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Multicriteria methodologies for the appraisal of smart grid projects when flexibility competes with grid expansion

Scientific Disciplinary Sector

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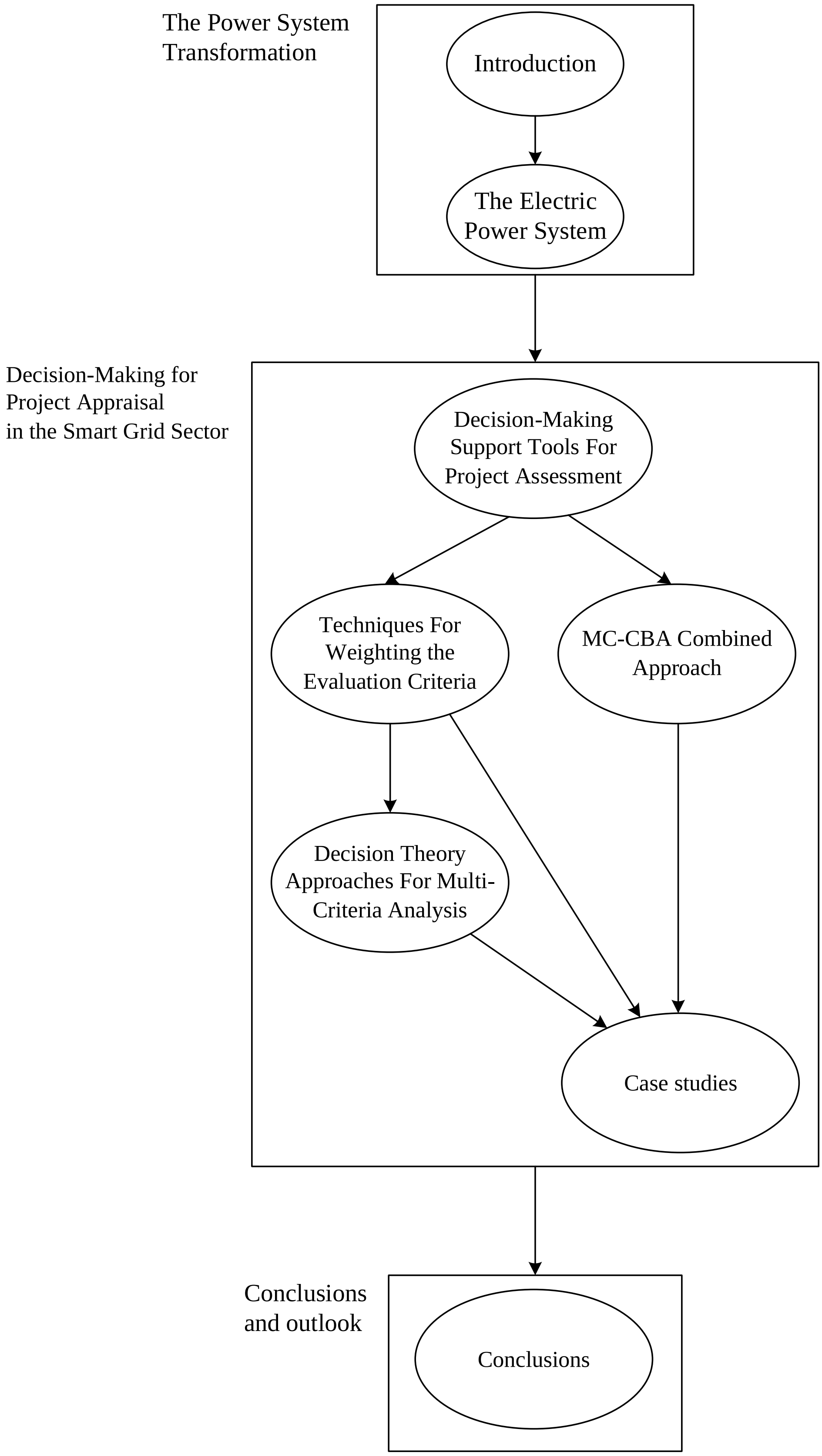
DISCLAIMER

To my parents

OUTLINE

GRAPHICAL OUTLINE



ABSTRACT

The severe consequences of the increased frequency and intensity of the expected extreme weather events call for improving the environmental sustainability of our society. The electricity sector is pivotal in the path toward a climate-neutral society. Nowadays, the massive use of renewable energy sources requires that electricity demand follows energy production. Demand has to be flexible, as well as the renewable generation and the grid infrastructures. The power system has to assume a decentralised structure and integrate the transportation and cooling & heating sectors. All customers connected to the electrical grid have to contribute to the power system management and participate in the related markets. The power system has to become smart; all technical and market processes have to be digitalised to enable new functionalities and services.

The power system transformation requires rethinking planning and operation practices to accommodate the changes and take advantage of the related opportunities. The novel features and services available in the active and flexible power system will influence the customers' daily habits; therefore, the impacts generated by planning initiatives will cross the power system borders by impacting society as a whole.

This thesis addresses the ongoing power system transformation by focusing on the distribution system, which will face unprecedented changes. This thesis concerns novel approaches for appraising the project initiatives based on the use of the users' flexibility connected to the grid. Traditional appraisal tools are no longer effective; therefore, decision-makers have to be supported with tools capable of capturing the complexity of the future power system in which flexibility measures compete with grid expansion.

This thesis proposes an assessment framework for smart grid initiatives that combines cost-benefit analysis and multi-criteria analysis. Based on international guidelines, the proposed framework allows for a systematic and simultaneous assessment of tangible and intangible impacts considering conflicting criteria. To complete the assessment framework, a novel methodology that combines Regret Theory and multi-criteria analysis is proposed. The proposed method represents one of the main contributions of this dissertation. It supports the decision-maker to identify the most valuable option by decomposing the complex decision-making problem of smart grid planning and rejecting personal biases by avoiding the need for defining specific evaluation criteria relevance. However, the stakeholders’ perspective can be included in the appraisal in terms of constraints for the minimax optimisation problem.

In conclusion, the contribution of the thesis is to provide decision-making support tools for strategical power system planning, particularly in the context of smart grids. The research activities described in this document have been aimed at supporting system operators and regulatory bodies by providing smart grid project appraisal tools to consider the novel context characteristics.

EXECUTIVE SUMMARY

Introduction

The severe consequences due to the increased frequency and intensity of the expected extreme weather events call for improving the environmental sustainability of our society. The electricity sector is pivotal in the path toward a climate-neutral society. Nowadays, the massive use of renewable energy sources requires that electricity demand follows energy production. The electricity demand has to be flexible, as well as the generation from renewables and the grid infrastructure. The power system has to assume a decentralised structure and integrate the transportation and cooling & heating sectors. All customers connected to the electrical grid have to contribute to the power system management and participate in the related markets. The power system has to become smart; all technical and market processes have to be digitalised to enable new functionalities and services.

The power system transformation requires rethinking planning and operation practices to accommodate the changes and take advantage of the related opportunities. The novel features and services available in the active and flexible power system will influence the customers' daily habits; therefore, the impacts generated by planning initiatives will cross the power system borders by impacting society as a whole. Since the electric power system will be operated closer to its technical limits, it is crucial to enhance the active management of the connected resources.

This thesis addresses the ongoing power system transformation by focusing on the distribution system, which will face unprecedented changes. This thesis concerns novel approaches for appraising the initiatives based on the use of grid-connected users' flexibility. In this context, traditional project appraisal tools are no longer effective; therefore, decision-makers have to be supported with tools capable of capturing the complexity of the future power system in which the flexibility measures compete with grid expansion.

In this thesis, an assessment framework for smart grid initiatives that combines cost-benefit analysis and multi-criteria analysis proposed. The proposed framework is based on international guidelines and allows for a systematic and simultaneous assessment of tangible and intangible impacts considering multiple conflicting criteria. To complete the assessment framework, a novel methodology that combines Regret Theory and multi-criteria analysis is proposed. The proposed methodology represents one of the main contributions of this dissertation. It supports the decision-maker to identify the most valuable option by decomposing the complex decision-making problem of smart grid planning and rejecting personal biases by avoiding the need for defining specific evaluation criteria relevance. However, the stakeholders’ perspective can be included in the decision making problem in terms of constraints for the minimax optimisation model.

In conclusion, the contribution of the thesis is to provide decision-making support tools for strategical power system planning, particularly in the context of smart grids. The research activities described in this document have been aimed at supporting system operators and regulatory bodies by providing tools for smart grid project appraisal that consider the novel power system characteristics.

The evolution of the electric power system

The energy sector, particularly the electricity sector, is pivotal in the path toward a climate-neutral society. The decarbonisation of the economy calls for an energy transition that requires an evolution of the power system's planning and operation procedures. The main trends that drive the transformation of the electricity sector are decarbonisation, decentralisation, cross-sector integration, digitalisation, and customer inclusion. These trends represent a big challenge for the electricity sector; profound changes are required to guarantee the security and reliability of the power supply.

The electric power system structure has been evolving since its dawn at the end of the 19th century. Initially, the power system has been characterised by isolated electricity systems which supplied cities and industrial districts. From this decentralised structure, the local power systems have started to grow and become interconnected since the need to increase the frequency control reliability. In the mid-20th century, the power system size reached countries and continents, serving a large number of customers and assuming a centralised model. The strong hierarchical structure of the power system has become evident in that period. Since the introduction of small generators fed by renewable energy sources at the end of the 20th century, the power system started evolving again towards a decentralised model in which the various layers have not clear borders.

In recent years, the pace of power system evolution has increased because of the need for integrating renewable energy sources at reasonable costs without jeopardising the reliability of the electric supply. Generators fed by renewables are considered as not dispatchable; hence the paradigm of the inflexibility of the electricity demand has been questioned. Furthermore, recent climate policies are oriented to decarbonisation and old power plant decommissioning; therefore, smaller generation facilities are encouraged. Consequently, considering the liberalisation of energy markets, the number of actors involved in power system management is increased. The connection of small generators at distribution level requires to revise the planning and operational practices since it casues bidirectional power flows in networks devised for being passive and crisscrossed by unidirectional power flows.

For facing the consequences of the power system transformation, the planning and operation practices have to be updated. Drastic changes are required for unlocking the already available power system flexibility and for introducing new flexibility sources. Flexibility represents a cost-effective measure for compensating the variability and uncertainty introduced in the power system by the renewable energy sources and the new loads. Enhancing flexibility is considered an alternative to network reinforcement since it may reduce or defer network investments. Flexibility is helpful for balancing the supply and demand of electric energy at any timescale; it allows to counterbalance the variability of loads and generation in regular operation. Furthermore, flexibility improves system resiliency since it can be exploited in emergency scenarios of large generator loss, outages, and extreme weather events. In this context, traditional approaches based only on network reinforcement would require unsustainable investments to face normal and emergency conditions. Therefore, flexibility is the key to achieving a more secure, resilient, affordable, and sustainable power system.

Since the newly connected assets (e.g., generators fed by renewals energy sources, controllable loads, electric vehicles, and storage devices) the distribution network turns active; consequently, it is essential to adapt the distribution grid to the new context requirements, and thus to rethink the distribution system planning process. In fact, in smart grids and flexible distribution systems, planning and operation activities have to be coordinated to consider the flexibility provided by the connected assets as an alternative to network expansion. It represents a radical change because distribution network planning has been traditionally based exclusively on the fit and forget approach.

Fit and forget is a deterministic planning approach in which the network is designed according to the worst scenario in terms of loading condition, voltage drop, and security constraints. Considered the worst loading scenario, lines, switches, and substations are sized without considering uncertainties. As the denomination suggests, the underlying idea is that all the operational issues are solved at the planning stage by considerable network oversizing. Then, the operational actions are minimised to cover only unforeseen events.

The fit and forget approach employed in the context of distributed generation means considering the *maximum generation - minimum demand* scenario, which rarely happens. Consequently, in those cases, the fit and forget approach will lead to an unreasonable and costly network upgrading. Considering the vast investments required, the use of the fit and forget for facing the contingencies related to high levels of distributed generation might limit the diffusion of such assets and the non-conventional loads.

In the future distribution system, to achieve an adequate hosting capacity at an acceptable cost, it is imperative to include active network solutions and flexibility as planning measures. Consequently, the planning activity becomes more complex since it involves third-party assets whose owners have conflicting goals. In fact, the Distribution System Operator (DSO) would be interested in minimising the overall grid cost while preserving the adequate quality of supply. At the same time, the flexibility service providers could be interested in maximising the revenues related to the service provision. Considering the increased number of potential planning measures and the diversity of the stakeholders involved, multi-criteria and multi-objective approaches are of interest to tackle the complexity of the planning activities of the future distribution system.

Designing a flexible and active distribution system requires planning methodologies that rely on stochastic approaches and optimisation techniques. Probabilistic approaches for planning design are fundamental for representing the increased uncertainty and the variability of demand and generation, while the use of optimisation techniques allows reducing the computational burden of the mathematical problem of defining the most effective upgrading plan.

Traditionally, the planning alternatives proposed for the distribution network have been evaluated in terms of the costs required for making the reinforcement considering the target of quality of service to be achieved. No elaborated tools have been exploited to select the initiative to implement; typically, the considered selection criterion has been the least capital cost while meeting the minimum service requirement.

The alternatives obtained according to the flexible planning approach are characterised by many impacts difficult to quantify and monetise. The lack of historical data and clear and acknowledged guidelines on monetary compensation mechanisms could lead to a burdensome appraisal process of questionable reliability. Consequently, an appraisal process based only on the cost equivalence becomes burdensome and untrustworthy. On the contrary, an appraisal approach able to compare costs and technical performances appears appealing. The comparison based on performance indicators avoids any bias introduced by the monetary conversion. Moreover, the liberalisation policies have encouraged the participation of novel stakeholders in the power system that have different roles and interests; therefore, the corresponding goals are conflicting.

The contribution to distribution system planning given by the use of approaches based on multi-criteria analysis is twofold; on the one hand, the use of these approaches allows to enlarge the set of appraised impacts; on the other hand, it allows to consider simultaneously the point of view of the different stakeholders.

Decision-making support tools for project assessment

The Cost-Benefit Analysis (CBA) is the most acknowledged tool for addressing the financial assessment of industrial investment projects. The CBA is based on neoclassical welfare economics principles and provides a systematic assessment framework that seeks the most profitable investment alternative. Typically, industrial projects are evaluated from the investor's perspective considering only the financial effects. Those effects are the monetary and direct monetisable impacts that the investment initiative produces. The investment option has to maximise the investors' profit; therefore, CBA relies on the Kaldor-Hicks criterion: the benefits of the deployment of the alternative must exceed the costs.

The CBA allows a comparative assessment in which the different options are compared considering a reference scenario. Among a set of investment options, the most advantageous one achieves the highest CBA performance indicators value. Therefore, CBA can be considered as a decision support tool for planning processes.

The CBA is widely used in the private sector; however, CBA does not represent a fully acknowledged tool for the assessment of large infrastructural initiatives that involve public bodies. These initiatives have to be assessed from the societal perspective and can generate impacts that are not monetary or quantifiable with accuracy. In this context, the use of monetary-based tools as the Societal Cost-Benefit Analysis (SCBA) for assessing the initiatives from a societal perspective reveals several conceptual flaws that may bias the project appraisal outcome. The public and private sectors have radical differences: the public initiative concern goods and services which are not traded within a market, the goal of the public sector is maximising the expense efficiency rather than maximising the profits, the model of the society as aggregated consumers fails in representing the real value of people as citizens.

Furthermore, the shortcomings of the CBA are emphasised when the intangible impacts are not negligible. Typically, intangible impacts are majoritarian in public sector initiatives. Even if some CBA methodology adjustments have been proposed, the validity of the obtained outcome is reduced because the CBA pillars are weakened. Monetising and discounting the intangible impacts distort the stakeholders' actual perspective by underestimating long-term effects (e.g., externalities and environmental impacts).

In several sectors, the planning activities are handled using tools for supporting decision-makers such as Multi-Criteria Analysis (MCA) or Multi-Criteria Decision Analysis (MCDA). This approach represents a broad class of methodologies proposed for addressing complex decision-making problems. Infrastructure planning activities, also in the context of smart grid, are complex decision-making processes since the most valuable option has to be identified among multiple options to be evaluated according to conflicting criteria while also considering the perspective of various stakeholders.

The MCA methodologies help the decision-maker in decomposing the decision problem into elementary problems that can be easily managed. The analysis of the alternative considers multiple conflicting criteria; the stakeholders' perspective can be included in the appraisal in terms of the evaluation criteria relevance. Numerous methodologies based on the MCA approach have been proposed in the literature; the peculiar decision-making philosophy and the particular mathematical procedure implemented characterise each methodology. In general, MADM methods are classified according to three main families: full aggregation approach (FAA), outranking approach (OA), goal, aspiration, or reference level approach (GAA). The MCA methodologies studied in the full document are the Analytic Hierarchy Process, the Multi-Attribute Utility Theory, and ELECTRE III.

MCA supports solving complex decision-making problems since its structured process for decomposing the problem, identifying the relevant aspects to be considered, evaluating the alternatives systematically, and interpreting the obtained results. The key features of the MCA are the decision matrix, the scoring stage of the options, the weighting stage of the evaluation criteria, and the algorithm for calculating the overall performance achieved by the options.

Unlike CBA, in MCA, there is no explicit need to define a rule which states that benefits must exceed costs. Therefore, the best option indicated by MADM may not fit the principle of the improvement of well-being. Moreover, since several criteria are involved in the appraisal, the risk of double-counting the same impact exists. Furthermore, the outcome of the MCA significantly depends on the assigned criteria weights values. Criteria relevance depends on the stakeholder perspective; therefore, it has to be acquired with considerable care. The use of incongruent weights may lead to a decision-making problem solution that does not satisfy the stakeholders. In any case, the definition of criteria weight values based on the stakeholder preferences introduces subjectivity in the analysis. If not adequately managed, personal biases and arbitrariness may influence the outcome of the MCA.

Techniques for weighting the evaluation criteria

In MCA, the weight values of the evaluation criteria play a crucial role since the considerable influence in defining the outcome of the multi-criteria analysis. Subjective, objective, and integrated methods for criteria weights have been proposed in the literature.

In subjective methods for determining the criteria weights, stakeholders play a pivotal role since the criteria weights are defined based on stakeholder preferences. Subjective weighting methods are the trade-off, swing, resistance to change, rank-sum, rank-reciprocal, rank-exponent, and rank-order centroid. The collection of stakeholders' perspectives is a critical element of the multi-criteria analysis of decision-making problems. In particular, determining criteria weights on the basis of the preferences expressed by the stakeholders shows relevant issues. Lack of time, insufficient information and awareness from stakeholders, the vagueness of language, and the particular method for collecting preferences influence the obtained result. These elements related to subjective methods for determining the criteria weights undermine the reliability of the result obtained from the entire multi-criteria analysis. It is advisable to exploit strategies that include objectivity in defining the evaluation criteria relevance to obtain an effective and reliable procedure for solving decision-making problems without introducing unwanted conditioning,

The objective methodologies for determining the criteria weights do not consider the stakeholders' preferences but only exploit the information on the alternatives available in the decision matrix. Objective methods for determining the criteria weights analyse the distribution of attribute values among the options and define the relevance of the criteria by quantifying the level of discrimination of the alternatives that each of them achieves. This concept is in line with the principle of multi-criteria analysis, which establishes that it is not of interest a criterion to which all the alternatives have the same performance. In the dissertation, some of the most used objective methods for criteria weights calculation are studied: the Shannon entropy-based method, the variance method, the standard deviation method, and the CRITIC method.

