in the theoretical and methodological domains within the Cohesion policy context.
Conclusions to chapter 3

All practical findings from the applied IMC approach contribute to a better understanding of regional policy problems with further insights on aspects and patterns of regional performance and funds’ distribution.

The hybrid version of the VIKOR method appeared to be the most effective in terms of a well-defined lagging cluster. The cluster is characterised by the lowest economic and medium socio-innovative levels of regional performance. The regional patterns of the Czech Republic and Hungary show that they prefer the way of socio-innovative development, giving them a slower transition to the second more developed cluster and more extended stay under the ESI funding.

Results of effectiveness measurement were compared with regional productivity, and this showed no correlation between them. Both concepts are considered nothing but the complementing aspects of the analysis. Amongst negative regularities, it is necessary to mention that in both years the most occupied quadrants are the “surviving” and “dying slowly” which can be referred to as the cluster of lagging regions. Polish regions in both 2013 and 2015 years show peculiar stability in populating the “dying wastefully” quadrant. The “capital” regions are the most stable and effective taking place in “thrilling outliers” and “surviving thrillingly” quadrants. The consideration of criteria interaction has proven to be not influential.

The measurement of regional competitiveness by the SAW method proved to be not robust and thus not sufficient for the precise regional policy interventions in Ukraine. The results based on resonance approach do not correspond with the economic (GDP) or competitiveness level (measured by SAW). It means that neither of these commonly used aggregated indicators corresponds to the resonance-based interventions. Besides, it was found the sufficient correlation (0.72) between resonance ranking and another based on the resource business group. Meanwhile, the set of resonance interventions based on hierarchical and spatial coincidence was determined for the western agricultural sector of six NUTS 2 regions. This sector has been identified as in need of business efficiency.

The analysis of the quality of clustering structures proved that 3 clusters are the most frequent optimal structure, which coincides with the traditional GDP based regional classification. The most suitable methods to obtain this structure are in average VIKOR and hierarchical clustering methods. Analysis of classifications proved that the regional MCDM classification is statistically significant and more balanced compared to the traditional GDP based classification.
as it has 22% of countries with the transitive status, while GDP classification does not define any country with dominating transitive cluster. Moreover, traditional classification is based on subjective GDP thresholds. However, the more significant share of transitive countries leads to the cutting of donors in the redistribution game, which will make it less effective in terms of Cohesion policy targets.

According to robustness analysis, the Fairly Pessimistic (OWA) sub-perspective of the Equal Weights method turned out to be the most appropriate for the measurement of regional performance. This leading method is followed by such MCDM methods, as VIKOR, SAW, and Choquet, which have the fitness score equal to 0.92. The general inference about the MCDM methods’ application is drawn from the constructed profiles, in particular from the analysis of bias-fitness score relations. It can be concluded that the stronger the bias of MCDM perspectives, the lower their fitness scores. Some other counterintuitive and unexpected results were obtained. The Hellwig’s method was assumed as bias free risk-loving method avoiding the consideration of weaknesses, but it appeared to be negatively biased. The VIKOR method vice versa was expected to be with a negative bias, but it does not have it at all. The effectiveness method turned out to be beyond the comparison what makes it principally different from other existent methods. The Pena’s DP-2 method, because of its ability to use only unique variance, was expected to be significantly different from the basic equal weights method (EW). However, the DP-2 method appeared to be neutral (without bias) and even more symmetrical. The most appropriate and selected methods (Choquet, SAW and VIKOR) happened to be neutral, but it is not a guarantee for the method to be the most suitable one.

Concerning the application of single-factor min variance optimisation model, amongst 83 generated distribution strategies only 3 of them were recognized as working ones, in particular 2% / 0.9, 3.5 % / 0.75 and 2.5 % / 1. In particular, it was defined that the optimal fund’s distribution (strategy 2% / 0.9) will be at 2% of capping rate and recipients with GDP/cap less than 90% of aver. EU 27. There are some win and loss relations between level of capping rate and certain country. For example, CZ gets more funds under the 2% capping rate, when HU gets minimum at such conditions. Such Member States as RO, PL, LV, LT, HR gain maximum with 4%, while CZ, EE, EL, ITC are the least favourable with it.

Comparing two distributions obtained by the multi-variable MCDM based optimisation model, the classification factor considered in the optimisation model appears to be decisive.
Comparing the GDP and MCDM based distributions, we observed the situation when relying on the GDP basis, SK is the donor and RO is the recipient, while with MCDM basis the roles are opposite. It means that two other indicators counted by MCDM approach influenced the status of regions and country. In particular, SK compared to RO has higher on average GDP / cap, but performs worse in terms of other criteria, which made SK less developed and more funded.

The main policy implications obtained from the application of the mean-variance optimisation model are the following. For the optimal distribution equity as a fairness sub-factor should be provided to increase effectiveness at the under-stimulated stage before the optimal point; while equality should be followed on the overstimulated stage after the optimal point, what will decrease the effectiveness and by this increase fairness. Low shares/effectiveness correlation is attributed to over supportive (under-stimulated) distribution characterised by high equality and low equity. Quite high correlation (>0.8) between shares of portfolio and regional effectiveness, on the contrary, is found on the overstimulated stage characterised by low equality and high equity. Eventually, regional effectiveness is a strong determinant for constructing the optimal portfolio of SF. At the point of optimal distribution, the correlation between shares and GDP reaches 0.3 at maximum. This makes the unorthodox effectiveness approach noticeably different and able to solve the free-rider problem by consideration of fairness distribution factors, such as equality, equity, and equitability. At the same, distribution aspects, taken into account to show the full methodological power of the mean-variance model, do not have preliminary deep philosophical, economic and sociological justification and sound references. Thus, all these aspects are new, quite controversial and need further deepening in the theoretical and methodological domains within the Cohesion policy context.
CONCLUSIONS

To sum up, all the results and findings can be classified concerning the following aspects of the multi-criteria approach to the practical problem of SF distribution: 1. measurement and classification of regional performance, 2. verification and selection of the appropriate MCDM methods, 3. optimisation of funds distribution. SF are the most powerful tool of the Cohesion policy. The importance of the proper SF distribution is mentioned massively in the literature by academic researchers, practitioners, policy commissioners and cannot be overemphasised. Nevertheless, if some problems have already been solved and deeply researched, others – just slightly touched on a conceptual level and left without due methodological regard. It should be stressed that all mentioned aspects of the multi-criteria approach to SF distribution have never been studied in the interrelated and systemic way. Relying on this, the research aim is to develop the IMC approach to a solution to the range of methodological problems underlying the process of SF distribution. The developed IMC approach allows consistent and subsequent application of MCDM methods (to measure), clustering methods (to classify), selection approaches (to choose the most suitable MCDM methods) and optimisation models (to optimise the fund’s distribution) considering the interdependence of methodological problems.

The research aim and the defined tasks predetermined the methodological character of suggestions and propositions. Thus, it is expected to contribute methodologically into the area of regional management and regional studies with further insights on the interrelated solution of the range of problems underlying the distribution of funds. The dissertation has the three chapters’ structure and consists of theoretical, methodological and application parts.

The first theoretical chapter introduces the knowledge gaps found in the area of MCDM application in the Cohesion policy context, the fundamentals of Cohesion policy and the drawbacks of the current mechanism of funds’ distribution. Based on this, the necessity for the development of IMC approach to SF’ distribution was defined as well as its prerequisites and assumptions (pseudo-objectiveness, exhaustiveness, unanimity, includes context relevancy and sequential consistency). All three sets of assumptions are responsible for the coordinated application of selected MCDM and clustering methods with the further application of optimisation models. Altogether, they form the methodological power of the multi-methodological IMC approach to SF distribution. Besides, the approach by its design assumes
different scenarios of application depending on the triggering conception, which can be of three types: traditional Monetary approach based on GDP criterion to funds distribution, multidimensional mainstream (competitiveness index) or unorthodox (effectiveness or efficiency).

The methodological foundation presented in chapter 2 is provided for the adequate and interrelated solution of measurement, classification, selection and optimisation problems. In connection to these problems underlying the main real-life problem of SF distribution the following methods, models and approaches were presented: 1. the range of MCDM methods introduced and discussed with regard to the measurement aspect, 2. clustering methods – in relation to the classification aspect, 3. selection approaches – for choosing the most suitable MCDM method for the further problem at hand, and 4. optimisation models – for the optimal funds’ distribution.

In the 2.1 sub-chapter, all MCDM methods were preselected according to their popularity, minimum subjectivity criterion, usefulness and applicability in the regional studies. The attention was paid to compromise distance-based methods (Hellwig’s, VIKOR, TOPSIS), basic methods dealing with dependent and independent criteria (SAW, OWA, Choquet, DP-2) and DEA.

Some other comprehensive measurement approaches and methods were suggested:

1. two-factor outranking approach to compromise methods accompanied by PCA is used for the determination of lagging regions. It overcomes the disadvantages of aggregation functions of original compromise MCDM methods and allows measuring the regional performance depending on the risk attitude;

2. unsupervised fuzzy identification method based on the correlation of criteria which extracts fuzzy measures necessary based on trigonometric function and optimisation model. Extracted fuzzy measures are utilised further by the Choquet method. With the help of the last one, the regional performance measurement was measured considering the criteria interaction effect (synergies);

3. ratio additive weighting method is used to measure the effectiveness as an unorthodox aspect of regional performance based on the concept of “doing the right thing”. This method is the result of the methodological synthesis of DEA and SAW;

4. resonance competitiveness approach is proposed to measure the intensive (technical efficiency) and extensive aspects (resource level) of regional performance of developing countries comprehensively. Besides, it considers the hierarchical aspects of performance at
NUTS 1 and NUTS 2 during the aggregation of synthetic indicators due to the application of DEA and Hellwig’s distance-based methods.