The integrated (or hybrid) methods for determining the weights of the evaluation criteria are based on optimisation models whose solution offers the optimal value of criteria weights for the studied decision-making problem. These methodologies can be defined as hybrid or integrated as they allow to include preference information in their model to constrain the values that criteria weights can assume. The use of optimisation methods to define the criteria weights allows solving the decision-making problem even when only partial or incomplete information on the decision-making problem is available. In the dissertation, some of the most used integrated methods for calculating the evaluation criteria weights are studied: Ideal Point, maximising the deviation of attributes, correlation coefficient and the standard deviation of attributes.

In the context of the weighting methods, functional relationships have been proposed for aggregating the numerical value obtained independently through an objective and a subjective approach. Moreover, the global sensitivity analysis of the criteria weights is useful for analysing the stability of the result obtained. The stability of the result can be represented as the invariance of the best alternative indication or terms of invariance of the entire final rank. Identifying the range of values within which the weights can vary without determining a change in the final result allows estimating the stability and robustness of the solution suggested by the MCA method.

Decision theory approaches for multi-criteria analysis

The MCA-type approaches require defining the relevance of criteria considering the overall goal of the decision-making problem. This step is crucial for the evaluation process; the distribution of weights on the criteria strongly influences the analysis outcome. As described, various methodologies have been proposed in the literature for criteria weighting.

As discussed in the dissertation, the theoretical analysis and the application of the most established methods for determining the criteria weights show that there is no technique of absolute validity. The various weighting techniques are based on different hypotheses, each of which is reasonable; applying different techniques to the same decision-making problem may provide discordant results. In decision-making problems, no general law is evident that would lead to prefer one technique over the others. Therefore, the choice to use a particular technique to determine the criteria weights is an arbitrary choice of the analyst. Moreover, the reviewed criteria weighting methods indicate the best alternative considering only one specific condition. In fact, the analysed methods define a particular scheme of weights useful for identifying the dominant option; however, the validity of the solution obtained can be assessed only afterwards.

To overcome the issues related to criteria weights determination, the use of optimisation techniques in combination with Regret Theory rules is proposed in this dissertation. The proposed Regret Theory-based MC-CBA methodology aims to find the best alternative by eliminating the need for criteria weight definition. The result provided by the optimisation model built on a decision rule can consider the multiplicity of the possible points of view; partial information on the relevance of the criteria can be provided to limit the eligible region in the weight space in which the options are evaluated.

To identify the most suitable decision rule to be encompassed within an MCA framework, the review of the main Decision Theory rules is provided in the dissertation. The analysis examines the decision-making rules proposed in the literature and assesses their application in the context of the smart grid decision-making problem. Decision rules combined with optimisation techniques allow overcoming the decision-makers subjectivity in determining the relevance of the impacts. The thesis proposes an evaluation approach that eliminates the cognitive burden and personal biases introduced by the decision-makers and indicates the option characterised by the highest acceptance considering the audience of stakeholders.

The Regret-Theory-based MCA approach represents one of the contributions of the thesis.

MC-CBA combined approach for the appraisal of smart grid initiatives

As described, both CBA and MCA are relevant tools for appraising investment initiatives; both approaches allow for a comparative assessment of the different options. CBA shows some fundamental lack in evaluating decision-making problems involving a significant share of intangible impacts and externalities. If the effects of those elements are considered negligible, a CBA limited to the tangible effects can be addressed. Intangible impacts and externalities can be mentioned alongside the CBA result to provide additional information to the decision-maker. Conversely, if intangible impacts and externalities are majoritarian, it is necessary to include them within a structured assessment framework. MCA allows to evaluate mutually conflicting criteria; the main advantage of MCA is that it does not require expressing all impacts in monetary terms; therefore, all intangible impacts and externalities can be directly assessed. Therefore, MCA outclasses the highlighted shortcomings of the monetisation techniques applied to intangible impacts. In conclusion, the flexibility of the approach based on MCA allows to include the results of the rigorous CBA carried on monetary impacts. Therefore, a structured appraisal of the decision-making problem that includes the largest number of impacts is possible

As discussed, smart grids are recognised as a relevant mean to achieve several strategic objectives. Since smart grids are capital intensive and capable of generating relevant impacts on society, a tailored approach for estimating the costs and benefits of smart grid initiatives is desirable. Regarding appraisal approaches, the European policymakers ask for adopting frameworks based on CBA for assessing smart grid initiatives. Following the European Commission proposals, the Joint Research Centre (JRC) developed methodological guidelines for a CBA of smart grid initiatives to provide a common appraisal framework for all Member States. The JRC guidelines define a comprehensive assessment framework whose core is the CBA. The guidelines help tailor the analysis to the local conditions, identify and monetise costs and benefits, and perform the sensitivity analysis. The JRC approach is considered comprehensive because, besides the CBA, the guidelines provide support for identifying externalities and social impacts resulting from the implementation of smart grid projects that cannot be easily monetised and then included in the CBA.

The assessment framework provided by JRC is formed by an economic-oriented CBA tailored for smart grid initiatives that aim is to appraise costs, benefits, and externalities. In particular, the JRC CBA approach recognises that the smart grid impact goes beyond what can be captured in monetary terms. Therefore, the economic analysis (monetary appraisal of costs and benefits on behalf of society) is accompanied by a qualitative impact analysis (non-monetary appraisal of non-quantifiable impacts and externalities) which covers, in particular, the contribution towards the policy goals and the social impacts. However, the combination of the CBA and the qualitative impact analysis is not completely formalised.

Based on the JRC guidelines, an MC-CBA approach for smart grid project appraisal is proposed in the dissertation. The MC-CBA approach proposed follows and completes the recommendations provided by the JRC guidelines; the formalisation of the MC-CBA represents one of the contributions of the present dissertation. According to the JRC guidelines, the proposed approach decomposes the decision-making problem using a hierarchical structure of evaluation criteria. Three areas of interest are considered: economic effects, enhanced smartness of the grid, and externalities.

A mathematical procedure is proposed for solving in a systematic and automated way the decision-making problem modelled according to the MC-CBA approach. On the one hand, the main strengths of the procedure are the support provided to the decision-maker in analysing and decomposing the decision-making problem. Moreover, the decision-maker is supported in solving the decision-making problem since the high complexity related to the large number of options and criteria. On the other hand, the main drawback is represented by the requirement of eliciting the criteria weights. Determining the evaluation criteria relevance is crucial since the considerable influence that criteria weights have in defining the decision-making problem. To outclass this drawback, the MiniMax Regret rule of the Regret Theory is combined with the MC-CBA methodology. By taking advantage of the optimisation model built combining the decision rule and the MC-CBA aggregation function, the decision-making problem is solved without requiring the evaluation criteria weight elicitation.

However, the Regret Theory-based MC-CBA can include the preferences on the evaluation criteria relevance expressed by stakeholders in terms of constraints for the optimisation model

The MC-CBA framework for the assessment of smart grid initiatives represents a general-purpose support tool for the decision-makers in the smart grids context. It aims to support system operators and regulatory bodies for smart grid projects appraisal by complying with the novel context requirements.

Case studies on the application of the MC-CBA approach for the appraisal of smart grid initiatives

Four case studies are developed for presenting the use of the multi-criteria analysis and the MC-CBA approach for project appraisal in the smart grid context. In the four case studies presented, four different realisations of the combined appraisal approach proposed in this dissertation are illustrated. In all case studies, the planning alternatives include flexibility measures that compete with traditional network reinforcement.

The first case study concerns the use of the multi-criteria analysis to the decision-making problem in which the options, based on the flexible distribution system planning, belong to a vast Pareto set. Flexibility providers are distributed energy storage devices.

The second case study concerns the application of the MC-CBA approach to a similar case study in which flexibility is provided by distributed energy storage devices and compete with network reinforcement.

The third case study is an evolution of the second one. The third case study investigates the influence of the weighting technique in the result of the MC-CBA approach. Moreover, the third case study presents the application of the Regret Theory-based MC-CBA approach proposed in this dissertation.

The fourth case study concerns the analysis of distribution planning initiatives in which several planning approaches are compared. The traditional *fit and forget* approach is compared with a probabilistic *fit and forget*, the use of storage flexibility, and the use of flexibility from generators and loads. The comparative analysis uses the proposed MC-CBA approach based on the Regret Theory-based MC-CBA methodology.

The four case studies presented aim to provide proof of concept for the use of the MCA-based methodology on the decision-making problems regarding the future distribution sector. Due to the new functionalities and services introduced by the smart grid paradigm and the use of the flexibility provided by third-party owned assets connected to the grid, the impacts caused by upgrading plans for the distribution cross the power system borders. More interests than the ones of the DSO proposing the upgrading plan are involved.

The novel functionalities and services enabled will influence daily-life habits and create new business opportunities. Therefore, it is of utmost interest to improve the distribution sector planning activities by broadening the assessed impacts. In distribution system planning initiatives in which flexibility competes with network expansions, more criteria than minimising reinforcement costs have to be considered for selecting the most valuable planning alternative.

Conclusions

This thesis investigates the topic of the ongoing power system transformation by focusing on the distribution system. The massive diffusion of non-programmable renewable energy sources dispersedly connected to the distribution system causes severe operation problems. It gives a leading role to the flexibility of demand, generation, and grid infrastructure. Facing the consequences of the power system transformation at a reasonable cost by taking advantage of the available opportunities without jeopardising the electric supply's security and quality requires updating the planning and operation practices.

In this context, the thesis aims to contribute to the appraisal of smart grid initiatives obtained from innovative methodologies to distribution system planning. An approach for the appraisal of smart grid initiatives based on the combination of multi-criteria analysis and cost-benefit analysis (MC-CBA) is proposed to contribute to the distribution sector planning. The MC-CBA approach follows and completes the international JRC guidelines recommendation. Furthermore, the dissertation presents a mathematical procedure for solving the decision-making problem systematically and automatedly. The scientific novelty of the proposed MC-CBA approach is the formalisation of the JRC guidelines for smart grid project assessment; it represents one of the contributions of this dissertation.

A further contribution of this thesis is the proposed Regret Theory-based MC-CBA methodology, which is an evolutionary step of the presented MC-CBA approach. The Regret Theory-based MC-CBA methodology indicates the best alternative by eliminating the need for criteria weight determination. The result provided by the optimisation model built on the decision rule considers the multiplicity of the possible points of view; partial information on the relevance of the criteria can be provided to limit the eligible region in which the alternatives are evaluated.

The case studies developed present the use of the multi-criteria analysis and the MC-CBA approach for project appraisal in the smart grid context. In all case studies, the planning alternatives include flexibility measures that compete with traditional network reinforcement.

The research activity on the decision-making support for the smart grid initiatives appraisal has represented part of the Italian contribution to the International Smart Grid Action Network (ISGAN) Annex 3. ISGAN Annex 3 is devoted to cost-benefit and socio-economic analyses of smart grids and related regulatory policies. From these analyses, toolkits and recommendation are developed to inform smart grid policy at global, regional, national, and sub-national levels and deployment priorities at the project- and utility-scales. In this context, the research activity presented in the dissertation led to the development of the software version of the MC-CBA framework, which is available online at https://smartgrideval.unica.it/ .

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The work of this thesis was carried out during my time as a PhD student at the Department of Electrical and Electronic Engineering of the University of Cagliari from 2017 to 2020. I take the opportunity to express my gratitude to several people who strongly supported me throughout the course PhD period.

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I would like to express my heartfelt thanks to my parents Alessandra and Enrico. Thanks for the love and care you gave me. I also want to thank Paola for her indispensable support and patience in this last period.

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LIST OF PUBLICATIONS

This dissertation describes the main outcomes of the research activity carried out during the doctoral degree period, part of the contents of this document are based on the following published papers done in collaboration with other researchers. The content in this dissertation is strictly related to the activities described in publication n. 1, n. 4, and the mentioned technical reports and discussion papers co-authored.

1 Celli, G.; Chowdhury, N.; Pilo, F.; Soma, G.G.; Troncia, M.; Gianinoni, I.M.
Multi-Criteria Analysis for decision making applied to active distribution network planning
Electric Power Systems Research, 2018, 164: 103-111.
DOI: https://doi.org/10.1016/j.epsr.2018.07.017

2 Pilo, F.; Pisano, G; Ruggeri, S.; Troncia, M.
Data analytics for profiling low voltage customers with smart meter readings
Applied Sciences. 2021; 11(2):500
DOI: https://doi.org/10.3390/app11020500

3 Troncia, M.; Galici, M.; Mureddu M.; Ghiani E.; Pilo F.
Distributed Ledger Technologies for Peer-to-Peer Local Markets in Distribution Networks
Energies 2019, 12 (17), 3249
DOI: https://doi.org/10.3390/en12173249

4 Troncia, M.; Chowdhury, N.; Pilo, F.; Gianinoni, I.M.
A joint Multi Criteria-Cost Benefit Analysis for project selection on smart grids
2018 AEIT International Annual Conference, Bari, Italy, 3-5 October, 2018
DOI: https://doi.org/10.23919/AEIT.2018.8577399

5 Pisano G.; Pilo F.; Ruggeri S.; Troncia M.
LV Customers Modeling Impact on Microgrid Optimal Management
2020 2nd IEEE International Conference on Industrial Electronics for Sustainable Energy Systems (IESES)
DOI: https://doi.org/10.1109/IESES45645.2020.9210703

6 Pisano G.; Pilo F.; Troncia M.
Models characterizing the final electricity demand
CIRED 2020 Berlin Workshop

7 Celli G.; Ghiani E.; Natale N.; Mocci S.; Pilo F.; Pisano G.; Ruggeri S.; Troncia M.
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NOMENCLATURE

AC	Alternating Current
ADN	Active Distribution Network
ADS	Active Distribution System
AHP	Analytic Hierarchy Process
AMI	Advanced Metering Infrastructure
ARERA	Italian Regulatory Authority for Electricity Gas and Water
BaU	Business as Usual
BRP	Balance Responsible Party
CAPEX	Capital Expenditure
CBA	Cost-Benefit Analysis
CBR	Cost-Benefit Ratio
CCS	Carbon Capture and Storage
CCSD	Correlation Coefficient and the Standard Deviation
CEM	Clean Energy Ministerial
CHP	Combined Heat and Power
COP21	2015 United Nations Climate Change Conference
CR	Consistency ratio
CRITIC	Criteria Importance Through Intercriteria Correlation
DC	Direct Current
DER	Distributed Energy Resource
DES	Distributed Energy Storage
DM	Decision Matrix
DSO	Distribution System Operator
DT	Decision Theory
EC	European Commission
ELECTRE	*ELimination Et Choix Traduisant la REalité*
ENEL	Ente Nazionale per l'energia Elettrica (National Entity for Electricity)
EPRI	Electric Power Research Institute
EU	European Union
FAA	Full aggregation approach
FACTS	Flexible AC Transmission System
FFR	Fast Frequency Response
GAA	Goal, aspiration, or reference level approach
GHG	Greenhouse Gas
HV	High Voltage
HVDC	High Voltage Direct Current

ICT	Information Communication Technology
IEA	International Energy Agency
IEM	Internal Electricity Market
IRR	Internal Rate of Return
ISGAN	International Smart Grid Action Network
JRC	Joint Research Centre
KPI	Key Performance Indicator
LAM	Linear Additive Model
LV	Low Voltage
MACBETH	Measuring Attractiveness by a Categorical-Based Evaluation Technique
MADM	Multi-Attribute Decision Making
MAUT	Multi-Attribute Utility Theory
MCA	Multi-Criteria Analysis
MC-CBA	Multi-Criteria - Cost-Benefit Analysis
MGD	Maximising the Generalized Deviation
MMR	MinMaxRegret
MODM	Multi-Objective Decision Making
MV	Medium Voltage
NECP	National Energy and Climate Plan
NPV	Net Present Value
OA	Outranking approach
OLTC	On Load Tap Changer
OPEX	Operational Expenditure
PC	Policy Criterion
PDF	Probability Density Functions
PM	Performance Matrix
PROMETHEE	Preference Ranking Organization METHod for Enrichment Evaluation
PSS	Power System Stabiliser
PST	Phase Shifting Transformer
PV	PhotoVoltaic
REMBRANDT	Ratio Estimation in Magnitudes or deci-Bells to Rate Alternatives which are Non- DominaTed
RES	Renewable Energy Source
RSO	Relevant System Operator
SAIDI	*System Average Interruption Duration Index*
SAIFI	*System Average Interruption Frequency Index*
SCBA	Social Cost-Benefit Analyisis
STATCOM	STATic synchronous COMpensator

SVC	Static Var Coompensator
TCP	Technology Collaboration Programme
TOPSIS	Technique of Order Preference Similarity to the Ideal Solution
TOTEX	Total Expenditure
TSO	Transmission Systems Operators
UNFCCC	United Nations Framework Convention on Climate Change
UPFC	Unified Power Flow Controller
US	Utility Score
VSC	Voltage Source Converter
WTA	Willingness to Accept
WTP	Willingness to Pay

1 INTRODUCTION

1.1 Dissertation overview

Climate change represents one of the main concerns of our modern society [1], [2]. The severe consequences due to the expected increased frequency and intensity of extreme weather events pushed international political agreements to improve the environmental sustainability of our society [1]–[3]. Concepts such as energy efficiency, use of renewables, and circular economy have been introduced and will determine a drastic transformation in the way the energy is generated and used [1], [2].

The energy sector, and particularly the electricity sector, are pivotal in the path toward a climate-neutral society [2]. Traditionally, the demand for electric energy has been supplied by large hydro-thermal power plants which power generation have always been adapted accordingly. The use of renewable energy sources such as wind and solar require to change this paradigm, the demand for electricity has to follow energy production, the electricity demand has to be flexible. Furthermore, the energy transition requires the power system to face profound changes. Energy consumption and generation, as well as the grid infrastructure, have to be flexible, the power system has to assume a decentralised structure and be integrated with other sectors such as transportation and cooling and heating. All customers connected to the electrical grid have to contribute to the power system management and be able to participate in the related markets. The power system has to become smart; all technical and market processes have to be digitalised to enable new functionalities and services [4], [5].

The undergoing power system transformation requires rethinking planning and operation practices to accommodate the changes and take advantage of the related opportunities. The novel features and services available in the active and flexible power system will influence the customers' daily habits; therefore, the impacts generated by planning initiatives will cross the power system borders by impacting on society as a whole. Therefore, novel approaches for the appraisal of project initiatives are required since the traditional tools used, typical of the private sector, are no longer effective due to several fundamental flaws. Decision-makers have to be supported with valuable tools capable of capturing the complexity of the future power system in which flexibility measures compete with grid expansion.

This thesis addresses the topic of the ongoing power system transformation by focusing on the distribution system, which will face unprecedented changes due to the advent of distributed energy sources fed by renewables and new loads due to the trending electrification of consumes. This thesis concerns the necessary changes required for the planning activities and the related appraisal of the possible planning options. The contribution of the thesis is to provide decision-making support tools for strategical power system planning, especially regarding the smart grid initiatives. The research activities described in this document have been aimed at supporting system operators and regulatory bodies by providing tools for smart grid project appraisal considering novel context characteristics.

This document is organised as follows.

The first chapter describes the motivation of the research activity, the reasons, the consequences, and the challenges of the ongoing power transformation are illustrated. Finally, the objectives and the contribution of this dissertation are presented.