The sub-chapter 2.3 considers the issue of MCDM methods selection, which logically follows from the massive variety of MCDM methods applicable to the regional problems. With regard to this, the pragmatic approach to the selection of MCDM methods was suggested. This approach assumes separate or complementing usage of two practical criteria steamed from the coming after classification or optimisation problems. The first criterion (sec. 2.3.1) relates to the quality of the clustering structure, which is obtained based on the application of MCDM and clustering methods. The most suitable MCDM method for the classification is selected according to its clustering power corresponding to the quality of the clustering structure measured by the integration of results obtained from the 15 validating indices. As well, due to this pragmatic approach, the subjective thresholds defining the eligibility for receiving the funds can be avoided.

The second criterion (sec. 2.3.2) comes from the other aspect of MCDM application, in particular, the distribution of funds. It was shown that the funds’ distribution depends on correctly identified recipients and donors of funds. Therefore, the rigorous ranking of regions is of high importance and requires the selection of the correctly verified MCDM method. For this purpose of verification, the robustness analysis of the ranks is proposed. The MCDM method appears to be robust when it places on the key positions (donors and recipients for sure) regions with low variability (high certainty) of possible rankings obtained from the panel of MCDM methods. The robustness of ranks is measured by fitness function representing the level of the measurement error, which has to be minimised or centred (fig. C.7, Appendix C).

In addition, for the better understanding of the MCDM methods differences and similarities, the approach to profiling (sec. 2.4.3) and comparison of applied MCDM methods was suggested. The profile is based on the defined distinctions between MCDM methods and the set of so-called basic sub-perspectives formed by the OWA operator.

The next direction of methodological suggestions (sub-chapter 2.4) is the development of the optimisation models applicable to the SF distribution and incorporating the results from the measurement of regional performance based on MCDM methods application. Therefore, based on the defined disadvantages and sources of the subjectivity of the current distribution Berlin formula, the general variance minimisation approach was proposed. In the frame of the mentioned approach, three principally different solutions in the form of optimisation models were
elaborated. One is based on the single variable optimisation, such as GDP based optimisation, another is oriented on the multi-variable optimisation with the application of MCDM methods and regression models, and the other is based on Markowitz mean-variance portfolio theory. The first single variable optimisation model (sec. 2.4.1) is the improvement of the current Berlin formula and provides objective, rigorous and transparent redistribution of SF, what cannot be said about the current mechanism.

The second and the third multi-variable models are the extensions of the first minimum variance optimisation model and allow consideration of more than one variable that makes such approach multi-dimensional and more realistic, first in terms of measuring regional performance. However, with the greater complexity of models, more limitations and weak points come on the scene. Therefore, the second optimisation model (sec. 2.4.2) considers the utility values produced by MCDM and incorporates them due to the regression model built into the optimisation model. It is necessary to notice that this multi-variable MCDM based optimisation model the first in its kind model connecting the results of MCDM application with the distribution of funds. Before this research, MCDM methods have been applied with the methodological gap between the measurement and optimisation problems. Therefore, this and the following models show how to incorporate utility values from the MCDM method into the problem of distribution and optimisation model. Speaking of drawbacks, this model suffers from the embodied into the regression model inaccuracy that can lead to the essential distortions in the funds’ distribution.

The third type of optimisation model (sec. 2.4.3) is based on the Markowitz mean-variance portfolio theory. It helps avoid the free-ride problem originated by lagging regions being reluctant to improve their status considerably not to lose the wanted allocations of SF. This model assembles an optimal portfolio of SF, such that effectiveness is maximised for a given level of fairness factors (equality, equity, and equitability) considering the free ride problem simultaneously and favouring more effective lagging regions. The model has its drawbacks as to the theoretical justification of the mentioned fairness factors.

Chapter 3, in a similar sequence, presents the practical results obtained from the application of all methodological suggestions made in chapter 2. Obtained practical results are divided into the three categories related to the discussed problems. The first group shows the essential findings concerning regional performance measurement by proposed methods and approaches (sub-chapters 2.1, 2.2). In section 3.1.1 the two-factor outranking approach to compromise
MCDM methods allowed identification of patterns of Visegrad countries’ performance and determination of lagging regions cluster (fig. 3.1) respecting the attitude to risk and two principal components obtained by PCA. In section 3.1.2, the RAW method was used to measure and classify the performance of Visegrad regions in terms of their productivity and effectiveness (fig. 3.2). Negative regularities in the placement of regions we analysed. The consideration of criteria interaction effect proved to be not influential during the measurement of regional effectiveness (fig. 3.3). In section 3.1.3, the hierarchical resonance approach helped define the resonance interventions targeted on the business efficiency for the defied lagging cluster (fig. 3.5) of Ukrainian NUTS 1 and NUTS 2 regions. Also, the results from the resonance approach proved to be more insightful and significantly different from the GDP criterion and competitiveness index (table 3.7) measured by the low robust SAW method.

The second group of suggestions addressed the issues of justified selection of MCDM methods and has led to the following results. The pragmatic approach to selection showed in section 3.2.1 bright pieces of evidence that VIKOR and hierarchical average linkage methods (table 3.9, table 3.10) are the most suitable and helpful pair in finding the significant genuine and more balanced classification of 276 EU NUTS 2 regions compared to traditional based on subjective GDP thresholds. Selection approach based on robustness analysis in section 3.2.2 has pointed at VIKOR’s best ability (amongst the inclusive panel 8 MCDM methods) to provide the most robust ranking for further distribution of funds requiring the minimum error in recipients and donors identification (fig. 3.9). The OWA based approach to profile construction in section 3.2.3 shed light on some counterintuitive specificity, differences and generalities of 8 applied MCDM methods (table 3.15, table 3.16). With these profiles, some unexpected and counterintuitive insights about methods were obtained. The Hellwig’s method was assumed as bias less risk-loving method, but it appeared to be negatively biased. The VIKOR method, while being expected to have a slight negative bias, vice versa, does not have any bias at all (defined as neutral). The effectiveness method (RAW) turned out to be beyond the comparison what makes it principally different from other methods. Because of Pena’s DP-2 method’s ability to use only unique variance, we expected it to be significantly different from the basic equal weights methods (EW). However, the DP-2 method appeared to be neutral (without bias) and even more symmetrical. The most appropriate and selected methods (Choquet, SAW and VIKOR) happened
to be neutral without a bias. Meantime, the neutrality is not a guarantee for the method to be the most suitable.

The third group reveals the practical results from the analysis of SF distribution based on the application of proposed optimisation models. Minimum variance single-factor optimisation model as the improvement of the current Berlin formula in section 3.3.1 assisted in generating and comparing 83 distribution strategies based on real distribution parameters (Table C.20, Appendix C). By the proposed utility function, the best strategy for 276 EU NUTS 2 regions were defined. Patterns of over- and underfunded countries were discovered (fig. 3.12, fig. 3.13) due to the comparison of current and optimal distribution. The advantages of leading strategies (fig. 3.15) for specific countries were discussed in relation to EU-28. The multi-variable MCDM based optimisation model (sec. 3.3.2) allowed to incorporate the measurement results from MCDM methods and showed that consideration of classification factor could significantly reduce the number of active players (donors, recipients) and by this make the distribution less effective in terms of disparities reduction (fig. 3.17). The application of Markowitz mean-variance optimisation model (sec. 3.3.3) entailed the development of the adjusted to the model conceptual basis for the concept of “fair distribution” referring to such aspect as equality, equity, equitability and elimination of the free-ride problem. Based on the model application to the data sample of 35 Visegrad NUTS 2 regions valuable policy recommendations (fig. 3.21) were made concerning optimisation of SF distribution concerning fairness sub-factors (equity and equality aspects).