The second chapter discusses the electric power system; the traditional structure is described as well as the characteristics of its recent and future evolution. The smart grid paradigm is introduced, the concept of flexibility is described and discussed in technical terms from the distribution system perspective. Then the traditional and future practices of distribution system planning practices are described to highlight strengths and challenges, such as the requirement for novel approaches to project appraisal.

The third chapter is devoted to the decision-making support tools for project assessment. The Cost-Benefit Analysis and Multi-Criteria Analysis are discussed in detail to underline the strengths and weaknesses of this approach in the context of smart distribution planning. An extensive survey of the most acknowledged methodologies for Multi-Criteria Analysis is presented to identify the features of the different approaches.

The fourth chapter is focused on the techniques for modelling in terms of numerical weights the relevance of the criteria used for project appraisal with Multi-Criteria Analysis. In this chapter, the most acknowledged subjective, objective, and integrated methodologies for computing the evaluation criteria weights are reviewed. Techniques for aggregating weights obtained according to different weighting techniques and for studying the stability of the available ranking are also discussed.

The fifth chapter discusses the exploitation of decision rules from Decision Theory within a Multi-Criteria Analysis framework. The most acknowledged decision rules are reviewed and analysed in light of compliance with the Multi-Criteria Analysis problem. This chapter proposes a novel approach that combines the minimax regret rule and the linear full aggregation approach for Multi-Criteria Analysis. The proposed approach takes advantage of an optimisation model to produce the result of the decision-making problem without requiring criteria weights as input parameters.

The sixth chapter is focused on the topic of project appraisal made combining Multi-Criteria Analysis and Cost-Benefit Analysis. First, the features of the two approaches are described for highlighting their compliance. Then, the European guidelines on smart grid project assessment are studied to capture relevant key messages and suggestions. Finally, the project appraisal approach that combines Multi-Criteria Analysis and Cost-Benefit Analysis is proposed in that chapter. The mathematical procedure is formalised and described in detail.

The seventh chapter presents the four case studies developed for demonstrating the effectiveness of the combined project appraisal approach described in chapter six. Four case studies illustrate four different realisations of the combined appraisal approach proposed in this dissertation. All case studies involve the project selection problem in which the planning alternatives are characterised by the competition of network reinforcement measures with the flexibility offered by storage devices, distributed generators, and controllable loads.

Finally, the eighth chapter resumes the key messages from the research activity on which this dissertation is based and presents the concluding remarks.

1.2 Climate policies as primary drivers of the electricity sector evolution

Nowadays, one of the most significant concerns is climate change since the severe consequences expected in terms of increased frequency and intensity of extreme weather events that would undermine productivity, infrastructures, health, biodiversity, ability to produce food, and political stability [1], [2]. Unprecedented international initiatives have been proposed to face risks and threats expected due to climate change; in 2015, the United Nations Climate Change Conference (COP21) led to the Paris Agreement, which represents a legally binding international treaty on climate change [3]. In this context, the commitment of the European Union (EU) to the secretariat of the United Nations Framework Convention on Climate Change (UNFCCC) is characterised by the definition of a long-term strategy aimed at achieving net-zero greenhouse gas emissions (GHG) by 2050 though a cost-efficient and socially-fair transition [1], [6]. The energy sector is responsible for more than 75% of the overall EU GHG emission; therefore, the European Union energy policy plays a crucial role in achieving the stated objective [1], [2].

The EU strategy for fulfilling the commitment to the Paris Agreement prescribes that each Member State defines its national mid-century long-term plan for reducing GHG emissions [1], [2], [6]. These national mid-century long-term plans are in addition to and have to harmonise the national energy and climate initiatives for 2021-2030 already established by the EU regulation [7], [8]. Since this commitment, the UE and the Member States have the aspiration to lead the global transition toward a climate-neutral society by leveraging economic growth opportunities, new business models, markets, jobs, and the technological development that the long-term plans would trigger [6]. Within the EU climate commitment, the Member States have to choose the mix of energy sources and technology that best fits the internal context to guarantee energy security and competitiveness [6].

The ambitious objective of the EU strategy of achieving a net-zero GHG emission economy by 2050 requires radical changes in crucial sectors such as energy, transport, industry, and agriculture [1], [2]. The initiatives that will impact these sectors concern citizens' empowerment, the strategical coordination of industry, finance, research, and the adoption of existing and emerging technology solutions [9]. The initiatives proposed by the EU strategy can be classified into seven blocks [9].

1. Energy efficiency.
   Maximisation of the benefits of the energy efficiency measures in all sectors.
2. Deployment of renewables.
   Maximisation of renewable energy sources use and electrification of the demand.
3. Network infrastructures.
   Development of smart and highly interconnected network infrastructures.
4. Mobility.
   Achieving a clean, safe, and connected mobility.
5. Circular economy.
   Introduction of the circular economy paradigm while preserving industry competitiveness.
6. Bio-economy and Natural carbon sinks.
   The exploitation of renewable biological resources from land and see to produce food, materials, and energy [10]. Creation of carbon sinks such as forests and other ecosystems for absorbing the emitted GHG.
7. Carbon Capture and Storage (CCS).
   Adoption of CCS technologies to avoid residual GHG emissions.

The overall goal of the *Energy efficiency* measures package is to half the energy demand to 2050 in reference to 2005 [2]. New technologies, digitalisation, home automation, and new standards will be introduced to increase the energy efficiency already achieved thanks to the previous measures such as eco-design and energy labelling [9]. Energy efficiency supports the decarbonisation of the industrial and building sectors since the reduced primary energy demand. Considering the building sector, new energy performance standards, including the zero-emission concept, are introduced. Renovation of existing buildings has to be based on energy sustainability principles that consider renewables sources for heating and cooling, the exploitation of efficient appliances, the introduction of smart management systems, and passive solutions such as improved insulation [9]. Financial instruments, a qualified workforce, and consumer engagement are required for achieving the energy efficiency target [9]. Moreover, since the extensive use of renewable resources and new electric loads, relevant impacts are expected on the electric power system.

The initiatives of the *Deployment of the renewable* objective have the ambition to make renewables the main primary energy source. Besides supporting GHG emissions reduction, this objective also has strategic and geopolitical relevance since it will reduce the share of imported energy from 55% to 20% in 2050 [9]. The increased share of renewable energy production will increase the overall electricity production, which renewable energy sources will cover 80% of the overall electrical energy generated in the EU [9]. Moreover, it is expected that electrical energy will represent half of the final energy consumption in 2050, leading to the increased electrification of the final energy uses [9]. Regarding the present electrical energy production, the future electrified consumption requires increasing the electrical energy production up to 2.5 times [9]. The *Deployment of the renewable* objective concerns initiatives such as the electricity system decentralisation, local energy communities, customer participation in markets, the introduction of e-fuels, and electrification of transport, climatisation, and industry. Moreover, it is also envisioned increased regional interconnectivity, the exploitation of large-scale energy storage, and demand response policies trough digitalisation to make the electric grid more flexible [2], [9].

The *Network infrastructure* objective concerns the realisation of smart and interconnected network infrastructures to increase cross-border cooperation and sector coupling [9]. Besides the increased cross-border links within Europe, the *Network infrastructure* objective considers electric transmission and distribution network and their interaction with communication networks, and in general, the intensification of the sector-coupling initiatives for enhancing the effectiveness of the energy use among different sectors (e.g., electricity and transport, electricity and gas) [2].

The *Mobility* objective regards the realisation of a sustainable mobility system composed of low or zero-emission vehicles (e.g. electric vehicles). The fulfilment of the *Mobility* objective also would reduce air pollution, traffic noise, and accidents [9]. Moreover, the measures of the *Mobility* objective concern climate-neutral e-fuels (e.g. hydrogen and biogas) in heavy-duty vehicles, shipping, and aviation [9]. Furthermore, the adoption of smart traffic management systems is promoted to obtain a more efficient transportation sector through digitalisation and data sharing.

The focus of the *Circular economy* objective is the massive introduction of effective recycling practices for steel, glass, and plastic without jeopardising the EU industrial sector competitiveness [9]. Digitalisation and automation are the key processes to modernise industrial facilities and reduce GHG emissions. The modernisation of the industrial facilities also includes the electrification of production chains and the introduction of climate-neutral e-fuels and CCS technologies [9].

The *Bio-economy and Natural carbon sink* objective regards adopting sustainable practices for producing food, feed and fibre to relieve the problems caused by the increasing demand for goods and the parallel decreasing productivity due to climate-change consequences. [9]. Biomass combined with CCS systems is identified as the measure for heating and producing biogas and biofuels [9]. The use of synthetic additives and methane production has to be reduced in the agricultural sector [9]. Digitalisation and the introduction of precision farming technologies are considered to increase productivity [9]. Carbon sinks obtained through afforestation and restoration of degraded forest lands and similar ecosystems would negatively impact emissions.

The *Carbon Capture Storage* block represents the last resort to capture emissions that could not be eliminated. CCS technology can also support the production of hydrogen [9].

Adequate policies to foster synergies among the different sectors are required to maximise the effectiveness of the EU strategy. Mutually conflicting objective as to be considered in finding the most valuable compromise. Commercial and trading rules have to guarantee fairness and competitiveness while ensuring compliance with climate goals [9]. The externality costs have to be adequately considered to avoid the unfair distribution of the energy transition burden [9]. In the EU energy strategy, society is pivotal since the empowerment of citizens and their active involvement in future business models. The achievement of the EU climate goal also depends on adopting more sustainable lifestyles [9]. Furthermore, the transition to a zero-carbon society needs to foster research and innovation to make available the required technologies [9].

As already mentioned, the Member States are required to prepare and submit the long-term national strategies for 2050. The long-term plans are focused on the strategies for reducing the GHG emissions, which have to be consistent with the common EU target and the seven blocks illustrated. Therefore, the mid-century long-term plans have to focus on reducing the total GHG emissions in the main sectors such as electricity, industry, transport, heating and cooling, buildings sector (residential and tertiary), agriculture, waste, and land use [11]. Moreover, the long-term national plans have to analyse the socio-economic impact of the decarbonisation measures [11].

1.3 The transformation of the electricity sector

As highlighted by the EU strategy, the energy sector, and particularly the electricity sector, is pivotal in the path toward a climate-neutral society. The decarbonisation of the economy calls for an energy transition which requires an evolution of the power system planning and operation practices. Several global trends that would determine the future electric power system have been identified: decarbonisation, decentralisation, integration, digitalisation, and inclusion [4], [5].

The *decarbonisation* trend concerns the reduction of GHG emissions related to the electricity supply. As a primary energy source, fossil fuels have to be substituted with renewable energy sources and a more energy-efficient power system has to be achieved. The related market mechanisms have to allow close to real-time responses [5]. Therefore, flexibility in energy production and use have to be fully enabled.

The *decentralisation* trend involves the transition from the centralised production of electric energy from large power plants to the decentralised energy generation from small and dispersed electric power sources [4]. According to a distributed control scheme, small solar photovoltaics and energy storage devices connected to the distribution system have to be coordinated with flexible loads for enabling self-consumption and local markets mechanisms for prosumers and consumers [5].

The *integration* trend matters the creation of integrated electricity markets, the interconnection of independent grids, energy systems, and sectors [4], [5]. Integration is meant spatially as well as concerning the trading and operation activities. Independent grids and electricity markets have to be combined in a unique interconnected power system in which the actor competes, enabling cross-border trading. Moreover, planning and operation activities have to be coordinated. Moreover, the integration trend concerns sector coupling considering, in particular, the electricity, transport, and heating and cooling sectors [5].

The *digitalisation* trend regards the extensive use of information and communication technologies (ICT) to take advantage of extensive data availability [4], [5]. The ICT can facilitate the planning and operation of the power system, enable new functionalities and services, improve the sustainability of using the electricity, increase transparency and fairness of market mechanisms.

The *inclusion* trend embraces the increasing demand for universal access to sustainable and affordable energy. It would come with increased electrification of energy use, particularly in the transportation and industrial sectors [4]. The increased electrification and the urbanisation needs require demand-side solutions and sector coupling [5].

Accommodating these trends represents a big challenge for the electricity sector; profound changes in the power system are required to guarantee the security and reliability of the power supply. Since the increased use of the assets will bring the power system operation closer to its critical limits, it is crucial for the future electricity system to achieve an effective quantification and management of uncertainties [4]. A better knowledge of the actual operational state of the power system is fundamental for frequency, voltage, and rotor angle stability [4], [12]. It can be achieved by enhancing the accuracy of measurements and models for forecasting the load and generation behaviour [4]. The considerable share of renewable energy sources connected to the power system thought a power electronic interface and the reduction of the presence of traditional power plants equipped with the synchronous generator would lead to a considerable reduction of the rotating inertia [4], [13], [14]. In this context, the dynamic response of the power system dramatically changes, and new operating practices and novel additional sources of inertia are required for preserving the stability of the electricity supply [4], [13], [14]. The presence of a high share of distributed generators fed by volatile renewable energy sources and the emergence of new loads due to the electrification of mobility and heat and cooling produce new electricity utilisation patterns [4]. Consequently, the net-load of the power system is characterised by increased uncertainty and variability, which undermine the effectiveness of the traditional planning and operation approaches [13].

Therefore, the main factors to be taken into account considering the power system transformation triggered by the climate goals are the availability of affordable wind and solar electric energy sources, the decentralisation of the electric energy production, the advent of new loads due to electrification policies, and the digitalisation which enables cost reductions, new functionalities, and contributes in improving system resiliency [15], [16].

Facing the consequences of the power system transformation at a reasonable cost by taking advantage of the available opportunities without jeopardising the security and quality of the electric supply requires to updated the planning and operation practices. Drastic changes are necessary for unlocking the already available power system flexibility and for introducing new flexibility sources [4], [13], [15]. Flexibility represents a cost-effective measure for compensating the variability and uncertainty introduced in the power system by the renewable energy sources and the new loads [15]. Enhancing flexibility is considered an alternative to network reinforcement since it may lead to reduce or indefinitely defer network investments [17]. Flexibility is useful for balancing the supply and demand of electric energy at any timescale; in regular operation, it allows to counterbalance the variability of loads and generation [15]. Furthermore, flexibility improves system resiliency since it can be exploited in emergency scenarios such as large generator loss, outages, and extreme weather events [15]. In this context, traditional approaches based only on network reinforcement would require unsustainable investments for facing normal and emergency conditions [18]. Therefore, flexibility is seen as the fundamental tool to achieve a more secure, resilient, affordable, and sustainable power system [15].

Flexibility is a general term that concerns the ability of the power system to manage changes. To enable the flexibility of the resources, several layers are involved: the technical layer that includes the hardware and infrastructure involved, the policy, regulatory, and market layer that concerns the technical rules and the economic incentives, and the institutional layer that regards the roles and responsibilities of the actors involved in flexibility [4], [15]. From a technical point of view, flexibility is related to the availability of generators, loads, and network assets that are able to modify their behaviour for complying with operational needs [13]. Therefore, flexibility involves both action and measures which pertain to the system operator assets and the participation of connected assets such as generator, loads, and storage which third parties own. The introduction of flexibility in the power system represents a significant paradigm change; traditionally, the electricity system has been based on the load following paradigm; hence, the inflexibility of the electricity demand [17]. Moreover, the distributed generators fed by renewable connected in the last decades have not been involved in the power balancing mechanism; therefore, the related generation could also be considered inflexible [19], [20]. Thus, the whole burden of achieving the power balance and managing voltage control has been on system operators and the synchronous generators of large power plans. The introduction of flexibility implies the involvement in grid management of users that have historically played a passive role. The introduction of flexibility in the power system requires to inflexible generation and demand to be flexible; therefore, significant changes are expected in the way electricity is generated, stored, distributed, and used. Since the novelty of the topic and the relevance of the consequences on the habits of utilising the electricity supply, innovative approaches for designing and assessing the initiatives of upgrading the power system are required.

1.4 Transformation of distribution system planning and project appraisal practices

To foster the power system transformation, political drivers, such as the Clean Energy for All Europeans package, require network and system operators to regularly submit a transparent development plan in which have to be specified the innovative assets and services which will be used for enabling the system flexibility to maximise the exploitation of the existing infrastructure [21]. In these development plans, flexibility (e.g. generation management, demand-side management, system reconfiguration) have to compete with traditional network reinforcement; hence, a reliable approach for project appraisal which allows comparing the different measures is of utmost interest [13], [22], [23].

In the distribution system, flexibility is intertwined with the Active Distribution Network (ADN) concept that describes a distribution network in which the Distribution System Operator (DSO) can manage the electricity flows by exploiting a flexible network topology and the distributed resources (loads, generators, storage) which have some responsibility in terms of system support [24]. Flexibility in the distribution system is also tied with the smart grid concept, which describes an electricity network that integrates all connected users' behaviour and actions to ensure an economically efficient, safe, secure, and sustainable energy supply [25].

In smart active and flexible distribution systems, characterised by the active network management and the exploitation of the flexibility from connected users, the traditional planning approach, named *Fit and Forget,* based on traditional network reinforcement (e.g., building new lines and substations and upgrading the existing ones) is no longer effective. The opportunities from the active management of the distribution network and the exploitation of the flexibility can maximise the exploitation of the existing grid infrastructure and produce more cost-effective solutions if uncertainties are adequately managed [22], [24]. Moreover, in smart distribution systems, the multiplicity of flexible solutions that can be exploited increases the complexity of the planning process, which has to satisfy more goals than the cost minimisation constrained by the quality of supply. Therefore, modern distribution planning should be based on multi-objective approaches that can analyse, make compromises and select solutions among different alternatives [22], [24]. To illustrate, the planning option to be developed has to achieve a satisfactory level of performances in terms of energy losses, hosting capacity, self-healing, cyber-security, reduced emissions, customer participation [26]. Therefore, distribution planning requires considering objectives such as maximise hosting capacity, reduce energy losses, improve service quality, reduce capital expenditure (CAPEX) and operational expenditure (OPEX) [27].

Smart active and flexible distribution systems will enable novel features and services that influence customers' daily habits; therefore, the impacts generated by smart grid initiatives will cross the power system borders by impacting society as a whole. Thus, the complexity of the impacts generated by the smart grid initiatives makes them closer to public sector investments, which traditional approaches used for project appraisal in the private sector show several fundamental shortcomings [27]–[29]. Traditionally, the planning options are assessed using economic-based tools (i.e., Cost-Benefit Analysis – CBA) that require converting all project impacts in monetary terms. These methodologies are acknowledged tools for considering only costs and benefits that can be directly monetised. In contrast, the appraisal of projects showing broad effects and non-negligible intangible impacts shows some underlying shortcomings related to quantifying, monetising, and discounting the impacts [28]. In this context, the project selection process is biased. In fact, CBA is based on welfare economics principles [30], as the underlying hypothesis assumes people as consumers and considers goods and services as exchanged within a market [28]. In the private sector, tangible impacts are majoritarian, and the investor target is to maximise profits. Conversely, in the public sector initiatives, people are involved as citizens, and the offered goods and services do not have a market [28]. Moreover, intangible impacts are not negligible, and the main investor goal is to maximise the efficiency and the effectiveness of the investment [28]. Since these fundamental differences, CBA used in the public sector is not directly applicable: the required adjustments on quantifying, monetising, and discounting techniques weaken the CBA validity [28].

Planning is a decision-making activity that requires assessing a set of feasible investment options for identifying the best one. Typically, the optimal solution has to achieve a comfortable performance level on several conflicting criteria by minimising the related cost. Since those goals can be mutually conflicting, the decision-maker has to make trade-offs considering the stakeholder perspective. In the planning processes, Multi-Criteria Analysis (MCA) has been introduced in several sectors (e.g., transportation and environment) to consider sustainability aspects and improve the effectiveness of the process [31]. Similarly, planning in the context of active network and flexibility provision is a complex task since the multiplicity of objectives, conflicting interests of the stakeholders, and the wide range of impacts to be accounted as externalities. Even if services and impacts can have a related cost, the monetisation procedure may distort their actual relevance for the specific planning process. In this context, the need is for more transparent and objective output-based project selection approaches. Therefore, shifting from a traditional economic-based assessment to new assessment tools is recommended [22], [23].

In Europe, several guidelines have been released to promote the use of a multi-criteria framework on smart grid project assessment [32]–[35]. MCA is an operation research tool for complex decision making [36]. Among MCA methods, Multi-Attribute Decision Making (MADM) methods help in identifying the best option among an explicitly known set [37]. MCA allows for appraising heterogeneous and conflicting criteria: tangible and intangible impact can be simultaneously evaluated. Unlike CBA, MCA allows considering the impacts directly; the monetising procedure that introduces an undesired latent point of view is avoided. In addition, the uncertainties related to monetary conversion are prevented. Furthermore, the stakeholder point of view is directly involved in the evaluation process by means of the definition of criteria relevance, transparency on the project selection process is provided [36]. In fact, the consequences of a change of the analysis perspective are clear, as the stakeholders' point of view influences only the evaluation criteria relevance and not also the impact metrics. These features make MCA suitable for strategic decision-making within the public sector; however, no explicit rule such that benefits must exceed costs exists (Kaldor-Hicks criterion). Hence, the identified best option may not purse well-being improvement: the "doing nothing" principle might result preferable [36].

Nevertheless, MCA and CBA are not conflicting tools; the joint use can combine their strengths by mutual compensating their respective weaknesses [31], [38]. On the one hand, MCA lacks on imposing that overall benefits have to exceed costs; therefore, unlike CBA, MCA may be unable to identify the most cost-effective options [36]. On the other hand, MCA is a systematic approach that helps the decision-maker in finding the preferred solution among a set of options considering multiple conflicting criteria without requiring the conversion in monetary terms. Therefore, MCA and CBA can be combined in a unique approach for project appraisal to fill the respective gaps while preserving the individual strengths. Assessment approaches that combine MCA and CBA are promoted both at an academic and regulatory level on several sectors [29], [32], [39] and proposed in the literature [31], [38], [40]–[46].

1.5 Objectives and contributions

In this thesis, to contribute to the appraisal of smart grid initiatives, a combined MC-CBA assessment framework is proposed. The proposed framework is based on international recommendations and guidelines on project analysis; it allows for a systematic and simultaneous assessment of different impacts. Within the MCA framework, the economic criterion evaluates the result of a CBA focused on monetised impacts. Conversely, other tangible and intangible impacts are appraised through several evaluation criteria defined according to MCA principles. The overall assessment of each planning option is obtained by combining the results obtained from the monetary evaluation and the non-monetary one. The assessment methodology is based on the Analytical Hierarchy Process (AHP) [47], which has been automated for reducing subjectivity biases. Moreover, the decision rules of Decision Theory have been investigated, and an MCA approach based on the minimax regret rule [48] is proposed for eliminating the cognitive burden related to the elicitation of criteria relevance. The proposed MC-CBA methodology aims to provide a decision-making tool that supports both system operators and regulatory bodies for smart grid projects assessment by complying with the novel context requirements.

To present the MC-CBA assessment framework, four case studies focused on the decision-making problem of smart grid planning alternatives are described. Three case study focus on the comparison of several initiatives which involve traditional network reinforcement and the provision of grid services and flexibility from energy storage devices. The fourth case study also considers initiatives that include the exploitation of the flexibility from distributed generators and demand response. The aim is to discuss the characteristics of a project assessment that considers the impacts produced by the smart grid initiatives expressed not only in monetary terms.

In conclusion, the contribution of the thesis is to provide decision-making support tools for strategical power system planning, especially regarding smart grid initiatives. The research activities described in this document have been aimed at supporting system operators and regulatory bodies by providing tools for smart grid project appraisal considering novel context characteristics.

2 THE ELECTRIC POWER SYSTEM

This chapter is devoted to the electric power system. First, an overview of the structure and on the main components of the power system is provided. Then, the evolution of the electric power system from its early years to the current changes is described. The advent of the smart grid and flexibility concepts are discussed in light of the profound changes required in the planning and operation practices of the distribution system. Traditional and future planning approaches for the distribution system are described. The use of multi-criteria analysis in distribution system planning is discussed.

This chapter aims at answering the following questions:

- What is the electric power system?
- What does it mean that the power system structure is evolving?
- What is the meaning of smart grid and flexibility?
- How has the distribution system been planned since now?
- How the distribution system has to be planned in the future?
- What advantages Multicriteria analysis brings to distribution system planning?

2.1 The electric power system structure

The electric power system is the most extensive human-made system ever made [49]. The power system is spread worldwide and is formed by several subsystems constituted by a broad number of different components (e.g., overhead lines, cables, switches, generators, machines, electronic devices).

The electric power system is mainly operated as a three-phase alternating current (AC) system in which the voltage value imposed is constant [50]. The single-phase configuration is used for supplying small loads such as residential and commercial users.

Conventionally, the power system is considered formed by a hierarchical structure of several layers.

- Generation;
- Transmission;
- Distribution;
- Consumption.

The generation layer comprises all the necessary devices to generate electric power. Historically the generation layer has coincided with a relatively small number of large power plants located in the specific areas located far away from the consumption areas. The electric power generation in traditional generation facilities exploits mechanical energy conversion with rotating electrical machines characterised by voltages values at the terminals in the range of 11 to 35 kV [12], [50]. The generated electric power is injected into the transmission system through step-up transformers to increase the voltage level. Nowadays, electric power is also produced by small scale generators (e.g. photovoltaic systems, combined heat and power generators, fuel cells, small wind turbines, among others) located close to loads centres; therefore, since the size and location of these new-generation devices, these distributed resources are not connected to the transmission system but the distribution system [12].

The transmission system transports the electric power over long distances; it interconnects large power plants situated in the dedicated generation areas to the substations close to the consumption areas [12]. Since the long distances to be covered, the transmission system is operated at the highest voltage levels (i.e. 220 kV and higher) [50]. Typically, the transmission system topology is meshed; the main components are the overhead lines, power cables, transformers, circuit breakers, protection equipment [12], [49].

The distribution system main function is to bring electricity directly to the consumers [12]. It is characterised by the Medium Voltage (MV) (typically between 4.0 kV and 34.5 kV [50]) and Low Voltage (LV) (typically between 120 V and 0.4 kV [50]) sections. In general, the distribution system originates from a substation, and a weakly meshed or radial topology characterises it. Unless transmission, the distribution system has been historically a passive subsystem characterised by a unidirectional power flow; however, the appearance of renewable generation technologies and distributed resources have turned it to active [12].

The consumption layer represents the electric energy demand; typically, the electrical consumers are classified according to their commodity sector in industrial, residential, agricultural, and tertiary users [51], [52]. The electricity demand changes over time both in the long- and in the short-term. The variability of the electricity demand depends on several factors such as human activities, habits, weather conditions; in general, it changes during the day as well as over seasons [12], [51], [53], [54].

2.2 The evolution of the electric power system

The electric power system structure has been evolving since its dawn at the end of the 19th century. Initially, the power system was characterised by isolated electricity systems which supplied cities and industrial districts [55]. From this decentralised structure, the local power systems have started to grow and interconnect since increasing need for reliability and a better frequency control [55]. In the mid 20th century, the power system size reached countries and continents, serving a large number of customers and assuming a centralised model [49], [55]. A strong hierarchical structure for the power system has become evident in that period. Since the introduction of small generators fed by Renewable Energy Sources (RESs) at the end of the 20th century, the power system started evolving again towards a decentralised model in which the four layers (generation, transmission, distribution, consumption) have not clear borders [55].

The electric power system has grown to achieve its maturity in the period that goes from the mid-1930s to the 1980s [56]–[58]. In that period, the electricity sector has been considered a natural monopoly; in each territory (State or Region), the exclusivity of the electricity supply service was entrusted to a vertically integrated company which encompasses the control of production, transmission, and distribution activities [56]–[59]. Private companies were nationalised in Europe and Latin America, while in the US, they were bonded with strong regulation constraints [56], [59], [60]. The aim was to sustain the development of the countries by eradicating the abuse of market power in the electricity sector and pursuing rural electrification [60]. The power system development was characterised by strong State intervention; reasonable electricity prices were achieved thanks to the economies of scale in which large centralised power plants fired by cheap fuels were built [56]. Since the geographical monopoly, customers were captive; development plans aimed to meet the expected future demand without considering any technological advancement in the generation mix [56]. Development plans were conceived according to the least-cost solution approach, the investments made by the vertically integrated utilities were returned using a cost-recovery remuneration [60]. The regulation of "electricity as a regulated monopoly" allowed to sustain the growth of the power system and preserve low electricity prices [56], [57]. Since the energy crisis of the early 1970s, the higher cost of fossil-fuels accompanied by significantly high interest rates made unstainable the infinite growth model on which relied on the economy of scale of the power industry. The mutated context highlighted the inefficiencies of the regulated monopoly model. The high electricity prices, low supply reliability, and increased environmental awareness led the public opinion to require the electric power industry's reform [56].

The energy crisis has led to a paradigm change for the power system; the regulated monopoly framework has been phased out in advantage of competitive market mechanisms. The vertically integrated utilities have been forced to unbundling; a single company was no longer allowed to manage generation, transmission, distribution, and the retail supply of electricity. The electricity sector has been deregulated, and the public-owned utilities privatised [58]–[60]. Under the regulated monopoly regime, the vertically integrated utilities had little incentives in reducing costs and making investments in new technologies since all costs were covered by the remuneration established by the regulatory framework [59]. Electric power industry restructuring has been aimed at introducing competition for increasing efficiency, reducing prices, and introducing technology advancements [59]. The availability of combined-cycle gas turbines and the unprofitability of investments in large power plants have encouraged the development of small-scale generation and cogeneration [57], [59]. Moreover, the advancements in Information and Communication Technology (ICT) allowed implementing market platforms able to manage a massive number of transactions made by multiple agents [59].

In Europe, the electricity market restructuring has been fostered since 1988 by the European Commission's Green Book, whose objective was to harmonise technical and economic rules for member states' power system [58]. Defining common rules for Member States' electricity sector lay the foundation for a unified European electricity market, the Internal Electricity Market (IEM) [58]. The Directive 96/92/EC promoted the administrative unbundling of the vertically integrated utilities, the imposition of public service obligations, the open access to the transmission network for producers and consumers, incentives for the use of Renewable Energy Sources (RESs) [58], [61]. The Directive 96/92/EC enabled competitive electricity markets and imposed to the Member States to pursue a gradual liberalisation of the electricity sector [58], [61]. The subsequent step has been the Directive 2003/54/EC that accelerated the market opening, imposed the legal unbundling of the electric companies, a regulated regime for network access, and introduced updated public service obligations in terms of security, quality, prices, energy efficiency, environmental protection, protection of vulnerable customers [58], [62]. Moreover, Regulation 1228/2003 concerned several requirements for cross-border electricity trading [58], [63]. In 2009, the third energy package replaced the Directive 2003/54/EC and Regulation 1228/2003 [58]. Main measures contained in the *third energy package* were the ownership unbundling of energy companies regarding generation and transmission, updated requirements for independent national regulators, the creation of the Agency for the Cooperation of Energy Regulators (ACER), increased cross-border cooperation, and updated rules for the retail markets [64]–[68]. In 2019, the *Clean Energy for all Europeans package* has been presented for replacing the *third energy package* [7], [21], [69]–[75]. The new energy package aims to foster the use of RES and energy efficiency measures. Furthermore, measures such as the requirement of ten-year national energy and climate plans to the Member States and the redesign of electricity markets are introduced.

In Italy, the electric power system was ruled by the national ENEL company which owned and operated the vast majority of generation, transmission, and distribution assets. Power industry restructuring began in the late 1990s; in 1997, the national regulator was created, while in 1999, a first liberalisation of the generation, import, and export of electricity has been imposed [58]. From 2003, due to unbundling policy, ENEL has been forced in yielding part of its power plants and have been created a transmission system operator, a distribution network operator, and a single buyer [58]. In 2004 and 2007, respectively, the wholesale electricity market and the retail competition have been established in the Italian electricity sector [58].

2.3 The introduction of the smart grid paradigm for the power system

In the electric power system, the paradigm change started in the late 1980s has been characterised by three measures: unbundling, privatisation, and liberalisation. Due to unbundling, the vertically integrated utilities born in the mid of the 20th century have been broken up. The different power system roles (generation, transmission, distribution, retail supply) have been separated to be assigned to different and independent companies. The privatisation of the activities has allowed private investments in the electricity sector; the share of electrical companies owned by public bodies has decreased. The liberalisation of the power system has brought competition among the electric companies, the market power issues has been constrained, and the participation of new players in both the wholesale electricity market and the retail supply has been encouraged. Since the transmission and distribution networks, as well as the system operation, have been considered to have natural monopoly characteristics, regulated system operators for the transmission (TSO) and the distribution (DSO) systems have been created [59]. Their role is to own and operate the power system by guaranteeing the reliability of the electricity supply and the network access to third parties [62], [65], [76].

In recent years, the pace of power system evolution has increased because of the need for integrating RESs at reasonable costs without jeopardising the reliability of the electric supply [18]. Generators fed by renewables are considered as not dispatchable; hence the paradigm of the inflexibility of the electricity demand has been questioned. Furthermore, climate change policies are oriented to decarbonisation and old power plant decommissioning; therefore, the exploitation of smaller generation facilities is encouraged [9]; consequently, considering the liberalisation of energy markets, the number of actors involved in the power system management is increased. The connection of small generators at the distribution level requires revising the planning and operational practices because of the emergence of bidirectional power flows in networks devised for being passive and crisscrossed by unidirectional power flows [18].

The increased complexity of the power system at the distribution level can be faced by introducing intelligence to effectively integrate into the power system operation the assets connected to the grid. The concept of smart grid has been introduced for describing "*an electricity network that can cost-efficiently integrate the behaviour and actions of all users connected to it – generators, consumers and those that do both –to ensure economically efficient, the sustainable power system with low losses and high levels of quality and security of supply and safety*" [25].

The future power system will be characterised by an Active Distribution Network (ADN) in which several systems are "*in place to control a combination of distributed energy resources (DERs), defined as generators, loads and storage. Distribution system operators (DSOs) have the possibility of managing the electricity flows using flexible network topology. DERs take some degree of responsibility for system support, which will depend on a suitable regulatory environment and connection agreement*" [24]. A distribution system in which the AND concept is exploited is called Active Distribution System (ADS) [24].

It is expected that future distribution customers will be active or proactive, hence embedded in the operational activities of the power system [73], [77]. To enable smart grids and ADNs, it is required to introduce intelligence in the grid by exploiting the functionalities empowered by the Information and Communication Technologies (ICTs) [77].

The smart grid transition is required since the integration of intermittent RESs in the power system by traditional practices, such as *fit and forget*, will require network updates which cost is unsustainable [18]. In this context, it is of utmost interest to unlock demand-side flexibility and exploit the opportunities related to the smart exploitation of new loads such as energy storage equipment and electric vehicles. Achieving the coordination of the behaviour and actions of the users and assets connected to the grid will allow maximising the exploitation of the existing infrastructure; thus, investments in network upgrading can be postponed [18].

The decentralised, liberalised, and fragmented structure of the future power system makes no longer suitable the planning and operational practices in use before the electric power system restructuring. Since the significant number of actors involved, market mechanisms that rule the exchange of power and services are appealing. Moreover, due to user empowerment and the transition towards the generation following paradigm, smart grids represent a significant change in how electricity is supplied; thus, relevant broad impacts on the entire society are expected.

2.4 Flexibility needs of the power system

Flexibility is the key feature of the future power system based on smart grids and ADN. According to the definition provided by ISGAN Annex 6, flexibility is "*the ability of the power system to manage changes"* [4]. This definition encompasses all possible implementation of flexibility, considering the different needs and the resources available in the power system. The flexibility of power systems concerns technical, commercial, and social aspects since the introduction of the flexible electricity use encompasses users' active participation in the grid operation [4]. The exploitation of flexibility from connected assets requires the activation of dedicated services whose consequences go beyond the monetary impact and require defining a set of Key Performance Indicators for enabling a comprehensive assessment.

The flexibility needs of the power system can be described from a general and a local perspective [4]. On the one hand, according to the global power system perspective, flexibility is required for preserving the nominal frequency and guaranteeing a secure energy supply [4]. On the other hand, the local power system perspective requires flexibility for preserving the nominal bus voltages and transfer capacities [4]. Therefore, flexibility is needed by the power system for balancing demand and supply, maintaining bus voltages at an acceptable level, and ensuring adequate transfer capacities. Different dynamic and activation time characteristics are required from the flexibility providers to satisfy these needs [4]. In addition to the technical requirements that the technologies have to satisfy, providers' eligibility also depends on the grid context characteristics (e.g. technical restrictions), regulation, and commercial and environmental aspects [4].

Considering the power system perspective, flexibility can be described in terms of the operational need to be satisfied. To this end, four categories describe the flexibility for power, energy, transfer capacity, and voltage [4].

Flexibility for power includes all the actions useful for preserving the frequency stability; hence it involves the short-term equilibrium between power generation and demand. The sources have to show fast dynamic performances since the activation time ranges from sub-seconds to an hour. The reason behind the need for flexibility for power relies on the diffusion of intermittent power generators connected to the power system. Flexibility for energy is related to the long-term equilibrium between generation and demand. It involves the energy balance; hence the timescale required to the flexibility resources ranges from hours to years. The need for flexibility for energy raises from the decreased availability of traditional power plants. Flexibility for transfer capacity is required for avoiding network congestion and preserving the capability of transfer power. Due to the timing of the power markets and the operational practices, flexibility for transfer capacity concerns a timescale that ranges from minutes to hours. The requirement for flexibility for power capacity is due to the expected increase in peak generation and demand. The former is expected due to the increasing share of renewable energy sources connected to the power system; the latter is related to the consequences of the ongoing electrification policies, as highlighted in section 1. Generally, the peak of demand and generation are not homothetic [18]. Flexibility for voltage is required for supporting voltage control in keeping the bus voltages within the normal operational range. The dynamic of the voltage flexibility measures ranges from seconds to several minutes, depending on the voltage control layer interested by the need. The need for flexibility for voltage is caused, in particular, by the bidirectional power flows caused by the renewable energy sources connected to the distribution system. Moreover, avoid excessive voltage drops caused by new power-intensive loads (e.g. electric plug-in vehicles) [78].

According to the definition, the power system flexibility sources can be categorised in internal and external. Internal sources of flexibility are the network equipment and procedures for grid management. In contrast, external sources are the third-party resources that can modify their injection or consumption patterns to accommodate the power system need. Possible internal power system flexibility sources are the operational and planning procedures and the grid infrastructure equipment [4]. Among the external flexibility, sources can be considered the synchronous conventional power plants, the renewable power plants equipped with a power electronic interface, and controllable demand [4]. Energy storage can be part of both internal and external flexibility sources depending on the ownership of the device.