The benefits of all methodological suggestions incorporated into a single IMC approach in terms of its coverage of broad problem’s range, innovativeness and complexity far outweigh mentioned separate disadvantages of proposed methods, models and approaches. The methodological suggestions shaped into developed methods, models and approaches make the original contribution to the knowledge on the general topic of quantitative methods application in the context of Cohesion policy. The suggested IMC approach followed by objectivity and methodological pluralism does not restrict practitioners to solve the main problem of SF distribution in a certain way but suggests the set of possible solutions depending on the chosen triggering conceptual position. According to our knowledge, there is no similar systematic research in the literature driven by the real-life problem of Structural fund’s distribution. The exploitation of the suggested IMC approach would provide objective, verified and mathematically rigorous foundation for the distribution of Structural funds.


décision. *Colloq. d’aide a la decision, Universite Laval*, Quebec, Canada, Aou’t.

outranking methods in multicriteria analysis. In: J.P. Brans (ed.): *Operational Research*, 84,

41. BRANS, J.P., VINCKE, Ph. and MARESCHAL, B. (1986). How to select and how to rank
238.

42. BRAUKSA, I. (2013). Use of cluster analysis in exploring economic indicator differences

43. BREUSS, F. and ELLER, M. (2004). Fiscal decentralization and economic growth, is there

44. BUCHANAN, J.T, HENIG, E. J. and M. I. HENIG. (1998). Objectivity and Subjectivity in


46. CAMERON, A.J., VAN STRALEN, M.M., KUNST, A.E., TE VELDE, S.J., VAN
285. doi:10.1249/MSS.0b013e31826e69f0.

47. CAMERON, K.S. (1984). The effectiveness of ineffectiveness, in Staw B.M and Cummings,

doi:10.1111/j.1468-5965. 2010.02063.x

49. CAMPO, C., MONTEIRO, C., SOARES, J. (2008). The European regional policy and the
socio-economic diversity of European regions: A multivariate analysis. *European Journal of


Press, Rotterdam, the Netherlands.
151. HOTELLING, H. (1933). Analysis of a complex of statistical variables into principal
relation theory for the selection of an outsourcing provider. Expert Systems with Applications,
40(6), pp. 2297–2304.
Benchmarking, Regional Studies, Vol. 37, pp. 89-96.
Centre for International Competitiveness.
and Building Resilience (PDF). HDRO (Human Development Report Office) United Nations
Development Programme.
158. HUSCHKA, D., WAGNER, G. (2010): Sind Indikatoren zur Lebensqualität und zur
Lebenszufriedenheit als politische Zielgrößen sinnvoll? Research Note No. 43, RatSWD, Berlin,
159. HWANG, C.L. and YOON, K.P. (1981). Multiple Attribute Decision Making, Methods and
161. ISHIZAKA, A. and NEMERY, Ph. (2013). Multi-criteria decision analysis: methods and


300. SÁNCHEZ-DOMÍNGUEZ, Á. & RUIZ-MARTOS, M.J. (2014a). A multidimensional regional development index as an alternative allocation mechanism of EU Structural Funds


Consortium, October 1999, Glasgow: European policies Research Center, University of Strathclyde.


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<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Full Form</th>
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<tbody>
<tr>
<td>AV</td>
<td>simple additive weighting method with equal (average) weights</td>
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<td>CH</td>
<td>Choquet method</td>
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<tr>
<td>CI</td>
<td>competitiveness indicator</td>
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<tr>
<td>DM</td>
<td>decision-maker</td>
</tr>
<tr>
<td>DMU</td>
<td>decision-making unit</td>
</tr>
<tr>
<td>EF</td>
<td>effectiveness method or RAW</td>
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<tr>
<td>ESI</td>
<td>Structural and Investment Funds</td>
</tr>
<tr>
<td>EU</td>
<td>European Union</td>
</tr>
<tr>
<td>EW</td>
<td>equal weighting method</td>
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<tr>
<td>GDP</td>
<td>gross domestic product</td>
</tr>
<tr>
<td>H</td>
<td>Hellwig’s</td>
</tr>
<tr>
<td>HH</td>
<td>Hellwig’s Hybrid</td>
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<tr>
<td>IMC</td>
<td>interrelated multi-criteria</td>
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<tr>
<td>LDR</td>
<td>less developed regions</td>
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<td>MAUT</td>
<td>multi-attribute utility theory</td>
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<tr>
<td>MCDA</td>
<td>multiple-criteria decision analysis</td>
</tr>
<tr>
<td>MCDM</td>
<td>multi-criteria decision-making</td>
</tr>
<tr>
<td>MDR</td>
<td>more developed regions</td>
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<tr>
<td>NUTS</td>
<td>the nomenclature of territorial units for statistics</td>
</tr>
<tr>
<td>OWA</td>
<td>ordered weighted average operator</td>
</tr>
<tr>
<td>PCA</td>
<td>principal component analysis</td>
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<tr>
<td>PPS</td>
<td>purchasing power standards</td>
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<td>RC</td>
<td>regional competitiveness</td>
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<td>RI</td>
<td>resonance interventions</td>
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<tr>
<td>SAW</td>
<td>simple additive weighting method</td>
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<td>SF</td>
<td>Structural funds</td>
</tr>
<tr>
<td>T</td>
<td>TOPSIS</td>
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<tr>
<td>TFO</td>
<td>two-factor outranking approach</td>
</tr>
<tr>
<td>Acronym</td>
<td>Description</td>
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<tr>
<td>TH</td>
<td>TOPSIS Hybrid</td>
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<tr>
<td>TR</td>
<td>transitive regions</td>
</tr>
<tr>
<td>V</td>
<td>VIKOR</td>
</tr>
<tr>
<td>VH</td>
<td>VIKOR Hybrid</td>
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<tr>
<td>WAM</td>
<td>weighted arithmetic mean</td>
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### Table A.1: Papers with the application of multi-criteria methods in the regional studies field

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<thead>
<tr>
<th>Authors</th>
<th>Aspect of measurement</th>
<th>Multi-criteria method</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Czirákya, Sambtb et. al., 2006</td>
<td>regional development</td>
<td>multivariate statistical analysis</td>
</tr>
<tr>
<td>2. Soares, Marquês et. al., 2003</td>
<td>regional development</td>
<td>multivariate statistical analysis</td>
</tr>
<tr>
<td>3. Campo, Monteiro et. al., 2008</td>
<td>regional development</td>
<td>multivariate statistical analysis</td>
</tr>
<tr>
<td>4. Polednikova, E., 2014b</td>
<td>regional performance</td>
<td>multivariate statistical analysis</td>
</tr>
<tr>
<td>5. Stamenković, M. &amp; Savić, M., 2017</td>
<td>regional performance</td>
<td>multivariate statistical analysis</td>
</tr>
<tr>
<td>6. Önay, O. &amp; Yıldırım, B. F., 2016</td>
<td>regional performance</td>
<td>TOPSIS, MOORA, VIKOR</td>
</tr>
<tr>
<td>7. Ewusi, K., 1976</td>
<td>regional development</td>
<td>Hellwig’s (taxonomic)</td>
</tr>
<tr>
<td>8. Mahmad, S., Yusop, Z., 2010</td>
<td>regional development</td>
<td>TOPSIS</td>
</tr>
<tr>
<td>10. Polednikova, E., 2014a</td>
<td>regional development</td>
<td>AHP, SAW, TOPSIS</td>
</tr>
<tr>
<td>11. Poledniková, E., 2014c</td>
<td>regional development</td>
<td>AHP, VIKOR</td>
</tr>
<tr>
<td>16. Hollanders, Tarantola, Loschky, 2009</td>
<td>regional innovation</td>
<td>linear aggreg. (SAW)</td>
</tr>
<tr>
<td>17. Annoni, Dijsktra, 2013</td>
<td>regional competitiveness</td>
<td>linear aggreg. (SAW)</td>
</tr>
<tr>
<td>18. Annoni, Dijskra, Kozovska, 2011</td>
<td>regional competitiveness</td>
<td>linear aggreg. (SAW)</td>
</tr>
<tr>
<td>19. Annoni, Kozovska, 2010</td>
<td>regional competitiveness</td>
<td>linear aggreg. (SAW)</td>
</tr>
<tr>
<td>20. Gábor, Ottaviano, 2015</td>
<td>regional competitiveness</td>
<td>linear aggreg. (SAW)</td>
</tr>
<tr>
<td>22. Huggins, Thompson, 2010</td>
<td>regional competitiveness</td>
<td>linear aggreg. (SAW)</td>
</tr>
<tr>
<td>24. Snieška, Bruneczkienė, 2009</td>
<td>regional competitiveness</td>
<td>linear aggreg. (SAW)</td>
</tr>
<tr>
<td>25. UNDP, 2008</td>
<td>regional competitiveness</td>
<td>linear aggreg. (SAW)</td>
</tr>
<tr>
<td>27. Kiszová, Nevima, 2012</td>
<td>regional competitiveness</td>
<td>AHP</td>
</tr>
<tr>
<td>29. Oliva, Miguel, 2005</td>
<td>regional competitiveness</td>
<td>ELECTRE</td>
</tr>
<tr>
<td>30. Melecký, Stančíková, 2011</td>
<td>regional competitiveness</td>
<td>DEA</td>
</tr>
<tr>
<td>31. Ramík, Hančlová, 2012</td>
<td>regional competitiveness</td>
<td>DEA</td>
</tr>
<tr>
<td>32. Charles, Zegarra, 2014</td>
<td>regional competitiveness</td>
<td>DEA</td>
</tr>
<tr>
<td>33. Karkazis, J., &amp; Thanassoulis, E., 1998</td>
<td>regional development</td>
<td>DEA</td>
</tr>
<tr>
<td>34. Byrnes, P. E. &amp; Storbeck, J. E., 2000</td>
<td>regional development</td>
<td>DEA</td>
</tr>
</tbody>
</table>

*Source: author*
Table A.2: Papers with the application of clustering methods in the regional studies field