Considering the definition, the different possible classifications and the different means that can be resorted, in Table 2.1, Table 2.2, Table 2.3, Table 2.4, an overview of the flexibility for the electric power system is provided. These tables aim to offer an insight into the vast topic of power system flexibility. Starting from the discussion in [4], the classification is extended and completed by including in a methodical fashion the problem to be solved, the general solution to be adopted, and the internal or external nature of the flexibility considering the network operator perspective. Furthermore, the discussion in [4] is improved by highlighting the category of potential flexibility providers that can be involved in each service; moreover, it is enlarged the set of possible flexibility measures composed of assets, policies, and devices that can be exploited.

In Table 2.1, Table 2.2, Table 2.3, and Table 2.4, the classification of the flexibility service from the power system perspective is provided. Considering the different power system needs in terms of flexibility, each table describes the problem to be solved, the related general solution, need scale, system-level, scope, activation time, flexibility source origin, provider category, and potential flexibility measures.

Table 2.1 concerns the flexibility services for power balancing; Table 2.2 regards the flexibility service for energy balancing; Table 2.3 focuses on power system flexibility for congestion management, while Table 2.4 deals with power system flexibility for voltage control.

The classification of the flexibility described in the four tables starts defining the *problem to be solved*. In fact, the system operators’ need for the acquisition of grid service is different in the case of power balancing, energy balancing, congestion management, and voltage control. The type and characteristic of the problem to be solved are pivotal for identifying the service to be acquired, defining the features of the procurement mechanism, and finally, selecting the resources that form the set of potential providers.

Tied with the problem to be solved, the *general solution* adopted to satisfy the operational need represents the second column of the four tables. For each flexibility type, the general solution represents the goal of the mechanism for acquiring grid service. Since the existing differences among the needs described in the four tables, each available solution is different. The general solution can encompass one or more grid services and one or more products.

The *need scale* represents the extension of the network area corresponding to the need for grid services in which the potential flexibility providers are connected. The central need is characterised by a centralised procurement approach which considers an entire control area, as defined by Entso-E [79]. Conversely, a local need concerns the procurement of grid services and products that concern only part of a control area; i.e., the flexibility providers' location matters to fulfil the operational need (it is the case of voltage control and congestion management).

The *system level* considers the electric power system as formed by independent transmission and distribution systems [50]. It describes the power system level that grid service needs impacts. This attribute is relevant for identifying the system operators involved in the grid operation need, the type of potential providers, and required coordination among system operators in the cases in which more than one system level is involved.

The *scope* attribute identifies the aim of the exploitation of flexibility. This attribute is related to the classification of the power system flexibility needs proposed by [4]. It describes the particular aspect of power system operation that is influenced by the exploitation of flexibility. The scopes for the need for flexibility which are discussed in this dissertation, are power balance, energy balance, transfer capacity, and voltage. In combination with the activation time attribute, it is possible to define more specific scopes (e.g. voltage stability, voltage regulation, dynamic stability, steady-state stability).

The *activation time* attribute describes the timeframe required to provide flexibility to satisfy the operational need. It may range from sub-seconds to years according to the flexibility need to be satisfied.

The *flexibility source origin* describes an attribute related to the potential flexibility sources that can be exploited for satisfying the different flexibility needs. An internal flexibility source is an asset, a device, or a practice, that pertains to the system operator; hence, no interaction with third parties is required to activate it. The external flexibility sources are represented by all the assets and devices connected to the power system owned by third-parties. To activate the potential flexibility of the external sources the system operator has to interact with another power system actor.

The attribute *potential providers* classifies the flexibility sources according to six categories. The planning procedures are all the flexibility sources obtained through the measures adopted in network planning (e.g., building new lines or substations, upgrading existing lines of substations, widen operational limits). Similarly, the operational procedures are all the flexibility sources that can be enabled through operational practices (e.g., network reconfiguration, dynamic line rating). The network equipment category includes the devices connected to the network that are owned by the system operator and that are useful for the normal operation of the grid (transformer, shunt devices, series compensators). The category of power electronic-interfaced generators includes all the potential sources of flexibility represented by energy sources connected to the network through a power electronic converter. The controllable demand category includes all the sources of flexibility related to the control of the electric loads and, in general, of the electricity demand. The storage system category includes all sources of flexibility characterised by the ability to absorb and store electric energy for a defined period of time to be able then to inject energy in the grid (e.g., batteries, hydro-pumps, compressed-air storage, flywheel).

The last column describes some of the possible flexibility sources within each category of potential providers. Devices, assets, and practices are reported by highlighting the specific *flexibility function* that can be exploited to satisfy the flexibility need that each of the four tables considers.

Table 2.1. Power system flexibility overview for power balancing

Problem to be solved	General solution	Need scale	System level	Scope	Activation time	Flexibility source origin	Provider category	Flexibility measures
Compensate the intermittent power production	Procuring power balancing capability	Global	Transmission	Flexibility for power	Sub-seconds to an hour	Internal	Planning procedures	New interconnections (AC and DC) Widened dynamic range for generation [4] Increased power system operation limits [4]
							Operational procedures	Management of AC and DC interconnections [4] Dynamic Line Rating [14]
							Network equipment	Power control devices (FACTS, PST, HVDC, VSC) and short-term storage devices with Fast Frequency Response (FFR) inertia [4], [14] Synchronous energy storage [13]
						External	Synchronous generators	Inertia, FFR, PSS, generation curtailment [4] Changes in operational practices [16] Flexibility retrofit investments [16]
							Power Electronic-interfaced generators	Virtual inertia, FFR, PSS, generation curtailment [4], [80], [81]
							Controllable demand	Demand side management [4], [14], [82] Sector coupling [13]
							Storage devices	Virtual inertia and fast power flow compensation [4], [81]

Table 2.2. Power system flexibility overview for energy balancing

Problem to be solved	General solution	Need scale	System level	Scope	Activation time	Flexibility source origin	Potential providers	Flexibility functions
Compensate the decreasing availability of traditional power plants and then the uncertainty of future energy supply	Procuring energy balancing capability	Global	Transmission and distribution	Flexibility for energy	Hours to years	Internal	Planning procedures	Long-term forecast and management of energy production and demand [4], [14]
							Operational procedures	Management of large storage (pumped hydroelectric) [4] System Interconnections [4], [14]
						External	Synchronous generators	Availability of electricity generation
							Power electronic-interfaced generators	Availability of electricity generation
							Storage systems	Energy storage [14] Self-consumption
							Demand	Energy efficiency policies Sector coupling [14], [16]

Table 2.3. Power system flexibility overview for congestion management

<table>
<tr><th>Problem to be solved</th><th>General solution</th><th>Need scale</th><th>System level</th><th>Scope</th><th>Activation time</th><th>Flexibility source origin</th><th>Potential providers</th><th>Flexibility functions</th></tr>
<tr><td rowspan="6">Avoid congestions due to the increase of generation and consumption peaks</td><td rowspan="6">Increase the interconnection capability</td><td rowspan="6">Local</td><td rowspan="6">Transmission and distribution</td><td rowspan="6">Flexibility for transfer capacity</td><td rowspan="6">Minutes to hours</td><td rowspan="3">Internal</td><td>Planning procedures</td><td>New interconnections [4]
Upgrade existing interconnections [18]
Increase nominal voltages [4]</td></tr>
<tr><td>Operational procedures</td><td>Introduction of probabilistic reliability criteria [4]
Network reconfiguration [4], [18]
Management of interconnections [4], [14]
Dynamic Line Rating [4], [14]</td></tr>
<tr><td>Network equipment</td><td>Phase-shifting transformers [4]
Flexible AC Transmission Systems (FACTS) devices [4]
Series/shunt-compensation [4], [18]</td></tr>
<tr><td rowspan="3">External</td><td>Power Electronic-interfaced generators</td><td>Increase local power generation to limit power transfers over long distances
Generation curtailment [18]
Full flexibility [16]</td></tr>
<tr><td>Controllable demand</td><td>Demand side management [4], [14], [82]</td></tr>
<tr><td>Storage devices</td><td>Increase the local power supply and self-consumption</td></tr>
</table>

Table 2.4. Power system flexibility overview for voltage control

<table>
<tr><th>Problem to be solved</th><th>General solution</th><th>Need scale</th><th>System level</th><th>Scope</th><th>Activation time</th><th>Flexibility source origin</th><th>Potential providers</th><th>Flexibility functions</th></tr>
<tr><td rowspan="7">Avoid voltage problems due to the distributed generation and new power intensive loads</td><td rowspan="7">Enhance the voltage control capability</td><td rowspan="7">Local</td><td rowspan="7">Transmission and distribution</td><td rowspan="7">Flexibility for voltage</td><td rowspan="7">Seconds to minutes</td><td rowspan="3">Internal</td><td>Planning procedures</td><td>New lines [18]
Upgrade existing lines [18]
Widened voltage quality limits [4]</td></tr>
<tr><td>Operational procedures</td><td>Network reconfiguration [18]
Management of HVDC terminals [50], [83]</td></tr>
<tr><td>Network equipment</td><td>FACTS devices, e.g., static var compensators (SVC), static synchronous compensators (STATCOM), unified power flow controllers (UPFCs), Series-compensation [4], [12]
Synchronous compensators [84], [85]
Shunt capacitors and inductors [84], [85]
On Load Tap Changer Transformers [84], [85]</td></tr>
<tr><td rowspan="4">External</td><td>Synchronous generators</td><td>Improved active and reactive power control [83]
Changes in operational practices [16]
Flexibility retrofit investments [16]</td></tr>
<tr><td>Power Electronic-interfaced generators</td><td>Voltage support control logic (Active and reactive power control) [4], [18], [86], [87]</td></tr>
<tr><td>Controllable demand</td><td>Demand side management [4], [14], [82]</td></tr>
<tr><td>Storage devices</td><td>Voltage support control logic Series-compensation (Active and reactive power control) [4], [18]</td></tr>
</table>

2.5 Distribution System Planning

As highlighted in sections 1.4 and 2.3, the distribution network to which small scale generators fed by renewables, energy storage devices, and controllable load assets are connected has a pivotal role in the current power system transformation. Therefore, it is of utmost interest to understand how have to be updated the practices for devising the distribution grid reinforcements. To this aim, this chapter focuses on the state of the art of distribution network planning practices.

Since the newly connected assets (e.g., generators fed by renewals energy sources, controllable loads, electric vehicles, and storage devices) the distribution network turns active; consequently, it is essential to adapt the distribution grid to the new context, and thus to rethink the distribution system planning process [24]. In fact, in smart grids and flexible distribution systems, planning and operation activities have to be coordinated following an approach that allows to consider the flexibility provided by the connected assets as an alternative to network expansion [24]. It represents a radical change because distribution network planning has been traditionally based exclusively on the *fit and forget* approach.

Fit and forget is a deterministic planning approach in which the network is designed according to the worst scenario in terms of loading condition, voltage drop, and security constraints [24]. Considered the worst loading scenario, lines, switches, and substations are sized without pondering any uncertainties. As the denomination suggests, the underlying idea is that all the operational issues are solved at the planning stage by a considerable oversizing of the network. Then, the operational actions are minimised and expected only for solving cases related to unforeseen events.

The general framework of the *fit and forget* planning approach is resumed in Figure 2.1 [24]. Considering a portion of the distribution system, which requires to be upgraded, the development alternatives are devised and assessed considering the expected load conditions for the planning horizon. In general, the alternatives are designed for facing future network bottlenecks; the measures proposed for being implemented are sorted considering the urgency of the related issue [24].

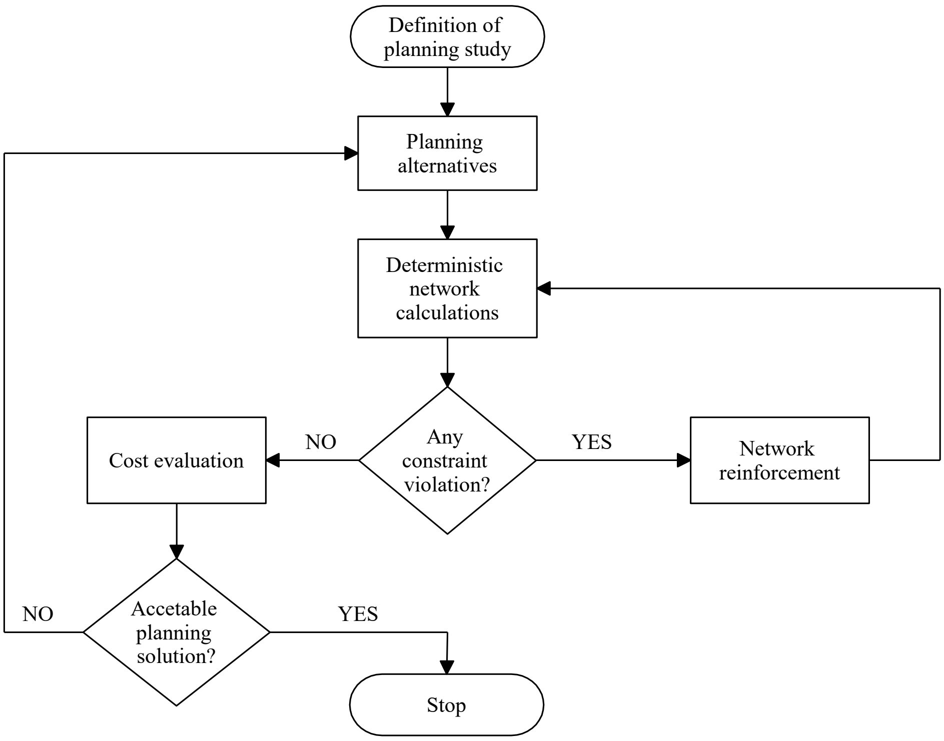

Figure 2.1.General framework of the fit and forget planning approach [24]

The technical feasibility of the alternatives is verified using deterministic network calculations. If the design alternative passes the technical check, the related costs are calculated. Contrarywise, the alternative has to be modified by implementing other traditional network reinforcements such as conductor and transformer size increase. Among the set of feasible distribution planning options, the most cost-effective solution is selected for being deployed [24].

The *fit and forget* approach employed in the context of distributed generation means considering the *maximum generation - minimum demand* scenario that rarely happens [24]. Consequently, in those cases, the *fit and forget* approach will lead to an unreasonable and costly network upgrading. Considering the vast investments required, the use of the *fit and forget* for facing the contingencies related to high levels of distributed generation might limit the diffusion of such assets and the non-conventional loads; therefore, it constraints the distribution system hosting capacity [24].

Traditionally, the planning alternatives proposed for the distribution network have been evaluated in terms of the costs required for making the reinforcement considering the target of quality of service to be achieved. No elaborated tools have been exploited for selecting the alternative to implement; the least capital cost while meeting the minimum service requirement has been typically considered as the selection criterion [24].

In the future distribution system, to achieve an adequate hosting capacity at an acceptable cost, it is imperative to include active network solutions and flexibility as planning measures [24]. Consequently, the planning activity becomes more complex since it involves third-party assets whose owners have conflicting goals. In fact, DSO would be interested in minimising the overall grid cost while preserving the adequate quality of supply. At the same time, the flexibility service provided could be interested in maximising the revenues related to the service provision. Considering the increased number of potential planning measures and the diversity of the stakeholders involved, multi-criteria and multi-objective approaches are of interests to tackle the complexity of the planning activities for the future distribution system [24].

Designing a flexible and active distribution system requires planning methodologies that rely on probabilistic approaches and optimisation techniques. Stochastic approaches are fundamental for representing the increased uncertainty and the variability of demand and generation, while the use of optimisation techniques allows reducing the computational burden of the mathematical problem of defining the most effective upgrading plan [24].

In Figure 2.2, the general framework of the flexible distribution system planning approach is depicted [24]. In addition to traditional network reinforcement measures, the flexible planning approach considers the flexibility of the connected assets and the network to solve network contingencies. Furthermore, considering *fit and forget,* the main differences introduced are:

- the enhanced representation of the behaviour of the customers (demand and generation);
- the use of probabilistic or stochastic methods for network calculation;
- the introduction of the concept of the risk violation for network constraints;
- the evaluation of the alternatives according to multiple objective or criteria.

The research activity presented in this thesis is related to several pillars of the active distribution system planning: the enhanced modelling of load consumption patterns and the use of the multi-criteria analysis to appraise the initiatives.

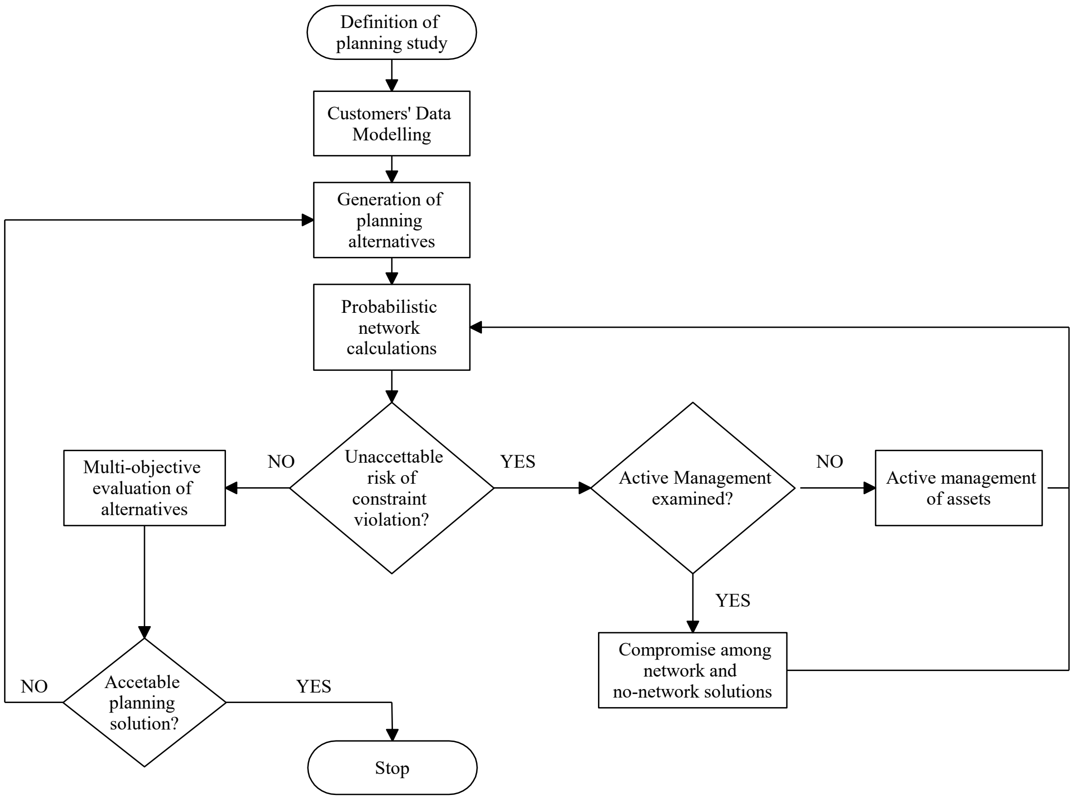

Figure 2.2.General framework of the flexible distribution system planning approach [24]

In the flexible distribution system planning approach, the concept of the risk violation for network constraints is introduced since probabilistic network calculation is used [24], [88], [89]. One of the approaches used for addressing stochastic network calculation is based on the probabilistic load flow. It allows to include in the network calculation the probability related to each scenario and then to quantify to what extent a possible network problem or network constraint violation is probable [24], [88], [89]. Other stochastic network calculation approaches have also been proposed in the literature. The definition of the stochastic behaviour of network customers could also be based on clustering methods to define the most probable generation and consumption condition and to reduce the overall number of load flows required to describe a simulation time horizon [90]. To properly assess the wide range of impacts caused by the development of the smart grid initiative is crucial the use of stochastic methods and probabilistic network calculations to fully include the management of uncertainties in the planning processes. Adequate management of uncertainties is of interest irrespective of the specific procedure used to address the probabilistic network calculation. It is out of the scope of this document to review the literature of the stochastic approaches used for designing the distribution system planning options. For the sake of completeness, in the following, a brief description of the probabilistic load flow calculation approach used in [24], [88], [89] is reported to provide the definition of risk of constraint violation. This concept is relevant for the dissertation since it is exploited in the fourth case study described in section 7.4.

In probabilistic load flow calculation, the risk to violate technical network constraints is assessed considering the load and generation behaviour modelled using a probability density function. Regarding a specific grid scenario, the annual risk of network constraint violation can be calculated by solving a multi-temporal power flow which considers, for each time step, consumption and generation values represented through a normal distribution [24], [88], [89], [91].

An extensive explanation of the probabilistic load flow calculation procedure is outside the scope of this document; a detailed description is available in [88], [89]. In this document, only a brief overview focused on the concept of the network constraint violation risk is provided. The risk assessment procedure requires simulating a network configuration scenario for a specific time step to calculate the nodal voltages and the branch currents expressed in terms of the mean value (μ) and standard deviation (σ) of a normal distribution [88], [89]. Given this result, it is possible to calculate for the given time step the corresponding probability to exceed the voltage and conductor thermal limits of the considered network [88], [89]. Figure 2.3 provides an overview of the probabilistic network design reasoning based on the concept of acceptable risk. The risk of network constraint violation calculation focuses on all the operating conditions in which the obtained extreme values of nodal voltages and branch currents (assumed equal to $\mu \pm 3\sigma$) have a non-negligible probability of exceeding the accepted values of minimum and maximum nodal voltages (V_{lim_min} and V_{lim_max}) and maximum branch current (I_{lim_max}). This scenario is depicted in Figure 2.3 (a) in which the probability of violating the technical constraints (p_{tcv}) is greater than zero [88], [89]. Conversely, an example of the operating conditions that determine a negligible probability to violate the technical constraints are depicted in Figure 2.3 (b), in which the probability of violating the technical constraints (p_{tcv}) is equal to zero [88], [89].

The risk of technical constraints violation (R_{bf}) for a specific operating condition in a particular time step is obtained as the product of the probability to violate the technical constraints (p_{tcv}) and the occurrence probability (p_{bf}) of the corresponding operating conditions.

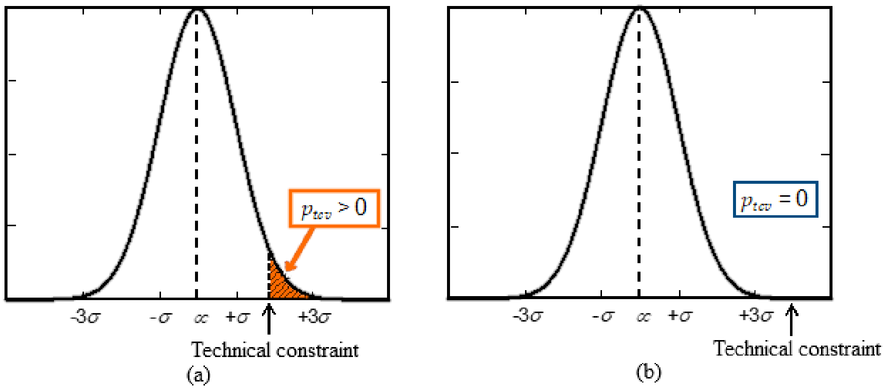

Figure 2.3. Identification of the operating condition with a risk of violating network constraints [88], [89].
(a) Operating condition with probability to violate the technical constraints (p_{tcv}) greater than zero
(b) Operating condition with probability to violate the technical constraints (p_{tcv}) equals to zero

The total risk (R_{TOT}) corresponding to the examined network configuration is calculated as the sum of all risk components obtained for the investigated time horizon [88]. Suppose the total risk is higher than the risk threshold defined by the planner. In that case, the planning option is considered in the planning procedure loop for implementing corrective measure (network reinforcement, active management of connected resources) helpful in reducing the corresponding total risk [88], [89]. Considering the upgraded network configuration, all risk components are updated, the updated total risk, the achieved risk reduction and the related planning cost are calculated [88], [89]. The residual risk that corresponds to a planning option is the total risk value that results when the planning procedure loop is completed [88], [89]. Suppose the residual risk is lower than the risk threshold defined by the planner as the maximum acceptable risk. In that case, the planning option is considered feasible and can be included in the decision-making portfolio.

2.6 Multi-Criteria approach in distribution system planning

The contribution given by the use of approaches based on multi-criteria analysis to distribution system planning is twofold; on the one hand, the use of these approaches allows to enlarge the set of appraised impacts; on the other hand, it allows to consider the point of view of the different stakeholders simultaneously.

Multi-criteria approaches allow to compare the impacts generated by the planning alternatives in terms of performance indicators. The different development plans obtained according to the flexible planning approach are characterised by a large number of impacts difficult to quantify and monetise. The related lack of historical data and clear and acknowledged guidelines on monetary compensation mechanisms could lead to a burdensome appraisal process of questionable reliability [24], [28]. Consequently, an appraisal process based only on the cost equivalence becomes burdensome and untrustworthy. On the contrary, appraisal approaches that compare costs and technical performances are appealing [18]. The comparison made based on performance indicators avoids any bias introduced by the monetary conversion assumptions.

As disclosed in Sections 1.4 and 2.2, novel stakeholders have become part of the power system due to liberalisation policies. Since the different roles and interests of these stakeholders, their goals are conflicting. To illustrate, in addition to the system operator, flexible distribution system planning activities involve regulatory bodies, generators owners, flexibility service providers, and aggregators. The regulatory bodies represent society's perspective; their main objective is to protect consumers and maximise social benefits. Differently, the goal of generator owners, flexibility service providers, and aggregators is the maximisation of the profit [24]. Therefore, it is of utmost interest to exploit planning approaches that can lead to a compromising solution that satisfies all stakeholders. Multi-criteria and multi-objective methodologies allow by default to include different stakeholders' perspectives in the appraisal process; it arises with defining the evaluation criteria and the attribution of the criteria relevance.

The set of criteria identified for the appraisal of the planning option reflects the perspective of the stakeholders. The decision-making problem of identifying the best grid planning option requires defining the meaning of the adjective *best.* In general, the best option is the one that achieves the highest overall consensus because it meets the expectations of the participants more than the other options. Therefore, the *overall value* of an option can be considered as composed of smaller elementary values; each element is related to a precise area of interest to which the option impacts. The *overall value* of an option corresponds to the overall expectation from stakeholders; each of the *elementary values* is linked to the expected effect of the option in the related area of interest. The definition of the overall expectation and the associated areas of interest to which appraise the effects involve the stakeholder perspective. Different categories of stakeholders would be interested in appraising the impacts of the same option considering different effects. The definition of the evaluation criteria is a critical step of the multi-criteria analysis, and it corresponds to transpose the stakeholders' perspectives and expectations in the decision-making problem.

Once the evaluation criteria are defined, all the impact areas of interest for all the involved stakeholders are represented in the decision-making problem. However, not all areas of interest may have the same relevance in the eye of stakeholders. To model the stakeholders' point of view in terms of the relevance that the different areas of impact selected for the appraisal of the option, criteria weights are required. The combination of the relevance of the areas of impact, expressed in terms of criteria weighs, with the effects determined by the option, the *elementary values*, allows to determine the *overall value* of the option.

Therefore, stakeholders play a crucial role in the multi-criteria analysis. Their perspective is fundamental for identifying the *best* option since the structure of the decision problem defined in terms of the goal, the evaluation criteria, and the criteria relevance is defined accordingly.

3 DECISION-MAKING SUPPORT TOOLS FOR PROJECT ASSESSMENT

In this chapter, the use of decision-making support tools for project assessment is discussed. First, the cost-benefit analysis, the most acknowledged tool for project appraisal in the private sector, is analysed. The pros and cons of cost-benefit analysis are identified and discussed. Then, multi-criteria analysis, the most acknowledged approach for complex decision making is studied. Key features, pros and cons are identified and discussed. Finally, a detailed survey of the main multi-attribute decision-making techniques is provided.

This chapter aims at answering the following questions:

- What is the cost-benefit analysis, and how does it work?
- What are the main advantages and disadvantages of cost-benefit analysis?
- What is the multi-criteria analysis, and how does it work?
- What are the main advantages and disadvantages of multi-criteria analysis?
- Which are the most acknowledged multi-criteria analysis methodologies for solving decision-making problems?

3.1 Cost-benefit analysis (CBA)

The Cost-Benefit Analysis (CBA) is the most acknowledged tool for addressing the financial assessment of industrial investment projects [92], [93]. The CBA is based on neoclassical welfare economics principles and provides a systematic assessment framework that seeks the most profitable investment alternative [92], [93]. Typically, industrial projects are evaluated only considering the financial aspects from the investor's perspective. Those aspects are the monetary and direct monetisable impacts which the investment alternative produces [94]. The investment alternative has to maximise the investors' profit; CBA relies on the Kaldor-Hicks criterion: the benefits related to the deployment of the alternative must exceed the costs [92], [93].

The CBA allows to assess a single investment option concerning a reference scenario and compare with each other different alternatives. Among a set of investment options, the most advantageous achieves the greatest value of the performance indicators computed by the CBA. Therefore, CBA can be considered as a decision support tool for planning processes [93], [94].

The CBA is widely used in the private sector; however, for the assessment of large infrastructural initiatives that involve public bodies, CBA does not represent a fully acknowledged tool [94]. These initiatives have to be assessed from the societal perspective and are capable of generating impacts that are not monetary or that are not quantifiable with accuracy. In this context, the use of monetary-based tools as the Societal Cost-Benefit Analysis (SCBA) for the assessment of the initiatives from a societal perspective reveals several conceptual flaws which may bias the outcome of the project appraisal [28], [94].

3.1.1 The CBA procedure

The procedure for conducting a CBA is essentially formed by five steps [94], [95].

Identification of the goal and the context of the investment

The first step of the CBA involves defining the goal to be achieved through the investment. The context in which the initiative to be implemented has to be carefully studied since it strongly influences the profitability of the investment. To this aim, common assessment frameworks and guidelines have been developed for adapting the analysis to the sector and regional peculiarities. The appraisal of the context has to audit the territory, stakeholders, and the time horizon.

Identification of the impacts caused by the investment

The impacts caused by the investment initiative are costs (negative impacts) and benefits (positive impacts). The impacts have to be identified and quantified in terms of the related unit of measurement. For this task, territorial and sectorial guidelines can be exploited. To illustrate, for the smart grid sector, several guidelines have been developed by the Electric Power Research Institute (EPRI) and the Joint Research Centre (JRC) [32], [33], [96].

Conversion of the impacts expressed in monetary terms

According to the CBA framework, to compare costs and benefits is necessary to convert all impacts into monetary terms. In the case of non-monetary impacts, the monetary value is obtained by exploiting techniques such as Willingness to Pay (WTP), Willingness to Accept (WTA), and the opportunity cost approach [93], [95]. Once the monetary values are obtained, the amount related to each impact is discounted for obtaining the equivalent monetary value with respect to the reference year [93], [95].

Composition of cost and benefit and evaluation of the CBA output indices

The overall performance indicators obtained as the outcome of the CBA are calculated by composing the discounted monetary equivalent of costs and benefits of the options. The main indicators are the Net Present Value (NPV), Internal Rate of Return (IRR), and Cost-Benefit Ratio (CBR) [94]. These three indicators provide complementary information about the monetary performance of the investment option.

The NPV is the net benefit which the investment option produces; therefore, the NPV measures the profitability of the investment. If the NPV is positive, the benefit produced outclass the costs; hence the investment is profitable for the investors [34], [35]. The IRR measures the investment quality; it represents the value of the discount rate that makes the NPV equal to zero [34], [35]. The viability of the investment is achieved if the IRR is greater than the discount rate. The CBR is a measure of the efficiency of the investment; it is calculated as the ratio of the present values of benefits and costs [34], [35].

Evaluation of the outcome and sensitivity analysis

The last step of the CBA consists of analysing the values of the indicators obtained for the investment options appraised. The alternative that achieves the highest NPV is considered the best option because it shows the highest profitability.

The sensibility analysis of the CBA outcome assesses the robustness of the results with respect to the parameters. The parameters range is defined according to the expected future scenarios; the alternatives are tested to identify the investment that achieves satisfactory robustness [95].

3.1.2 Pillars of the CBA

Monetising costs and benefits

The monetising techniques to which the CBA relies on for converting the impacts are based on neoclassic economics. The availability changes of each good are measured by the willingness to pay of stakeholders to obtain an availability increase or avoid a decrease [94]. The willingness to pay of stakeholders allows obtaining monetary values which represent the preferences of individuals and the whole society [94].

The main techniques for obtaining monetary values from stakeholders' preferences are WTP and WTA [36], [94]. The WTP quantifies the amount of money that the stakeholders are willing to spend to gain a unitary increment of a specific benefit. Similarly, the WTA measures the amount of money that stakeholders would spend for avoiding a specific negative impact [36], [94].

WTP and WTA show a different degree of reliability depending on the nature of the good underestimation. Their reliability is fully acknowledged for tangible impacts, while, since intangible impacts are not always quantifiable, the exploitation of the WTP and WTA techniques may lead to misleading monetary values [28]. For tangible goods traded within a near-perfect market, the obtained monetary value actually represents the stakeholders' preference. Whereas, if the perfect market condition lacks, the obtained monetary value needs to be correct.

Including intangible impacts in the CBA requires to relax some fundamental on which it relies on. Intangible impacts are not traded within a market since they represent generalised cost and benefit, which involve the environment, society, and health. The monetary equivalent of intangible impact can be estimated utilising indirect and direct methods [95]. The indirect methods assess the WTP and WTA of intangible impacts by analysing the behaviour of the stakeholders. The direct method estimates the WTA and WTP from individuals through surveys or involving them in bidding games. The techniques for monetising intangible impacts are highly time and resource consuming. The low reliability of the obtained monetary equivalents affects the reliability of the related CBA outcome [94].

Among indirect methods, the Hedonic Price determines the preferences of stakeholders about a specific intangible effect by analysing the market of several tangible goods. For example, the real estate market is analysed for estimating the monetary value of the environmental impact [36], [94]. The Stated Preference technique represents a direct method based on a survey concerning explicitly the good under analysis [94].

Furthermore, monetisation of intangible impacts can be obtained through the Benefit Transfer technique, which assigns the monetary value of an impact by considering the value that has been defined in similar CBAs [97]. The burden of monetisation is lower than in the case of direct and indirect techniques; however, its reliability depends on the availability of relevant information [28].

Discounting

The "Consumer impatience" represents the underlying hypothesis behind the discounting of impacts [98]. The impatient consumer model refers to the behaviours of individuals who prefer to obtain immediate benefits rather than waiting for enjoying the same benefit in the future [94].

Furthermore, investments are generally characterised by long time horizons within which the value of currency changes because of price inflation [94]. A coherent comparison of impacts that occur at different times is achieved if the corresponding monetary value is converted considering the discount rate value [95]. In general, the value of currency decreases in time; therefore, the discount rate value is positive. To illustrate, considering the same impact, the related actualised value decreases as the impact occurs far in future. For the different economic sectors, reference discount rates are generally provided by government bodies.

3.1.3 Strengths of CBA

CBA is claimed to be efficient, objective, and transparent [28]. CBA is considered efficient since it promotes the maximum spending efficiency by pointing out the option, which allows maximising the profits [94]. The objectivity of CBA is related to the fact that no subjective information is considered in the assessment process; therefore, because none of the stakeholders is intentionally favoured or penalised [94]. However, the objectivity of CBA is ensured if only monetary impacts are considered. Monetising intangible impacts to consider them in CBA requires preference information from stakeholders and individuals. Finally, the transparency of the CBA is related to the form in which the outcome of the analysis is presented. Since cost and benefits are expressed in monetary terms, also non-expert stakeholders would be able to understand the results and compare different options [94].

By satisfying the requirement of quantifying and monetising all the impacts of the investment under analysis, the CBA can be considered a multisectoral approach since it can be exploited for appraising initiatives that impact heterogeneous areas (e.g. economy, society, energy, technical) [94].

The CBA of an investment is possible in the different stages of the investment lifetime [99]. The CBA *ex-ante* is undertaking during the planning process to assess the profitability of the investment and identify the most suitable option to be implemented. The CBA *on progress* is undertaken for verifying the ongoing investment to identify weaknesses and devise ameliorative changes. At the end of the planning horizon, the CBA *ex-post* is being conducted for assessing the actual performance of the investment and define good practices for future initiatives.

CBA allows a comparative appraisal of investments concerning a reference scenario devised according to the Business As Usual projection of the status quo; therefore, the CBA is considered an incremental approach for initiatives appraisal [99].

3.1.4 The drawbacks of CBA for the appraisal of public investment

The CBA relies on market paradigms since it has been devised for the private sector investment appraisal [93], [94]. Since the goal of the private sector is to maximise profits, the CBA features make the most reliable and acknowledged tool for appraising the investment. However, the public and private sectors have radical differences; public investment appraisal undertaken through the CBA shows several shortcomings [28].

- The public initiative concern goods and services which are not traded within a market.
- The goal of the public sector is maximising expense efficiency rather than maximising profits.
- The model of the society as aggregated consumers fails in representing the real value of society considered as citizens.

Furthermore, the CBA shortcomings are emphasised when the intangible impacts are not negligible [28], [94]. Typically, intangible impacts are majoritarian in the initiatives of the public sector. Even if some CBA methodology adjustments have been proposed [93], the validity of the obtained outcome is reduced because the pillars of the CBA approach are weakened. Monetising and discounting the intangible impacts distort the stakeholders' actual perspective by leading to underestimate long-term impacts (e.g., externalities and environmental impacts) [28].

Quantification and monetisation of intangible impacts

The accuracy of the quantification process is fundamental for obtaining reliable monetary values for costs and benefits. In turn, the reliability of the CBA depends on the accuracy of the monetary values assigned to impacts. Due to this requirement, intangible impacts are often neglected from CBA since they are not always quantifiable with accuracy [28]. Therefore, for preserving the reliability of CBA, approaches in which only tangible impacts are considered while intangible impacts are assessed aside have been proposed [38].

Furthermore, since monetisation techniques are based on the hypothesis that the society is composed of aggregated consumers instead of groups of citizens, these techniques fail in collecting the societal perspective on intangible impacts such as life, health, and environment [94]. The results obtained using the WTP technique are not always consistent [28]. Typically, public-sector policies are devised for influencing the society at large and the individuals' private sphere; therefore, it is of utmost interest to achieve the highest accuracy in modelling the societal point of view on intangible impacts [94]. Moreover, monetising intangible impacts is a burdensome activity that can be non-sustainable considering the resources available for conducting the whole CBA [94].

Discounting of intangible impacts

The main concern related to the discounting of intangible impacts is due to the fact that by discounting negative impacts, the related burden is charged on future generations [28]. Due to discounting, the actualisation of future costs and benefits underestimates the actual effects of the related intangible impact. In facts, short terms impacts became more relevant than long term impacts even if the related order of magnitude is comparable [94]. To mitigate this issue, several CBA guidelines suggest reducing the used discount rate value [28]; however, it leads to reduced profitability of the investments and distorts the CBA. The questionability of discounting makes this technique not recommended for sectors such as the environment and health. The extent of the negative consequences increases with the delay in undertaking corrective actions [28], [94].