<table>
<thead>
<tr>
<th>Authors</th>
<th>Clustering techniques</th>
<th>Regions</th>
</tr>
</thead>
<tbody>
<tr>
<td>5. Avram, M. &amp; Postoiu, C., 2016</td>
<td>hierarchical and k-means</td>
<td>EU Regions</td>
</tr>
<tr>
<td>6. Dziembala, M., 2016</td>
<td>Ward’s hierarchical and k-means</td>
<td>EU Regions / Polish regions</td>
</tr>
<tr>
<td>8. Palevičienė, A., Dumčiuvienė, D., 2015</td>
<td>hierarchical and k-means</td>
<td>EU STATES</td>
</tr>
<tr>
<td>10. Pettersson, O., 2001</td>
<td>Ward’s hierarchical and k-means</td>
<td>EU regions / Swedish county</td>
</tr>
<tr>
<td>11. Ramzan, S., Khan, I. M., Zahid, F. M., Rasul, S., Rafiq, S., 2013</td>
<td>Ward’s hierarchical and k-means</td>
<td>Regions Pakistan</td>
</tr>
<tr>
<td>15. Vydrová, H. V., and Novotná, Z., 2012</td>
<td>Ward’s</td>
<td>EU regions / Czech Republic</td>
</tr>
<tr>
<td>17. Melecký, L., 2013</td>
<td>Ward’s</td>
<td>EU regions</td>
</tr>
<tr>
<td>18. Quadrado, L., Heijman, W., &amp; Folmer, H., 2001</td>
<td>Ward’s</td>
<td>EU regions / Hung</td>
</tr>
<tr>
<td>19. Peschel, K., 1998</td>
<td>Average-linkage hierarchical</td>
<td>EU regions / the Baltic Sea Countries</td>
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<tr>
<td>20. Melecky, L., 2014</td>
<td>Ward’s</td>
<td>EU regions</td>
</tr>
<tr>
<td>22. Lukovics, M., 2009</td>
<td>k-means</td>
<td>EU regions / Hungarian sub-regions</td>
</tr>
<tr>
<td>23. Bakaric, I., R., 2005</td>
<td>k-means</td>
<td>EU regions / Croatia</td>
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<tr>
<td>25. Munandar, T., Azhari, S., 2015</td>
<td>k-means</td>
<td>Regions / Central Java in Indonesia</td>
</tr>
<tr>
<td>27. Brauksa, I. (2013</td>
<td>k-means</td>
<td>EU Regions / Latvia</td>
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<tr>
<td>30. Spicka, J., 2013</td>
<td>medoid partitioning, average dissimilarity and silhouettes</td>
<td>EU-27</td>
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<tr>
<td>31. Stamenković, M., &amp; Savić, M., 2017</td>
<td>k-means and silhouette coefficient</td>
<td>EU Regions / Serbia</td>
</tr>
<tr>
<td>32. Cruz-Jesus, F., Oliveira, T., Bacao, F., 2012</td>
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<td>EU-27</td>
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Source: author
Table A.3: Cross-sectional analysis of methods applied in the regional analysis

<table>
<thead>
<tr>
<th>Methods \ measurement concept</th>
<th>regional competitiveness</th>
<th>regional development</th>
<th>regional performance</th>
<th>social wellbeing</th>
<th>regional innovation</th>
<th>Total</th>
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<tbody>
<tr>
<td>linear aggregation (SAW)</td>
<td>9</td>
<td>1</td>
<td>-</td>
<td>-</td>
<td>1</td>
<td>11</td>
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<td>DEA</td>
<td>3</td>
<td>2</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>5</td>
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<tr>
<td>multivariate statistical methods</td>
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<td>3</td>
<td>2</td>
<td>-</td>
<td>-</td>
<td>5</td>
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<tr>
<td>DP-2</td>
<td>-</td>
<td>2</td>
<td>1</td>
<td>1</td>
<td>-</td>
<td>4</td>
</tr>
<tr>
<td>AHP</td>
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<td>2</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>4</td>
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<td>TOPSIS</td>
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<td>1</td>
<td>-</td>
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<td>4</td>
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<td>Outranking</td>
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<td>-</td>
<td>-</td>
<td>-</td>
<td>2</td>
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<tr>
<td>VIKOR</td>
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<td>1</td>
<td>-</td>
<td>-</td>
<td>2</td>
</tr>
<tr>
<td>Hellwig's</td>
<td>-</td>
<td>1</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>1</td>
</tr>
<tr>
<td>MOORA</td>
<td>-</td>
<td>-</td>
<td>1</td>
<td>-</td>
<td>-</td>
<td>1</td>
</tr>
<tr>
<td>Total</td>
<td>16</td>
<td>15</td>
<td>6</td>
<td>1</td>
<td>1</td>
<td>39</td>
</tr>
<tr>
<td>Panel of methods applied</td>
<td>-</td>
<td>2</td>
<td>1</td>
<td>-</td>
<td>-</td>
<td>3</td>
</tr>
</tbody>
</table>

*Source: author*

fig. A.1: Visualization of the topic concepts

*Source: author*
fig. A.2: Interconnectedness of regional policy cycle and main problems identified

Source: author based on Molle (2007)
1. Measurement of performance
   - Is conventional monetary approach sufficient?
   - Is complementing mainstream approach better?
   - Is one MCDM method enough?
   - Which MCDM method is the best?
   - Should it be the combinations of MCDM methods?
   - Is there a search for substituting unorthodox approach?

2. Classification of EU regions
   - Is the conventional classification a sufficient one?
   - What clustering methods to choose?
   - Efficiency of regional performance?
   - Effectiveness of regional performance?
   - How to use MCDM results for the Cohesion funds redistribution?
   - How to select the best MCDM?
   - Is it worth using an eclectic or an exclusive panel of selected MCDM methods?
   - Is it enough to consider just NUTS2 level?

3. Optimisation of Structural funds distribution?
   - Is conventional Berlin formula sufficient?
   - Is there a way to improve it?
   - Which validating criteria should be used?

Cohesion policy

MCDM methods

Source: author
fig. A.4: Originality placement of proposed fuzzy identification method

Source: author
fig. A.5: Framework for initial allocation of ESI to Member States

fig. A.6: Regional economic development as a matrix of qualitative, quantitative, process

<table>
<thead>
<tr>
<th>Regional economic process</th>
<th>Regional economic product</th>
</tr>
</thead>
<tbody>
<tr>
<td>• Policy</td>
<td>• Employment</td>
</tr>
<tr>
<td>• Planning</td>
<td>• Wealth</td>
</tr>
<tr>
<td>• Analysis</td>
<td>• Investment</td>
</tr>
<tr>
<td>• Strategy</td>
<td>• Infrastructure</td>
</tr>
<tr>
<td>• Resource application etc.</td>
<td>• Quality of life etc.</td>
</tr>
</tbody>
</table>

Source: Stimson, Stough and Roberts, 2006, p. 7
Different geometrical shapes symbolise different aggregating methods

Source: author
fig. A.8: Assumptions for the development and application of the IMC approach

Source: author
fig. A.9: Logical and coherent structure of the dissertation

<table>
<thead>
<tr>
<th>knowledge gaps</th>
<th>main tasks</th>
<th>novelties / contributions</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. No systemic, multi-problem and objective view on the Structural funds' distribution</td>
<td>1. to form a logically coherent and systematic basis in the form of sequential interrelated approach to the solution of Structural funds' distribution problem</td>
<td>1. Interrelated multi-criteria approach for the complex and systemic solution of Structural funds' distribution problem</td>
</tr>
<tr>
<td>2. No combination of MCDM methods</td>
<td>2. to search for the new combinations of MCDM methods providing more comprehensive measurement</td>
<td>2. Hybridization and comparison of compromise distance-based MCDM methods concerning risk attitude</td>
</tr>
<tr>
<td>3. No simultaneous consideration of NUTS 1 and NUTS 2 levels</td>
<td>3. to investigate and measure new aspects of regional performance which are of high interest from a managerial point of view</td>
<td>3. Fuzzy identification method for the measurement of interaction effect using Choquet method and correlation</td>
</tr>
<tr>
<td>4. No consideration of interaction effect between criteria</td>
<td>4. to select the most suitable MCDM method for the measurement of regional performance</td>
<td>4. Ratio additive weighting method for the measurement of effectiveness of regional performance</td>
</tr>
<tr>
<td>5. No measurement of effectiveness of regional performance</td>
<td>5. to obtain the genuine classification of regions based on the best clustering structure</td>
<td>5. Resonance approach to measure intensive and extensive aspects of regional performance considering both NUTS 1 and NUTS 2 levels</td>
</tr>
<tr>
<td>6. No comparison study and selection approach to choose the most suitable MCDM method</td>
<td>6. to analyse and improve the current Berlin formula offering alternative solutions of the Structural funds' allocation</td>
<td>6. Complex verification approach to clustering structure to obtain a genuine classification and select the most suitable MCDM and clustering method</td>
</tr>
<tr>
<td>7. No justification of regional classification and profound verification of the clustering structure</td>
<td>7. Selective robustness approach to choose the most suitable MCDM method</td>
<td>7. Selective robustness approach to choose the most suitable MCDM method</td>
</tr>
<tr>
<td>8. No improvements and alternatives to distribution Berlin formula</td>
<td>8. Approach to construct the profile of MCDM method for the comparison of methods and more profound understanding of their nature (measurement bias)</td>
<td>8. Approach to construct the profile of MCDM method for the comparison of methods and more profound understanding of their nature (measurement bias)</td>
</tr>
<tr>
<td>10.</td>
<td>10. Mean-variance portfolio optimisation model to avoid free-rider problem concerning the fairness of distribution</td>
<td>10. Mean-variance portfolio optimisation model to avoid free-rider problem concerning the fairness of distribution</td>
</tr>
</tbody>
</table>