Objectivity, transparency, and equity

Since subjectivity is introduced by the techniques for quantifying, monetising, and discounting intangible impacts, the objectivity of the CBA used for the appraisals of public initiatives is no longer guaranteed. Furthermore, CBA critics claim that it lacks transparency because the complexity of the evaluation process does not allow the involvement of non-expert stakeholders. Moreover, since all impacts are converted in monetary terms, it leads to a biased assessment in which the economic performance is overestimated [28], [36]. The monetary values determined by the WTP and WTA differ between rich and poor communities; poor communities may show a higher willingness to accept negative impacts. Hence, WTP and WTA techniques may lead to inequalities since the risk of moving the burden of negative externalities to poor communities [28].

3.2 Decision making with Multi-Criteria Analysis

3.2.1 Introduction to Multi-Criteria Analysis

In general, complex decision-making processes consist of identifying the best option for solving a problem; the options are appraised according to several evaluation criteria. Since the complexity of such a decision-making process increases with the number of alternatives and criteria, tools for supporting decision-makers have been developed by Operation Research. In this context, Multi-Criteria Analysis (MCA), or Multi-Criteria Decision Analysis (MCDA), approaches represent the broad class of tools proposed for addressing complex decision making [36].

In literature, numerous methodologies based on the MCA approach have been proposed, each methodology is characterised by the peculiar decision-making philosophy exploited and the particular mathematical procedure implemented. Therefore, different but similar MCA methodologies are applied to the same decision-making problem may not provide the same outcome [36]. However, the MCA methodologies help the decision-maker decompose the decision-making problem into elementary problems that can be managed easily. Multiple conflicting criteria are simultaneously considered for analysing the alternatives; the stakeholders' perspective can be included in the analysis by introducing the relevance of the evaluation criteria. The MCA methodologies can be classified according to two main groups: Multi-Objective Decision Making (MODM) and Multi-Attribute Decision-Making (MADM) [37].

MODM methods are exploited for addressing continuous multi-criteria problems in which the alternatives are not explicitly known ex-ante [37]. It means that both the number of alternatives and their performances in terms of objective values are not defined in the early stages of the decision-making problem. The alternatives are built through an optimisation process which allows obtaining a set of optimal solutions which minimise the objective values while satisfying the constraints. Since the MODM methods use multi-objective optimisation for addressing multiple conflicting objectives according to the Pareto optimality, the outcome is represented by a set of non-dominated alternatives [37]. According to the literature, multi-objective optimisation methods are mainly based on four algorithms: *no-preference*, *a priori*, *a posteriori*, and *interactive* methods [37]. However, in the context of distribution system planning, *a priori*, and *a posteriori* methods are mostly adopted [24]. *A priori* methods require that the decision-maker provides information to weight the objectives or to define threshold coefficients. Conversely, the *a posteriori* methods are characterised by an iterative execution of the algorithm which allows obtaining a set of non-dominated solutions.

According to the information provided by the decision-maker, the procedure of *a priori* methods define a master objective function; therefore, the optimisation ends up being single-objective [24], [37]. The Pareto set of alternatives can be obtained by tuning the coefficients for building different master objectives. *A priori* methods show a relatively small computational burden; however, the outcome is strongly influenced by personal biases due to the information which has to be provided by the decision-maker for solving the problem [24]. Among *a priori* methods, the most acknowledged are the ε-constrained and the weighted sum techniques [24]. The former considers one of the objectives as the master to be optimised while the remaining objectives are turned into constraints considering the parameters provided by the decision-maker [37]. The latter builds the master objective to be optimised as the weighted sum of the initial objective functions; the objectives' weights are defined according to the a priori information provided by the decision-maker [37].

A posteriori methods do not require introducing subjective preferences before undertaking the optimisation process that builds the Pareto set of alternatives; the optimisation process has to handle more than one criteria simultaneously; hence *a posteriori* methods are considered "true" multi-objective algorithms [18], [24]. Multi-objective optimisation *a posteriori* methods such as the evolutionary algorithms are of interest and have been widely studied for devising Active Distribution Network (ADN) planning alternatives [100]–[104]. Multi-objective optimisation methodologies based on evolutionary algorithms allow devising a set of Pareto optimal alternative for the abstruse problem of network planning [27]. The main drawback of using multi-objective optimisation planning methods arises when the Pareto set contains a large number of alternatives, and the objective functions are more than two since became challenging to identify the most suitable option contained in the set [22], [24], [37]. Methodologies for accomplishing a systematic and automatized analysis of the Pareto set are required to support the decision-maker in selecting the planning alternative to be implemented [27].

MADM methods deal with decision-making problems in which the alternatives are known explicitly ex-ante; both the number of the alternatives and their performances with respect to the evaluation criteria are known since the early stages of the decision-making problem. MADM methodologies aim to support the decision-maker in identifying the best option from the alternatives' set. MADM methods do not assume the decision-maker's role by providing the final decision; their scope is supporting decision-makers in complex decision-making problems [36]. The great diversity of real decision problems has stimulated academics that have developed different methodologies based on the MADM approach. In general, MADM methods are classified according to three main families [105]:

- Full aggregation approach (FAA);
- Outranking approach (OA);
- Goal, aspiration, or reference level approach (GAA).

FAA methods assign each option an overall score obtained by combining the performance achieved on the evaluation criteria of the decision-making problem. According to the overall score achieved by each alternative, a complete ranking is obtained considering the whole evaluation set. The majority of FAA methods calculate the overall score as a linear additive combination of performance indicators and weights of criteria [94]. In general, FAA methods exhibit a compensative behaviour [36], i.e. considering one option, low scores on several criteria are compensated by the high scores achieved on the rest of the evaluation criteria. Methods of the FAA family are the Analytic Hierarchy Process (AHP), the Multi-Attribute Utility Theory (MAUT), and the Measuring Attractiveness by a Categorical-Based Evaluation Technique (MACBETH). The procedure of OA methods is based on the concept of dominance, which is a binary relationship defined between two options. The dominance between two alternatives is disclosed using a pairwise comparison process based on the performance achieved on the evaluation criteria [94]. The weights of the evaluation criteria can also be considered for defining the dominance relationships. Once the dominance relationships are built for the set of options, the concept of outranking is exploited to identify the best option that dominates the rest of the options' set. The exploitation of dominance relationships and the concept of outranking make OA not compensative [36]. The *ELimination Et Choix Traduisant la REalité* (ELECTRE methods) and Preference Ranking Organization METHod for Enrichment Evaluation (PROMETHEE) are the most widely used OA methods [94]. The methods which belong to the GAA rely their assessment on the distance measured between each option and an ideal option that can identify the ideal best or worst solution. Among the GAA family, the Technique of Order Preference Similarity to the Ideal Solution (TOPSIS) is the most acknowledged one [94]. Since their features, MADM techniques are suitable for underrating a systematic and automatized selection process among a vast set of options described in terms of many conflicting criteria. Therefore, MADM methodology can be considered as the complementary tool of *a posteriori* multi-objective optimisation methods to identify the most suitable option contained in the Pareto set.

The research activity described in this dissertation is motivated by the need to solve the decision-making problems of smart grid planning that come from the smart grid planning options design. Therefore, the main focus is on the MADM class since these methodologies allow to solve the selection problem. MADM methodology allows identifying the best option of a set of alternatives irrespective of the methodology used for designing that options. MODM methods have been analysed and described since their use in distribution system planning option design. Moreover, the description of MODM methods is useful to highlight the existing need of identifying the best planning option within a Pareto set of alternatives, which are Pareto optimal, and therefore, nominally equivalent.

3.2.2 Decision making according to MADM methods

Even though the variety of MADM available in the literature, the evaluation process of a decision-making problem undertaken according to the MADM approach has to follow the structure described in Table 3.1.

The procedure described in Table 3.1 ensures that the decision-making problem is addressed according to a systematic approach that minimises the influence of subjectivity and personal biases on the obtained outcome.

Table 3.1. Structure of a decision-making process according to the MADM approach (adapted from [36], [94]*)*

1. Establish the decision context.
   a. Establish the goal of the decision-making problem.
   b. Identify decision-makers and other key players.
   c. Consider the context of the appraisal.
2. Identify the options to be appraised.
3. Identify the evaluation criteria.
   a. Identify evaluation criteria for appraising the options' impact.
   b. Organise the criteria in a structure (hierarchical or flat).
4. Scoring. Assess the performance of each option with respect to each criterion.
   a. Describe the consequences of the options.
   b. Score the options on the criteria.
   c. Check the consistency of the scores on each criterion.
5. Weighting. Assign a weight to each criterion according to the relevance for the decision-making problem.
6. Combine weights and scores to obtain the overall score for each option.
   a. Calculate the overall weighted scores at each level in the hierarchy.
   b. Calculate the overall weighted scores.
7. Examine the results.
8. Sensitivity analysis.
   a. Sensitivity analysis concerning performance and weight values.
   b. Analyse if the obtained outcome satisfies the stakeholders.
   c. Introduce new options if stakeholders are not satisfied with the outcome.
   d. Repeat the above steps until stakeholder expectations are met.

3.2.3 Key features of MADM methods

Irrespective of the family to which a MADM method belongs, several common features can be identified and represent the pillars of the MADM techniques: the decision matrix, the scoring and weighting stages, the computation algorithm. These common features are part of the evaluation made according to the MADM methods and allow to obtain the overall appraisal of the options in the evaluation set. Figure 3.1 depicts the high-level schema of the MADM appraisal procedure. One of the inputs of the MADM-based appraisal approaches is represented by the set of the alternative to be evaluated described considering their relevant attributes. As described in section 3.2.3.1, the information regarding the options to be evaluated is contained in the decision matrix that contains, for each option, the values of the attributes considering the evaluation criteria of the decision-making problem. The criteria hierarchy represents the structure of the decision-making problem; it is formed by the criteria that have been considered relevant for evaluating the options. The decision-making problem structure can be characterised by several layers in which parent criteria on the upper levels are related to the corresponding child criteria on the lower levels. The stakeholders' perspective is a relevant input for solving a decision-making problem using an MCA/MADM approach. The stakeholders' perspective is not formalised as a specific element as the criteria hierarchy or the decision matrix; however, it represents an underlying input that guides the whole MCA/MADM procedure. To illustrate, the stakeholders' perspective is fundamental in defining the goal of the decision-making problem, in identifying the criteria that are of interest for appraising the alternatives, in assigning the relevance to the set of evaluation criteria which form the criteria hierarchy. The MCA/MADM technique represents the computational block of the MCA/MADM evaluation approach, any of the techniques belonging to the FAA, OA, and GAA families can be used to combine the inputs and provide the overall appraisal of the options in the evaluation set, which represents the output of the MCA/MADM evaluation.

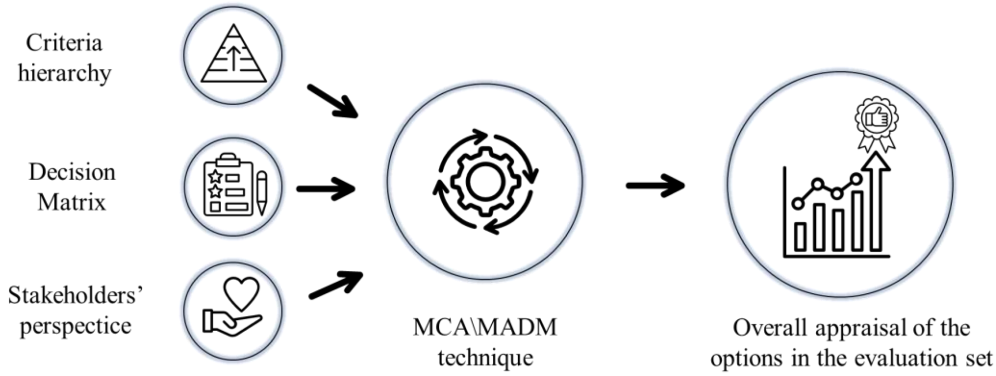

Figure 3.1. High-level schema of the MADM appraisal procedure

An option (or alternative) is a specific set of actions that can potentially allow achieving the main goal and, then, solving the decision-making problem [36]. In the context of the MCA/MADM problems, the options are expressed in terms of the attributes defined considering the evaluation criteria of the decision-making problem. To illustrate, a car selection decision-making problem can be formed by several options which belong to the set of available cars. Each option, i.e. each car, is described in terms of the attribute values corresponding to the evaluation criteria relevant for solving the decision-making problem (e.g., cost, speed, technology, colour, design, safety, travel range) [106], [107].

The structure of the decision making problem, modelled in terms of the criteria hierarchy, is composed of the main goal, the evaluation criteria, and the corresponding metrics [36]. The main goal represents the overall objective that has to be achieved: the problem to be solved, the target to be reached [108]–[111]. In line with the main goal, the evaluation criteria represent the operational definitions that are useful to measure the extent to which each option complies with a particular aspect related to the achievement of the main goal [36]. Therefore, each criterion has to be quantitative or qualitative measurable. To this aim, each criterion corresponds to an indicator that defines the metrics used to measure the option's performance on that specific aspect. The metric of an indicator can be quantitative (for tangible impacts) or qualitative (for intangible and not quantifiable impacts) [36]. Typically, tangible impacts or performances are measurable using a quantitative scale, while intangible ones are expressed in qualitative terms [36]. An example of a quantitative, and then tangible, attribute could be any measurable characteristics (e.g., weight, volume, speed, cost), while a qualitative, hence intangible impact, is any attribute that cannot be measurable with a quantitative scale because of its nature or the lack of information (e.g., beauty, design, biodiversity loss, social acceptance) [112].

3.2.3.1 The Decision Matrix (DM) or Performance Matrix (PM)

The MADM methods are decision support tools that allow the decision-maker to identify the best option within an already designed set. The options to be appraised are the main inputs of the decision-making problem and are described considering their performances in quantitative or qualitative terms to the corresponding evaluation criteria. The options to be appraised expressed in these terms form the Decision Matrix (DM), also known as Performance Matrix (PM), which is the starting point of the evaluation made employing a MADM technique [36]. It contains the input data used for evaluating the fulfilment of the evaluation criteria and calculating the overall score of the options. To illustrate, considering a decision-making problem in which the options under analysis are evaluated on the basis of their impact measured in terms of performance indicators, the DM contains a number of rows equals to the number of the alternatives, and a number of columns equals to the number of the performance indicators. The entries of the DM are the performance values achieved by the options on each evaluation criteria. In Table 3.2, the general structure of a DM is reported. The general decision-making problem to which Table 3.2 refers is characterised by *M* alternatives and *N* criteria. The entry $P_{i,j}$ is the performance value of the alternative *i-th* with respect to the *j-th* criterion. In general, the entries related to different columns of the DM can be expressed in terms of a different unit of measurement; moreover, the related performances can be expressed in quantitative or qualitative terms.

Table 3.2. The general structure of a Decision Matrix (DM)

	Criterion 1	⋯	Criterion *j*	⋯	Criterion *N*
Alternative 1	$P_{1,1}$	⋮	$P_{1,j}$	⋮	$P_{1,N}$
⋮	⋮	⋮	⋮	⋮	⋮
Alternative *i*	$P_{i,1}$	⋮	$P_{i,j}$	⋮	$P_{i,N}$
⋮	⋮	⋮	⋮	⋮	⋮
Alternative *M*	$P_{M,1}$	⋮	$P_{M,j}$	⋮	$P_{M,N}$

3.2.3.2 The scoring stage

To allow the comparison of impacts related to different criteria, the MADM methods require converting the information contained in the DM to a common scale [94]. The conversion process is called the scoring stage; typically, the DM is converted according to a normalised numerical scale. In general, the scoring procedure is undertaken criterion by criterion; the scoring process exploits monotonic scaling functions: in the normalised numerical scale the highest score is assigned to the alternative that better satisfies the considered criterion. Therefore, the value of the assigned score is higher, as it increases criterion satisfaction. The scoring process is characterised by two elements: the method for defining the reference points for the scaling interval and the methodology used for converting performance into normalised scores. Several approaches can be used for defining the reference points of the scaling interval [36], [94]:

- Local Scaling: for each criterion, the extreme score values of the normalised scale are related to the highest and the lowest value in the DM for the considered criterion.
- Global Scaling: for each criterion, the extreme score values of the normalised scale are related to performance values arbitrarily chosen by the analyst.

Local scaling allows obtaining normalised scores that are strictly related to the set of alternatives under analysis, whereas global scaling is preferred when it is likely to consider further new options which may have performances outside the range of the initial set of options [94].

The conversion of the performance in the DM into a normalised score can be addressed according to three approaches [36]:

- Using a scaling Function:
    - Linear increasing function;
    - Linear decreasing function;
    - Non-linear function;
- By making a direct rating based on subjective information from stakeholders;
- By making a rating based on a pairwise comparison of the alternatives.

3.2.3.3 The weighting stage

Typically, addressing decision-making problems using a MADM method require determining the relevance of the criteria for the decision-making process. Determining the criteria relevance with respect to the goal of the decision-making problem represents a crucial activity since it strongly influences the outcome of the analysis. The weighting stage is the process that allows assigning to the evaluation criteria a numerical value that reflects the relevance of criteria for the decision-making problem. In MADM, the weighting stage has to be addressed according to systematic procedures which allow obtaining a reliable set of weights. Several weighting techniques have been proposed in literature which can be classified according to three families: subjective, objective (or synthetic), and integrated (or hybrid) [113].

The subjective approach methods determine the criteria weights by collecting the point of view of stakeholders directly or indirectly. In general, subjective methods are useful for directly involving stakeholders or experts in the decision-making process. Subjective methods exploit systematic procedures to reject personal biases; however, collected preferences could still lack consistency. Moreover, several techniques have been proposed for aggregating the preferences expressed by homogenous and heterogeneous groups of individuals. The most widely used subjective methods are [114]: the pairwise comparison [47], sorting by relevance [115]–[117], Trade-off [118], Swing [119], and Resistance To Change [120]. Objective weighting approaches determine the criteria weights from the information contained in the DM. An algorithm is used to calculate the weights from alternatives' attributes without considering any subjective information of stakeholders and decision-makers. The most widespread weighting methods are [114]: the Shannon's Entropy [121], the standard deviation method [122], the CRITIC method [122]. Integrated or hybrid methods mix subjective and objective weighting approaches. Typically, criteria weights are calculated using an optimisation model; the objective function is defined to emphasise some peculiarity of the alternatives. Subjective information about criteria relevance can be embedded in the optimisation model regarding constraints on the variables. Therefore, the result obtained by means of integrated methods has some degree of subjectivity. When the model constraints are not set, the integrated method turns to objective since no subjective information is considered. Some of the integrated methods proposed in literature are the method of maximising the deviation of attributes [123], [124], the Ideal Point method [125], and the Correlation Coefficient and the Standard Deviation (CCSD) method [126]–[128].

In addition, some aggregation strategies for combining the weights obtained by means the subjective, objective and integrated methodologies have been proposed in the literature [113]. In general, employing aggregation strategies, a single set of weights is synthesized from sets already obtained by exploiting a subjective and an objective weighting method. Some of the aggregation strategies proposed in the literature are the aggregation by multiplication (or product) [129], by linear combination [130], and by exponential relevance [131]. Subjectivity is introduced in MCDA when is required a coefficient that quantifies the relevance of subjective weights over objective weights [113].