Source: author
Appendix B. Methodological foundation of the interrelated multi-criteria approach

table B.1: Conditions of preferences

<table>
<thead>
<tr>
<th>Preferences</th>
<th>Two-factor threshold condition</th>
</tr>
</thead>
<tbody>
<tr>
<td>aPb, if</td>
<td>( M_a &lt; M_b - p(M) \land R_a &lt; R_b - p(R); )</td>
</tr>
<tr>
<td>bPa, if</td>
<td>( M_a &gt; M_b + p(M) \land R_a &gt; R_b + p(R); )</td>
</tr>
<tr>
<td>aQb, if</td>
<td>( M_a &lt; M_b - p(M) \land R_a &lt; R_b - p(R) \lor ) ( M_b - p(M) \leq M_a \leq M_b + p(M) \land R_a &lt; R_b - p(R); )</td>
</tr>
<tr>
<td>bQa, if</td>
<td>( M_a &gt; M_b + p(M) \land R_a &lt; R_b - p(R) \lor ) ( M_b - p(M) \leq M_a \leq M_b + p(M) \land R_a &lt; R_b + p(R); )</td>
</tr>
<tr>
<td>alb, if</td>
<td>( M_a &lt; M_b - p(M) \land R_a &gt; R_b + p(R) \lor ) ( R_a &lt; R_b - p(R) \land M_a &gt; M_b + p(M). )</td>
</tr>
</tbody>
</table>

Source: author

table B.2: Comparison of un-supervised fuzzy identification methods

<table>
<thead>
<tr>
<th>Name / authors</th>
<th>Disadvantages</th>
<th>Advantages</th>
</tr>
</thead>
<tbody>
<tr>
<td>Information-theoretic functionals by Kojadinovic I. (2004, 2008)</td>
<td>1. very large data sample is required; 2. only redundant interaction can be modelled; 3. introduced intermediary concept such as joined or mutual entropy; 4. involved information theory; 5. cognitively difficult, especially for practitioners.</td>
<td>1. the first in its kind.</td>
</tr>
<tr>
<td>Complexity-based approach by Shieh et al. (2009)</td>
<td>1. large data sample is required; 2. introduced intermediary concept such as complexity-based measure with information substructures consideration; 3. involved complexity theory; 4. cognitively difficult, especially for practitioners.</td>
<td>1. both complementary and redundancy effects are processed; 2. works better with smaller sample size.</td>
</tr>
<tr>
<td>Non-interacting equivalents approach by Rowley H. V. et al. (2015)</td>
<td>1. large data sample is required; 2. only linear relationships between criteria are considered; 3. introduced intermediary concept such as non-interacting equivalents; 4. involved method such as PCA.</td>
<td>1. both complementary and redundancy effects are processed; 2. cognitively easier to understand.</td>
</tr>
<tr>
<td>Geometrically based approach by Guliak</td>
<td>1. only linear relationships between criteria are considered; 2. basic trigonometric analysis involved.</td>
<td>1. both complementary and redundancy effects are processed; 2. cognitively easier to understand 2. the large size of data sample is required as long as a correlation is significant; 3. free of extraneous concepts and methods; 4. reveals the nature of criteria interaction in terms of two-dimensional space.</td>
</tr>
</tbody>
</table>

Source: author
fig. B.1: Example of synergy consideration

Source: author

fig. B.2: Graphical representation of DP-2 method

Source: author
fig. B.3: Triangle as the combination of elements (criteria)

Source: author

fig. B.4: Reduction of competing approaches to the one most generic “Goal attainment”

Source: author

fig. B.5: Extension (ratio decomposition) of an initial criteria set

Source: author
fig. B.6: Innovative effectiveness decomposition according to the importance vector

Source: author

EIG – exported innovative products;
SIG – sold innovative goods (services);
IP – innovative processes;
IE – innovative enterprises;
E – number of enterprises.

Source: author

fig. B.7: Geometrical representation of the SAW method

Source: author

fig. B.8: Regional competitiveness policy aspects

Source: author
fig. B.9: Hierarchical structure of competitiveness index

\[ A_{base} = \{ A_n \mid n = 1, 3 \} \]

**Competitiveness**

\[ COMP = \{ C_{j,k} \mid j = 1, k \} \]

space reduction:

\[ A_1 \times \cdots A_n \rightarrow C_1 \times \cdots C_j, j < n \]

**Structural effectiveness**

\[ C_{j,r} = \{ St_{j,k} \mid j = 1,3 \} \]

- Human capital, \( St_{1,k} \)
- Business capital, \( St_{2,k} \)
- Meso-level, \( St_{3,k} \)

**Efficiency**

\[ C_{j,r} = \{ E_{j,k} \mid j = 1,3 \} \]

- Human capital, \( E_{1,k} \)
- Business capital, \( E_{2,k} \)
- Meso-level, \( E_{3,k} \)

**Resource level**

\[ C_{j,r} = \{ R_{j,k} \mid j = 1,3 \} \]

- Human capital, \( R_{1,k} \)
- Business capital, \( R_{2,k} \)
- Meso-level, \( R_{3,k} \)

\[ \{ \text{Inputs} \} \lor \{ \text{Outputs} \} \subset A_{base} \]

\[ \{ X \} \mid X \subset A_{base} \]

- DEA method (CCR)
- Ratio additive weighting method (RAW)
- Ward’s method for clustering
taxonomy Hellwig’s method

Source: author
fig. B.10: Algorithm for the selection of an appropriate MCDM method

1. Formation of a panel of MCDM methods
   - Exclusive
   - Inclusive

2. Preliminary results of a MCDM measurement
   - 2.1 Utility values
   - 4.2 Ranks

3. Constructing of a selecting criteria
   - 3.1 Cluster based criteria (classification problem)
   - 3.2 Robustness based criteria (optimisation problem)

4. Selection of methods
   - 4.1 Analysis of clusters
     - 4.1.1 Distance measure selection
     - 4.1.2 Linkage selection and its cophenetic verification
     - 4.1.3 Clustering method selection
     - 4.1.4 Formation and measurement of validating criteria
     - 4.1.5 Measurement of methods’ discrimination power
     - 4.1.6 Test for the significance of clustering structures
     - 4.1.7 Selection of the most suitable MCDM method for clustering or ranking
   - 4.2 Robustness analysis
     - 4.2.1 Subjective measurement
     - 4.2.2 Pseudo-objective robustness measurement
     - 4.2.3 Normalization of pseudo-objective robustness
     - 4.2.4 Transformation of subjective ranks
     - 4.2.5 Weight determination for transformed ranks
     - 4.2.6 Fitness function measurement
     - 4.2.7 Selection the most suitable MCDM method for a further distribution of Structural funds

Source: author
fig. B.11: Quasi-clustering based on the utility values of MCDM methods

Source: author

Table B.3: The description of applied validating indices

<table>
<thead>
<tr>
<th>#</th>
<th>Name of the index in NbClust package</th>
<th>Optimal value</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>&quot;ch&quot; (Calinski and Harabasz 1974)</td>
<td>Maximum value of the index</td>
</tr>
<tr>
<td>2</td>
<td>&quot;cindex&quot; (Hubert and Levin 1976)</td>
<td>Minimum value of the index</td>
</tr>
<tr>
<td>3</td>
<td>&quot;ccc&quot; (Sarle 1983)</td>
<td>Maximum value of the index</td>
</tr>
<tr>
<td>4</td>
<td>&quot;ptbserial&quot; (Milligan 1980, 1981)</td>
<td>Maximum value of the index</td>
</tr>
<tr>
<td>5</td>
<td>&quot;db&quot; (Davies and Bouldin 1979)</td>
<td>Minimum value of the index</td>
</tr>
<tr>
<td>6</td>
<td>&quot;hartigan&quot; (Hartigan 1975)</td>
<td>Maximum difference between</td>
</tr>
<tr>
<td>7</td>
<td>&quot;ratkowsky&quot; (Ratkowsky and Lance 1978)</td>
<td>Maximum value of the index</td>
</tr>
<tr>
<td>8</td>
<td>&quot;scott&quot; (Scott and Symons 1971)</td>
<td>Maximum difference between</td>
</tr>
<tr>
<td>9</td>
<td>&quot;ball&quot; (Ball and Hall 1965)</td>
<td>Maximum difference between</td>
</tr>
<tr>
<td>10</td>
<td>&quot;friedman&quot; (Friedman and Rubin 1967)</td>
<td>Maximum difference between</td>
</tr>
<tr>
<td>11</td>
<td>&quot;kl&quot; (Krzanowski and Lai 1988)</td>
<td>Maximum value of the index</td>
</tr>
<tr>
<td>12</td>
<td>&quot;silhouette&quot; (Rousseeuw 1987)</td>
<td>Maximum value of the index</td>
</tr>
<tr>
<td>13</td>
<td>&quot;dunn&quot; (Dunn 1974)</td>
<td>Maximum value of the index</td>
</tr>
<tr>
<td>14</td>
<td>&quot;sdiindex&quot; (Halkidi et al. 2000)</td>
<td>Minimum value of the index</td>
</tr>
<tr>
<td>15</td>
<td>&quot;sdbw&quot; (Halkidi and Vazirgiannis 2001)</td>
<td>Minimum value of the index</td>
</tr>
</tbody>
</table>

Source: author
fig. B.12: OWA based profiling approach

Table B.4: Additional formulas for single-factor min variance optimisation model

\[ n_i = \frac{N_i}{\sum_{j=1}^{n} N_j}; \]  
\( (b.1) \)

\[ x_{i_{\text{min}}}^\alpha = \begin{cases} 
  \text{if } x_{i_{\text{t-1}}} > (x_{i_{\text{t-1}}} \cdot \gamma) \Rightarrow \frac{Y_{i_{\text{t-1}}} \cdot (1 - \alpha / 100)}{n_i}, \\
  \text{if others } \Rightarrow x_{i_{\text{t-1}}}. 
\end{cases} \]  
\( (b.2) \)

\[ x_{i_{\text{max}}}^\beta = \begin{cases} 
  \text{if } x_{i_{\text{t-1}}} < (x_{i_{\text{t-1}}} \cdot \gamma) \Rightarrow \frac{Y_{i_{\text{t-1}}} \cdot (1 + \beta / 100)}{n_i}, \\
  \text{if others } \Rightarrow x_{i_{\text{min}}}^\alpha. 
\end{cases} \]  
\( (b.3) \)

\[ F_{\text{pot.}} = \frac{F_{i_{\text{t-1}}}}{7} - \sum_{i=1}^{n} F_{i_{\text{t-1}}}; \]  
\( (b.4) \)

\[ S_{\text{GDP}} = \frac{F_{\text{pot.}} \times 7}{CPF}; \]  
\( (b.5) \)

\[ \alpha = \frac{F_{\text{pot.}}}{\sum_{i=1}^{n} Y_{i_{\text{t-1}}}}; \]  
\( (b.6) \)

\[ \beta = \beta \ast S_{\text{GDP}}; \]  
\( (b.7) \)

\[ \sum_{i=1}^{n} F_{i_{\text{act.}}} = \sum_{i=1}^{n} F_{i_{\text{act.}+}} + \sum_{i=1}^{n} F_{i_{\text{act.-}}} = 0; \]  
\( (b.8) \)
\[
\sum_{i=1}^{n-l} F_{i}^{act.+} = \sum_{i=1}^{n-l} (x_i^{+t} - x_i^{-t-1}) \cdot N_i; \\
F_{pot} = \sum_{i=1}^{n-l} F_{i}^{act.+} + \epsilon; \\
F_{j}^{act.} = \sum_{j=1}^{f} (x_j^{t} - x_j^{t-1}) \cdot N_i; \\
F_{j}^{opt.} = F_{j}^{act.} + F_{j}^{pot.}; \\
\Delta F_{j} = 7 \times F_{j}^{opt.} - (F_{j}^{t-1} - 7 \times P_{i}^{t-1}); \\
\text{Opt.} = 1 - \sum \Delta F_{j}^{+/-}.
\]

where: 
- \( x_i^{t} \) – GDP per capita of \( i \)-th regions at the moment \( t \) after optimisation;
- \( \bar{x} \) – weighted average GDP per capita in the European Union;
- \( \sum_{i=1}^{n-l} F_{i}^{act.+} \) – sum of GDP optimized Funds actively redistributed, in particular, received by \( n-l \) recipients (+) or deducted from \( l \) donors (-);
- \( F_{j}^{opt.} \) – sum of optimized GDP based Funds distributed to the \( j \)-th Member State;
- \( F_{j}^{t-1} \) – actual allocations to the LDS and TR according to Cohesion Policy 2014-2020;
- \( x_i^{+t} \) – increased (decreased) GDP per capita of \( i \)-th regions at the moment \( t \) after a distribution due to received (deducted) GDP/cap Funds.
- \( n_i \) – population weight coefficient;
- \( x_i^{\alpha} \) – minimal level of \( i \)-th region GDP/cap;
- \( x_i^{\beta} \) – maximal level of \( i \)-th region GDP/cap;
- \( CPF \) – amount of total Cohesion Policy Funds assigned 2014-2020;
- \( P_{i}^{t-1} \) – Unemployment premium allocated to the \( i \)-th region;
- \( S_{GDP} \) – share of Regional Policy Funds based on the GDP/cap;
- \( F_{pot} \) – potential Funds based on the GDP/cap level and \( \alpha \) parameter;
- \( \epsilon \) – part of \( F_{pot} \), which is not redistributed according to the optimisation model.
F. Control parameters:

\( \alpha \) – modelling deduction rate, which means the complex percent of \( i \)-th deducted GDP going to form potential Funds based on the GDP/cap \( (F_{i}^{\text{pot}}) \), \( \{0.5;0.6;0.7;0.8;0.9;1\} \);

\( \alpha^* \) – rate of own resources ceiling for the budget (BGD) formation, which in current practice equals 1.23 % of the total EU GDP;

\( \beta^* \) – capping rate (ceiling or absorption rate) assigning the max of regional policy funds (in current practice it equals to 2.5 % of the \( i \)-th GDP);

\( \beta \) – modeling capping rate (ceiling or absorption rate) assigning the max amount of Funds, which can be absorbed by the \( i \)-th region, \( \beta = \{2;2.5;3;3.5;4\} \);

\( \gamma \) – threshold percent level of the average GDP per capita of the EU-27, defining regions eligible to get GDP/cap Funds, \( \gamma = \{0.75;0.9;1\} \) (in current practice it equals <75 % – for the LDR, less than 90 % – for the TR and more than 90% – for the MDR);

Table B.5: Steps for the measurement of the difference between optimized and existent distribution of Structural funds

1. to define exact \( \alpha \) parameter:

\[
\alpha = \frac{\sum_{i=1}^{n} F_{i}^{l-1}}{\sum_{i=1}^{n} Y_{i}^{l-1}}; \tag{b.15}
\]

2. to find potential funds \( (F_{i}^{\text{pot}}) \) for each region:

\[
F_{i}^{\text{pot}} = Y_{i}^{l-1} \cdot \alpha; \tag{b.16}
\]

3. to calculate optimal value of funds for \( i \)-th region \( (F_{i}^{\text{opt}}) \) and \( j \)-th Member state \( (F_{j}^{\text{opt}}) \):

\[
F_{i}^{\text{opt}} = F_{i}^{\text{pot}} + F_{i}^{\text{act.+/−}}; \tag{b.17}
\]

\[
F_{j}^{\text{opt}} = \sum_{j=1}^{m} F_{i}^{\text{pot}} + \sum_{j=1}^{m} F_{i}^{\text{act.+/−}} \tag{b.18}
\]

when \( \sum_{i=1}^{n} F_{i}^{\text{pot.}} = \sum_{i=1}^{n} F_{i}^{\text{opt.}} \) \( \tag{b.19} \)
4. to find the difference between optimally and Berlin allocated GDP/cap. Funds at the regional \((\Delta F_i)\) and Member states’ \((\Delta F_j)\) level:

\[
\Delta F_i = F_{i, \text{opt}} - F_{i, t-1},
\]

\[
\Delta F_j = \sum_{i=1}^{m} F_{i, \text{opt}} - \sum_{i=1}^{m} F_{i, t-1};
\]

(b.20) \hspace{1cm} (b.21)

5. to determine the percent \((N)\) of not non-optimally redistributed GDP/cap. Funds in the EU at the current practice:

\[
N = \frac{\sum_{i=1}^{n} \Delta F_{i, \text{act}, t-1}}{F_{i, \text{opt}} \cdot 100\%}.
\]

(b.22)

where: \(F_{i, t-1}\) – current GDP/cap. Funds assigned to the \(i\)-th region;

\(F_{i, \text{opt}}\) – optimal GDP/cap. Funds as alternative to the current assigned to the \(i\)-th region.

Table B.6: Sub-problem D determining the coefficients of the mean-variance model

Step 1
Objective function:

\[
E_{j, s-f} [U(W)] = E(W) - Unf_{j, s-f} \rightarrow \text{max}.
\]

Constraint:

\[
\sum_{i=1}^{n} w_i = 1000 \quad |w_i| \geq 0 \quad \forall i
\]

\(w_i \in \mathbb{R}^+\) for \(i, j = 1, 2, \ldots N\).

\(k_{s-f} = x_j \in \mathbb{R}^+\) for \(i, j = 1, 2, \ldots N\).

while \(Unf_{j, s-f} = k_{j, s-f} \cdot \sigma_{s-f}^2\) for every sub-factor separately.

where \(Unf_{j, s-f}\) – sub-factor unfairness with \(j\)-th coefficient.

All other equations and descriptions are adopted from the problem A.

Step 2
Objective function:

\[
Unf_{j, s-f} \rightarrow \text{max}.
\]

All other constraints, equations and descriptions are adopted from the problem A and step 1 of problem D.

Source: author
fig. B.13: Conceptual basis of optimisation models

**Variance minimization**  
GDP based model

- Equality
- Supporting
- Optimal

- Free-rider problem
- Problem of disparities decrease

**Fairness**

- Stimulating  
- Supporting

**Equity**  
**Equitability**  
**Equality**

**Markowitz Mean-Variance**  
effectiveness based model

- distribution
- influence
- approaches
Appendix C. Application of suggested methods, models and approaches

Table C.1: KMO and Bartlett's

<table>
<thead>
<tr>
<th>Indicator / Data</th>
<th>Data sample</th>
</tr>
</thead>
<tbody>
<tr>
<td>Kaiser-Meyer-Olkin Measure of sampl. adeq.</td>
<td>.692</td>
</tr>
<tr>
<td>Bartlett's Test of Sphericity</td>
<td></td>
</tr>
<tr>
<td>Approx. Chi-Square</td>
<td>290.16</td>
</tr>
<tr>
<td>df</td>
<td>36</td>
</tr>
<tr>
<td>Sig.</td>
<td>.00</td>
</tr>
</tbody>
</table>

Source: author

Table C.2: Indicators’ correlation and variance coefficient

<table>
<thead>
<tr>
<th>Indicators</th>
<th>DI</th>
<th>EAR</th>
<th>ER</th>
<th>TE</th>
<th>UN</th>
<th>PROD</th>
<th>GFC</th>
<th>TRD</th>
<th>JVR</th>
<th>BRD</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>EAR</td>
<td>0.68</td>
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<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>ER</td>
<td>0.70</td>
<td>0.94</td>
<td></td>
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<td></td>
<td></td>
<td></td>
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<td></td>
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<tr>
<td>TE</td>
<td>0.63</td>
<td>0.31</td>
<td>0.37</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>UN</td>
<td>-0.51</td>
<td>-0.52</td>
<td>-0.78</td>
<td>-0.35</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PROD</td>
<td>0.52</td>
<td>0.32</td>
<td>0.34</td>
<td>0.63</td>
<td>-0.26</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>GFC</td>
<td>0.68</td>
<td>0.46</td>
<td>0.52</td>
<td>0.72</td>
<td>-0.45</td>
<td>0.95</td>
<td>1</td>
<td></td>
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<td></td>
</tr>
<tr>
<td>TRD</td>
<td>0.41</td>
<td>0.59</td>
<td>0.67</td>
<td>0.38</td>
<td>-0.57</td>
<td>0.32</td>
<td>0.49</td>
<td>1</td>
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</tr>
<tr>
<td>JVR</td>
<td>0.24</td>
<td>0.26</td>
<td>0.384</td>
<td>0.21</td>
<td>-0.45</td>
<td>0.04</td>
<td>0.21</td>
<td>0.55</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>BRD</td>
<td>0.19</td>
<td>0.46</td>
<td>0.54</td>
<td>0.12</td>
<td>-0.49</td>
<td>0.15</td>
<td>0.29</td>
<td>0.88</td>
<td>0.56</td>
<td>1</td>
</tr>
<tr>
<td>var. coef.</td>
<td>17.7</td>
<td>6</td>
<td>8.4</td>
<td>26.9</td>
<td>30.3</td>
<td>76.3</td>
<td>67.8</td>
<td>64.7</td>
<td>62</td>
<td>78.5</td>
</tr>
</tbody>
</table>

Source: author

Table C.3: Variance explanation by principal components division

<table>
<thead>
<tr>
<th>Component</th>
<th>Initial Eigen values</th>
<th>Extraction Sums of Squared Loadings</th>
<th>Rotation Sums of Squared Loadings</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Total</td>
<td>% of Var.</td>
<td>Cumul. %</td>
</tr>
<tr>
<td>1</td>
<td>4.762</td>
<td>52.915</td>
<td>52.915</td>
</tr>
<tr>
<td>2</td>
<td>1.883</td>
<td>20.920</td>
<td>73.835</td>
</tr>
<tr>
<td>3</td>
<td>.825</td>
<td>9.164</td>
<td>82.999</td>
</tr>
<tr>
<td>4</td>
<td>.608</td>
<td>6.760</td>
<td>89.759</td>
</tr>
<tr>
<td>5</td>
<td>.397</td>
<td>4.408</td>
<td>94.166</td>
</tr>
<tr>
<td>6</td>
<td>.331</td>
<td>3.674</td>
<td>97.840</td>
</tr>
<tr>
<td>7</td>
<td>.115</td>
<td>1.272</td>
<td>99.112</td>
</tr>
<tr>
<td>9</td>
<td>.015</td>
<td>.169</td>
<td>100</td>
</tr>
</tbody>
</table>

Source: author
Table C.4: The scores of principal components for the NUTS 2 regions of Visegrad group

<table>
<thead>
<tr>
<th># of regions</th>
<th>Abbrev.</th>
<th>Comp. 2</th>
<th>Comp. 1</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Czech Republic</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>CZ01</td>
<td>2.052</td>
<td>1.993</td>
</tr>
<tr>
<td>2</td>
<td>CZ02</td>
<td>2.195</td>
<td>-0.256</td>
</tr>
<tr>
<td>3</td>
<td>CZ03</td>
<td>1.523</td>
<td>-0.407</td>
</tr>
<tr>
<td>4</td>
<td>CZ04</td>
<td>-0.108</td>
<td>-0.619</td>
</tr>
<tr>
<td>5</td>
<td>CZ05</td>
<td>1.184</td>
<td>-0.527</td>
</tr>
<tr>
<td>6</td>
<td>CZ06</td>
<td>1.714</td>
<td>0.032</td>
</tr>
<tr>
<td>7</td>
<td>CZ07</td>
<td>0.750</td>
<td>-0.545</td>
</tr>
<tr>
<td>8</td>
<td>CZ08</td>
<td>0.390</td>
<td>-0.431</td>
</tr>
<tr>
<td>2. Hungary</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>HU1</td>
<td>1.180</td>
<td>0.699</td>
</tr>
<tr>
<td>10</td>
<td>HU21</td>
<td>1.075</td>
<td>-1.022</td>
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<tr>
<td>11</td>
<td>HU22</td>
<td>0.712</td>
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<td>12</td>
<td>HU23</td>
<td>0.065</td>
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<td>13</td>
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<td>HU32</td>
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<td>15</td>
<td>HU33</td>
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<td>-1.125</td>
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<tr>
<td>3. Poland</td>
<td></td>
<td></td>
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<tr>
<td>16</td>
<td>PL11</td>
<td>-0.731</td>
<td>0.499</td>
</tr>
<tr>
<td>17</td>
<td>PL12</td>
<td>-0.442</td>
<td>3.486</td>
</tr>
</tbody>
</table>

Source: author

Table C.5: Ranks, relative net flows and clusters based on the Hybrid methods

<table>
<thead>
<tr>
<th>region #</th>
<th>abbrev.</th>
<th>Original methods</th>
<th>Hybrid methods</th>
<th>Relative net flows from Hybrid methods, %</th>
<th>Clusters</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>CZ01</td>
<td>2</td>
<td>3</td>
<td>1</td>
<td>2</td>
</tr>
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Source: author

Table C.6: Changes in effectiveness measurement with interaction effect

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### Table C.6: Continuation

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Source: author

Table C.7: The structure of Ukrainian regions

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<th>NUTS 1 region</th>
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Source: administrative territorial division on 2013 year; Różańska-Putek J. et al. (2009)
Table C.8: Division of factors for DEA and rates of growth analysis

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<td>Public assistances and another received current transfers</td>
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<tr>
<td>Population</td>
<td>persons</td>
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<tr>
<td>Staff training and developing</td>
<td>persons</td>
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<tr>
<td>Demand for labour force</td>
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<td><strong>1.2 Outputs of human capital group (H)</strong></td>
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<td>Total wages of population</td>
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<td>Job placement of registered unemployed</td>
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<td>Housing stock</td>
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<td>Final households consumption</td>
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<td><strong>2.1 Inputs of business group (B)</strong></td>
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<td>Employed aged 15–70</td>
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<td>Staff engaged in R&amp;D</td>
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<td>Total expenditure by innovation activity direction</td>
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<tr>
<td>Capital investment</td>
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<td><strong>2.1 Outputs of business group (B)</strong></td>
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<td>Sold industrial products (operations, services)</td>
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<td>Innovation products output</td>
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<td>Gross value added</td>
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<td>Agricultural output</td>
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<tr>
<td>Activity of enterprises operating in services sphere</td>
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<td><strong>3.1 Inputs of meso-level group (M)</strong></td>
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<td>Economically active population</td>
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<tr>
<td>The number of used advanced technologies</td>
<td>units</td>
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<tr>
<td>Number of innovation active enterprises in industry</td>
<td>units</td>
</tr>
<tr>
<td>Number of Business register entities</td>
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<tr>
<td><strong>3.2 Outputs of meso-level group (M)</strong></td>
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<td>Total exports of goods</td>
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<td>Total exports of services</td>
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<td>Direct foreign investment (equity capital)</td>
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<td>Taxes excluding subsidies</td>
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<td>Final consumers expenditure</td>
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Table C.9: Relative indices describing the level of resource component

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<td>Population density</td>
<td>persons / square kilometre</td>
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<td>Social current transfers per 1 person</td>
<td>money units / person</td>
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<tr>
<td>Share of trained staff in economically active population</td>
<td>%</td>
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<tr>
<td>Labour demand for 1 job vacancy</td>
<td>persons</td>
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<td>2. Business group (B)</td>
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<tr>
<td>Employment rate</td>
<td>%</td>
</tr>
<tr>
<td>Personnel engaged in research and development activities per business</td>
<td>persons / enterprise</td>
</tr>
<tr>
<td>Innovative expenditures per 1 business unit</td>
<td>money units / business unit</td>
</tr>
<tr>
<td>Investments per 1 business unit</td>
<td>money units / business unit</td>
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<tr>
<td>3. Meso-level group (M)</td>
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<td>Number of business entities per persons</td>
<td>units / person</td>
</tr>
<tr>
<td>Share of innovation active enterprises in industry from business</td>
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<tr>
<td>The number of advanced technologies used per enterprise utilizing</td>
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<td>innovative technologies</td>
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<tr>
<td>Share of economically active population in whole population</td>
<td>%</td>
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Source: State Statistics Service of Ukraine (Available from: https://ukrstat.org/en) and transformed by author

Table C.10: KMO and Bartlett's Test

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<tr>
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<td>.000</td>
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</table>

Source: author

Table C.11: Correlation between GDP, CI and sub-indicators for 26 NUTS 2 regions

<table>
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<tr>
<th>Indicators</th>
<th>RH</th>
<th>EH</th>
<th>RB</th>
<th>EB</th>
<th>EM</th>
<th>CI</th>
<th>GDP</th>
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<td>.731**</td>
<td>.460*</td>
<td>.783**</td>
<td>.698**</td>
<td>.810**</td>
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<tr>
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<td>0.013</td>
<td>0</td>
<td>0.018</td>
<td>0</td>
<td>0</td>
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<tr>
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<td>.482*</td>
<td>1</td>
<td>.627**</td>
<td>.738**</td>
<td>.695**</td>
<td>.890**</td>
<td>.842**</td>
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<tr>
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<td>0.001</td>
<td>0.006</td>
<td>0</td>
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<tr>
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<td>.627**</td>
<td>1</td>
<td>.528**</td>
<td>.745**</td>
<td>.748**</td>
<td>.871**</td>
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<tr>
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<td>0.006</td>
<td>0.001</td>
<td>0</td>
<td>0</td>
<td>0</td>
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</tr>
<tr>
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<td>.460*</td>
<td>.738**</td>
<td>.528**</td>
<td>1</td>
<td>.605**</td>
<td>.872**</td>
<td>.812**</td>
</tr>
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<td>.695**</td>
<td>.745**</td>
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<td>.889**</td>
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<td>0</td>
<td>0</td>
<td>0.001</td>
<td>0</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>CI Pearson corr.</td>
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<td>.890**</td>
<td>.748**</td>
<td>.872**</td>
<td>.889**</td>
<td>1</td>
<td>.958**</td>
</tr>
<tr>
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<td>0</td>
<td>0</td>
<td>0</td>
<td>0.001</td>
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<td>GDP Pearson corr.</td>
<td>.810**</td>
<td>.842**</td>
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<tr>
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<td>0</td>
<td>0</td>
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<td>0</td>
<td></td>
</tr>
</tbody>
</table>

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

Source: author
Table C.12: Clusters and ranks of the regions in the light of two NUTS levels, three aspects and three dimensions

<table>
<thead>
<tr>
<th>Regions</th>
<th>Cluster</th>
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<th>$S, L$ indices (NUTS 2)</th>
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<td></td>
<td></td>
<td>$H$</td>
<td>$B$</td>
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<tr>
<td></td>
<td></td>
<td>$r^B_m$</td>
<td>$r^{EM}_m$</td>
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<tr>
<td>4</td>
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<td>1</td>
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<td>9</td>
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<td>8</td>
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<tr>
<td>22</td>
<td>III</td>
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<td>9</td>
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<td>25</td>
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Source: author

Table C.13: Variability of NUTS 2 ranks

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<tr>
<th># of NUTS 2</th>
<th>Cluster</th>
<th>$\bar{r}_i$</th>
<th>$\sigma_i$</th>
<th>$r^\text{max}_i$</th>
<th>$r^\text{min}_i$</th>
<th>$\bar{R}^\min\max$</th>
<th>$\bar{R}^\sigma$</th>
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<td>0</td>
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<td>4</td>
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continuation of Table C.13

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<th>$\sigma_i$</th>
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<th>$r_{i}^{\text{min}}$</th>
<th>$\bar{R}_{\text{min max}}$</th>
<th>$\bar{R}_{\sigma}$</th>
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Source: author

Table C.14: Correlation between initial indicators

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<th>Indicator</th>
<th>ear, %</th>
<th>tert, %</th>
<th>hrst, %</th>
<th>empl, %</th>
<th>unempl_r, %</th>
<th>gdp_av, %</th>
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<td>0,37</td>
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<td></td>
</tr>
<tr>
<td>hrst, %</td>
<td>0,37</td>
<td>0,91</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>empl, %</td>
<td>0,90</td>
<td>0,30</td>
<td>0,31</td>
<td>1</td>
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<td></td>
</tr>
<tr>
<td>unempl_r, %</td>
<td>0,59</td>
<td>0,07</td>
<td>0,07</td>
<td>0,79</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>gdp_av, %</td>
<td>0,50</td>
<td>0,55</td>
<td>0,61</td>
<td>0,50</td>
<td>0,35</td>
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</table>

Source: author

Table C.15: Descriptive statistics

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<th>Indicator</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Mean</th>
<th>Std. Deviation</th>
<th>Skewness</th>
<th>Variance coefficient, %</th>
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</thead>
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<tr>
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<td>44,00</td>
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<td>64,06</td>
<td>5,598</td>
<td>-.72</td>
<td>8,7%</td>
</tr>
<tr>
<td>tert, %</td>
<td>.14</td>
<td>.88</td>
<td>.39</td>
<td>.11</td>
<td>.69</td>
<td>28,7%</td>
</tr>
<tr>
<td>hrst, %</td>
<td>.69</td>
<td>.45</td>
<td>.214</td>
<td>.06</td>
<td>.98</td>
<td>27,5%</td>
</tr>
<tr>
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<td>71,80</td>
<td>58,13</td>
<td>7,89</td>
<td>-.68</td>
<td>13,5%</td>
</tr>
<tr>
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<td>.40</td>
<td>.15</td>
<td>.08</td>
<td>.79</td>
<td>54,7%</td>
</tr>
<tr>
<td>gdp_av, %</td>
<td>13,00</td>
<td>737,00</td>
<td>96,57</td>
<td>60,15</td>
<td>4,68</td>
<td>62,2%</td>
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Source: author

Table C.16: Silhouette correction

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<th>silhouette width</th>
<th>initial cluster</th>
<th>final cluster</th>
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<tr>
<td>AT21</td>
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<td>1</td>
</tr>
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<td>2</td>
<td>1</td>
</tr>
<tr>
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<td>2</td>
<td>1</td>
</tr>
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<td>UKE4</td>
<td>-0,076</td>
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</table>

Source: author
Table C.17: ANOVA analysis of clustering solution based on Hybrid VIKOR

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<th>Variables</th>
<th>Sum of Squares</th>
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<th>Mean Square</th>
<th>F</th>
<th>Sig.</th>
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<td>0,077</td>
<td>26,111</td>
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<td>Within Groups</td>
<td>0,794</td>
<td>270</td>
<td>0,003</td>
<td>–</td>
</tr>
<tr>
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<td>Total</td>
<td>0,948</td>
<td>272</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
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<td>Between Groups</td>
<td>0,931</td>
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<td>0,466</td>
<td>146,744</td>
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<td>Within Groups</td>
<td>0,856</td>
<td>270</td>
<td>0,003</td>
<td>–</td>
</tr>
<tr>
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<td>Total</td>
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<td>272</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
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<td>Between Groups</td>
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<td>2</td>
<td>217846,501</td>
<td>107,283</td>
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<td>548255,994</td>
<td>270</td>
<td>2030,578</td>
<td>–</td>
</tr>
<tr>
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<td>Total</td>
<td>983948,996</td>
<td>272</td>
<td>–</td>
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</table>

Source: author

Table C.18: Abbreviations of EU 28 countries

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<th>Member State</th>
<th>Abbrev.</th>
<th>№</th>
<th>Member State</th>
<th>Abbrev.</th>
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<td>RO</td>
<td>16</td>
<td>Spain</td>
<td>ES</td>
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<td>HR</td>
<td>17</td>
<td>Italy</td>
<td>ITC</td>
</tr>
<tr>
<td>4</td>
<td>Latvia</td>
<td>LV</td>
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Source: author

table C.19: Funding mismatch of optimal 2 % strategy compare to the current one

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continuation of Table C. 19

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Source: author

fig. C.1: Measurement of 273 EU regions’ performance (effectiveness and SAW methods)

Source: author
fig. C.2: Measurement of 273 EU regions’ performance (effectiveness and DP-2 methods)

\[ y = 0.7707x + 31.41 \]
\[ R^2 = 0.594 \]

Source: author

fig. C.3: Dynamic of strategies in terms of specific altruistic criterion

Source: author
fig. C.4: Dynamic of strategies in terms of general impact criterion

Source: author

Table C.20: Evaluation of distribution strategies

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Source: author
fig. C.5: Clusters of strategies depending on the aggregating function

![Graph showing clusters of strategies](image)

a. Additive function

b. Additive weighted function

c. Multiplicative function

d. Multiplicative weighted function

Source: author

Table C.21: Wilcoxon Test Statistics

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a. Based on negative ranks.
b. Based on positive ranks.

Source: author

fig. C.6: Weights coefficients and accumulated value

![Graph showing weights and accumulated value](image)

Source: author
fig. C.7: Distribution of measurement errors by different MCDM methods

Source: author

fig. C.8: Selection of parameters of unfairness sub-factors

Source: author

fig. C.9: Dependence of regional effectiveness and variance

Source: author
Table C.22: Correlation of MCDM methods based on the obtained ranks

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* MCDM methods applied with respect to three and seven criteria extension

Source: author