3.2.3.4 The computation algorithm

The core of the MADM methods is the computation algorithm that provides the overall appraisal of the alternatives by combining scores of the alternatives and criteria weights [94]. Each MADM method is based on different assumptions that define the characteristics of the calculation algorithm. To preserve control of the decision-maker on the analysis, a general recommendation is to prefer simple MADM methods [36].

3.2.4 Advantages and disadvantages of using MADM methods

Multi-criteria analysis, and in particular of MADM, represents an important support tool for complex decision-making. In fact, identify the best option in decision-making problems characterised by a large set of options or a large number of evaluation criteria to be considered is burdensome and may lead to suboptimal solutions.

As described in section 3.2.2, MCA and the MADM methods provide a structured approach for tackling the decision-making problems. It encourages the identification of the decision context and a clear definition of the goal that has to be achieved by the best option. The overall decision problem is then broken down into elementary decision problems which solution can be identified straightforwardly compared to the overall problem. The MCA approach is flexible; it allows to address decision-making problems from different sectors and characterised by huge diversity.

Since the decomposition process, multiple conflicting criteria are considered simultaneously to appraise the set of options. The performance of the options with respect to the evaluation criteria is evaluated through a dedicated set of indicators; therefore, an output-based assessment of the impacts is possible. However, both subjective judgments and objective data can be used to appraise the extent to which each alternative meets the primary goal. Even if MADM requires defining measurable criteria, the performances of the alternatives can be expressed in quantitative or qualitative terms. Therefore, it allows involving simultaneously in the analysis indicators which describe the tangible and intangible impacts. Thus, a decision-making problem addressed through the MCA/MADM approach can encompass evaluation criteria that measure the options' performances expressed in quantitative and qualitative terms.

Moreover, in MADM, stakeholders play an essential role during the whole evaluation process. In fact, the final goal, the evaluation criteria, their relative importance, and the measure of the option performances strongly depend on the stakeholder's preferences. Accordingly, a certain degree of subjectivity is intrinsic in the MADM outcome [36], [94].

However, unlike CBA, there is no explicit need to define a rule which states that benefits must exceed costs [94]. Therefore, the best option indicated by MADM may not fit the principle of the improvement of well-being, namely, the "doing nothing" principle might result as preferable [36]. To avoid this behaviour, the final goal and the criteria have to be carefully defined.

Moreover, since more than one criterion are involved in the appraisal, the risk of double-counting the same impact exist. Moreover, the outcome of the MCA is significantly dependent on the criteria weights that have been assigned. Criteria relevance depends on the stakeholder perspective; therefore, it has to be acquired with considerable accuracy. The use of incongruent weight may lead to a solution to the decision-making problem that does not satisfy the stakeholders. In any case, the definition of the criteria weights based on the stakeholder preferences introduces subjectivity in the analysis; if not adequately managed, personal biases and arbitrariness may influence the MCA outcome.

Due to the highlighted disadvantages, MCA and MADM approaches have to be considered as decision support tools for decision-makers. These approaches should not substitute the decision of the decision-makers [36]. Among the activities of formalising and modelling the decision-making problem, the analysts are in charge of supervising the appraisal process and providing the required corrective actions in the cases in which the outcome of the appraisal seems unable to meet the stakeholder expectations. It may happen in cases in which some aspect has been not considered or not adequately modelled in the analysis. Therefore, corrective actions are required to adapt the structure of the MCA decision-making process and improve the solution provided.

3.2.5 Survey on MADM techniques

The MADM techniques represent fully structured procedures in all steps of the assessment procedure are defined according to the principles of the underlying approach. Each MADM technique has particular scoring and weighting stages which are coordinated for providing a coherent outcome.

3.2.5.1 The Analytic Hierarchy Process (AHP)

The Analytic Hierarchy Process (AHP) is one of the most acknowledged MADM techniques; it has been employed in various sectors [36]; Thomas L. Saaty has proposed it in the mid-'70s [132]. The key features of the AHP are the formalisation of the decision problem according to a hierarchy of elementary decision-making problems, the ratio scale used for expressing preferences, and the pairwise comparison procedure for the scoring and the weighting stages [94]. The decision -making problem has to be studied by the analyst to identify the relevant evaluation criteria which form a hierarchical structure. A ratio scale is used for collecting the preferences for stakeholders or converting the quantitative performance indicators. The pairwise comparison process supports the decision-maker in converting the judgement provided by stakeholders and quantitative information in a systematic way in both the scoring and the weighting stage. The outcome of AHP is an overall score assigned to each alternative; the overall score is calculated by a linear combination of scores and weights. Therefore, the option which achieves the highest overall score is the best alternative of the evaluation set.

AHP presents a structured approach that allows to solve complex decision-making problems. It can simultaneously handle input data expressed in quantitative and qualitative terms; moreover, the reliability of the pairwise comparison process for scoring and weighting is widely recognized [36]. However, despite the success of AHP, some criticism about its theoretical pillars exist. According to AHP detractors, the main weakness of AHP are related to the absence of a clear theoretical foundation between the Saaty’s verbal scale and the Saaty’s ratio scale; the internal inconsistency of the Saaty’s ratio scale (i.e., if A/B→3 and B/C→5 then A/C→15 that is greater than 9, the maximum value allowed by the Saaty’s scale); the final rank of the alternative can change if new alternatives are introduced or some alternative is removed [36]. The rank reversal problem is felt like the most alarming one, although Saaty considers it acceptable [132].

In literature, several adjustments on the AHP have been proposed to outclass its shortcomings while preserving its strengths [36]. One of the main changes on AHP concerns the evaluation of priorities based on the normalised geometric mean of the preference matrix rows. Furthermore, to avoid rank reversal problems, the Ratio Estimation in Magnitudes or deci-Bells to Rate Alternatives which are Non-DominaTed (REMBRANDT method) has been devised [133], [134]. In particular, the REMBRANDT method substitutes the Saaty’s ratio scale with a logarithmic scale and uses the geometric mean method for computing priorities. Moreover, AHP assumes that criteria are mutually independent, to face decision-making problems with dependence and feedbacks among criteria the Analytic Network Process (ANP) has been proposed by Saaty [135].

The assessment procedure of the AHP involves several steps, as described in the following.

3.2.5.1.1 The formalisation of the decision-making problem

The decision-making problem has to be analysed to define the goal to be pursued and the evaluation criteria. Accordingly, the features of the alternatives and the stakeholders have to be identified. Once that criteria and alternatives are explicitly known, the hierarchical structure of criteria and the DM of alternatives have to be built.

3.2.5.1.2 Pairwise comparison procedure for scoring the alternatives and weighting the criteria

In AHP the pairwise comparison procedure is used both in the scoring and in the weighting stages. Using the pairwise comparison, the preference between two objects is appraised. In authentic AHP, both scoring and weighting stages are influenced by the subjectivity of the decision-maker or stakeholders [136]. In fact, the judgment of the decision-maker is quantified on a standardized judgment scale (Saaty's scale) [132], as shown in Table 3.3.

In the weighting stage, the pairwise comparison requires to formulate according to Saaty's scale preference statements related to criteria relevance. The pairwise comparison of criteria depends on the hierarchical structure of the decision-making problem. For each sub-branch, the weights of the criteria belonging to the same level of the hierarchy are defined according to the decision-maker preference. The judgements are collected by posing questions such as "To fulfil the parent criterion, how much criterion A is relevant with respect to criterion B?" [36]. The preferences of the stakeholders collected in verbal terms are converted into numerical values utilizing Saaty's ratio scale (Table 3.3). A preference that lies between two adjacent judgments can be expressed by using the intermediate integer values (2, 4, 6, 8).

Table 3.3. Saaty's judgment scale [132]

Verbal judgement	**Saaty's ratio scale (w_j / w_k)**
Absolute preference for object w_k	1/9
Demonstrated preference for object w_k	1/7
Strong preference for object w_k	1/5
Weak preference for object w_k	1/3
Indifference/equal preference	1
Weak preference for object w_j	3
Strong preference for object w_j	5
Demonstrated preference for object w_j	7
Absolute preference for object w_j	9

Similarly to the weighting stage, in the scoring stage the alternatives are pairwise compared criterion by criterion. As a result, for each criterion is obtained a preference matrix. For each terminal criterion, the preference matrix of the alternatives contains as entries the judgments expressed in terms of the Saaty's ratio scale.

As the number of the criteria and of the alternatives increases, it also increases the number of required pairwise comparisons. However, the decision-maker is assumed as coherent in his judgments about each pair of compared objects; hence the entries of the lower triangle of the preference matrix are the reciprocal of the corresponding entries in the upper triangle (i.e., $q_{i,j}^{(k)} = 1/q_{j,i}^{(k)}$). The entries of the main diagonal are equal to 1. To illustrate, in Table 3.4, an example of a preference matrix is presented.

Table 3.4. AHP preference matrix example

	A	**B**	**C**
A	1	7	9
B	1/7	1	2
C	1/9	1/2	1

Even if the consistency of judgment within a pairwise comparison is guaranteed by the hypothesis of coherent pairwise comparison, the consistency of the preferences expressed on the whole set of objects in the preference matrix is not guaranteed. Therefore, it is required to check the consistency of the preference matrix. The original method for checking consistency is based on the evaluation of a consistency ratio (CR) compared to a threshold value (e.g., CRthreshold= 0,1) [137], while statistical approaches have been proposed for checking the consistency of large matrices [138].

3.2.5.1.3 Calculation of priorities

In AHP, priorities are the normalised values obtained from a preference matrix. If the preference matrix is related to the pairwise comparison of alternatives made in the scoring stage, the priorities represent the normalised scores of each alternative concerning the considered criterion. Alternatively, if the preference matrix comes from the weighting stage, the priorities represent the local weights of criteria relevant for the related subbranch.

In general, once a consistent preference matrix is obtained, the corresponding priorities are evaluated. Priorities from preference matrices can be evaluated by using different approaches; the original approach states that the priorities are equal to the normalised eigenvector of the maximum eigenvalue of the preference matrix. If the decision-making problem is not flat (i.e., more than one level of criteria exists), the priorities obtained from a preference matrix of criteria are considered as local priorities. The global priorities are evaluated using the hierarchical composition principle [132].

3.2.5.1.4 Computation of the overall score

AHP assigns to each alternative an overall score which is calculated as the linear combination of the normalised score of the alternatives and the global weights of terminal criteria. The alternative that achieves the highest overall score is the one that the AHP indicates as the best alternative of the analysed set.

3.2.5.2 Multi-Attribute Utility Theory (MAUT) Methods

The Multi-Attribute Utility Theory (MAUT) methods family is adopted mainly in Anglo-Saxon countries. Its main feature is the utility function U which models the DMs' preferences [105]. The underlying hypothesis relies on the fact that the decision-maker tend to optimise a function which aggregates the preferences; this behaviour may be conscious or not. Moreover, at the beginning of the decision-making process the utility function may be unknown; hence MAUT methods require to build it.

Generally, MAUT methods manage quantitative information on performances and criteria relevance. Nevertheless, qualitative information can be treated if previously converted to a normalised quantitative scale. In fact, qualitative data implicitly describe quantitative data classes [97]. MAUT methods require a scoring stage of the DM and a weighting stage for assessing the criteria weights. In general, the methods of the MAUT family involve the following steps:

- Verify the mutual independence of the evaluation criteria.
- Determine the parameters of the utility function U.

By means of the utility function U, the extent to which each alternative is attractive to the decision-maker is evaluated. The attractiveness is measured through the utility score that represents the well-being that each alternative gives to the decision-maker. The global utility score (US) of each alternative is evaluated by aggregating the marginal utility scores (MUS) obtained on each evaluation criteria [105]. A ranking of the alternatives is devised based on the preference and indifference relationships (3.1) ruled by the values of the US [105].

$$\begin{gathered}\forall\ a, b\ \in A\colon a\boldsymbol{P}b\ \Leftrightarrow U(a) > U(b)\colon a\ is\ preferred\ to\ b\\ \forall\ a, b\ \in A\colon a\boldsymbol{I}b\ \Leftrightarrow U(a) = U(b)\colon a\ and\ b\ are\ indifferent\end{gathered} \tag{3.1}$$

Where:

A*:* is the set of the alternatives under analysis;

$U(a)$: is the US of the alternative a;

$U(b)$: is the US of the alternative b;

Incomparability among alternative is not allowed because the numeric values of the USs are always comparable. Moreover, the preference relation is transitive among alternatives.

The Linear Additive Model (LAM) is the simpler way to define the *utility function U*; it involves a linear relationship among performance scores and criteria weights [97]. The LAM requires decision-making problems with certainty and mutually independent criteria. In general, a pair of criteria is mutually independent if the performance score on one criterion can be assigned without any knowledge about the performance score on the other criterion [36].

A scaling process of the DM is made by converting the performances ($f_i(a)$) in terms of MUS ($U_j(f_i(a_i))$). Next, the MUSs related to different criteria are aggregated through a weighted sum (3.2), to evaluate the global utility score of the alternative $U(a_i)$ [105].

$$a_i \in A: U(a_i) = \sum_{j=1}^{q} U_j(f_j(a_i)) \cdot w_j \tag{3.2}$$

In which:

$f_i(a_i)$ represents the performance of the i-th alternative on the j-th criterion;

w_j is the relative weight of the j-th criterion;

q is the number of the evaluation criteria;

$U_j(f_j) > 0$ is the j-th marginal utility function.

Usually, the marginal utility functions are non-decreasing; on each criterion, the MUS value 1 is assigned to the best alternative. Conversely, the 0 value of MUS is assigned to the worst alternative. Therefore, if the sum of all criteria weights is equal to one, the US of each alternative fall on the 0-1 range.

The shape of each marginal utility function depends on the risk attitude of the decision-maker [105]. Concave functions are related to risk-averse attitudes, whereas convex functions are related to risk-prone attitudes. Concave functions are therefore assigned to criteria in which a small difference on low values of performance matters. Conversely, convex functions are assigned to those criteria in which a small difference on high values of performance matters. The shape of the marginal utility functions can be determined by collecting preferences utilizing direct or indirect methods.

A drawback of LAM is the high share of information required for building the marginal utility functions. OA methods have been devised to overcome this drawback; OA fundamentals combine the MAUT principles with the outranking dominance relationship [105].

A particular case of LAM is the weighted sum of the scored performances on the evaluation criteria. In this case, the marginal utility functions are modelled as linear functions; the utility score of an alternative i-th is evaluable by (3.3) [105].

$$\forall a_i \in A: U(a_i) = \sum_{j=1}^{q} f_i(a_i) \cdot w_j \tag{3.3}$$

3.2.5.3 Outranking Approach Methods

The OA methods are based on the outranking concept: "Option A outranks Option B if, given what is understood of the preferences of the decision-maker, the quality of the evaluation of the options and the context of the problem, there are enough arguments to decide that A is at least as good as B, while there is no overwhelming reason to refute that statement" [36], [139]. In OA methods, the alternatives are pairwise compared in terms of their performances to define the outranking binary relation. Weights of criteria influence the dominance relation within each pair. Unlike FAA methods, the OA methods are not compensative, i.e., in the overall assessment of an alternative, good performances on some criteria cannot counterbalance poor performances on other criteria. Thanks to this feature, OA methods capture the real decision-making behaviour related to the rejection of the alternatives that show an intolerable level of performances on some criteria [6]. Furthermore, OA methods allow the incomparability of the alternatives if the outranking relation is undefinable because of missing data [120]. Conversely, indifference exists when two alternatives are equally good, and therefore no one dominates the other. In general, the output provided by outranking methods is the set of dominating options identified by analysing the outranking relationships of the given set of alternatives. The OA has been proposed by Roy in mid-'60s, and it has obtained wide diffusion in continental Europe [36], [105]. Despite its advantages, the complexity of outranking methods limits their more comprehensive application [36].

In general, the MCA based on OA methods starts from the DM. Therefore, options, criteria, performances, and weights of criteria have to be already defined according to the MCA principles. In addition, criteria have to be mutually independent. OA methods have been initially devised to face flat decision-making problems, although methods for appraising hierarchical structures of criteria have been devised in recent years [140]. Each OA method involves the pairwise comparison of the alternatives to define the outranking relationships and identify the dominating set. The differences among OA methods lie on the particular methodology used for addressing these steps. Commonly, an option outranks another if it has higher performances on the criteria of highest relevance, while on the remaining criteria, it has not significantly worse performances. Therefore, weights measure the extent to which each criterion influences the outranking relationships between options [120].

3.2.5.3.1 The ELECTRE Methods

Among the OAs, the family of ELECTRE methods is one of the main branches [105]. Since the first version presented by Roy in [141], several evolved versions of the ELECTRE method have been proposed. Each new version has been devised to outclass drawbacks and to adjust the methodology to specific decision-making problem characteristics. Despite the high complexity, ELECTRE methods have been employed in several sectors, e.g., environmental, agriculture, water management, energy, finance, transportation, and military [105].

In general, for effectively exploiting the ELECTRE methods, the decision-making problem has to satisfy at least one of the following conditions [142]:

i. The number of criteria is equal to or greater than 3;

ii. The performances are evaluated by means of ordinal or interval scales;

iii. The performances on criteria are measured in terms of heterogeneous indices;

iv. The compensation of performances is not acceptable for the decision-maker;

v. The decision-making problem requires the use of indifference and preference thresholds on the difference of performances.

Since the performances are handled through an interval scale, the scoring stage is not required on ELECTRE methods.

In general, the operators used to describe the binary relation between each pair of alternatives are:

- S: outranking operator (i.e., aSb: a is at least as good as b);
- P: strictly preference operator (i.e., aPb: a is strictly preferred to b);
- I: indifference operator (i.e., aIb: a is indifferent to b);
- R: incomparability operator (i.e., aRb: a is incomparable to b).

The possible binary relations among each pair of alternatives are four [142]:

1. aSb and not bSa (hence aPb): a outranks b;
2. bSa and not aSb (hence bPa): b outranks a;
3. aSb and bSa (hence aIb);
4. not aSb and not bSa (hence aRb).

The outranking relation (aSb) between each pair of alternatives is not transitive, it can be crisp, fuzzy or embedded, and it is built on the concepts of Concordance and Discordance of the criteria on the aSb statement [142]. Concordance exists if a sufficient majority of criteria agree with the dominance relationships while none of the discordant criteria strongly disagree on aSb.

The dominance relationships can be represented graphically to give an easier understanding of the outranking set (Figure 3.2).

The outranking relationship between two alternatives is defined according to the performances on the evaluation criteria. In addition, the dominance of an alternative on another is influenced by the relative importance of the criteria and the performance difference thresholds.

Considering 3 options: ***a***, ***b***, ***c***.

Outranking relationships:
bSa; ***bSc***; ***cSa***:

The dominant option is ***b****;*

b dominates ***a*** and ***c***;

b is not dominated by any of the remaining options.

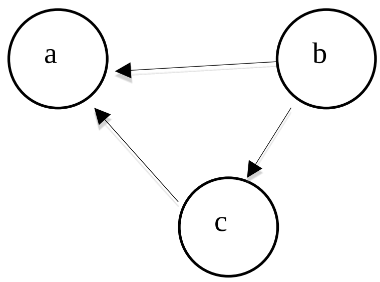

Figure 3.2. Example of dominance relationships [143]

3.2.5.3.2 The ELECTRE III Method

ELECTRE III is one of the most acknowledged methods among ELECTRE family; its algorithm is divided into two stages [105]: computation of the outranking relationships, exploitation of the obtained outranking relationships.

In the first stage, the decision-maker has to define the weights of criteria and the preference, indifference, and veto thresholds. Then, the outranking relationship of each pair of alternative can be built. In the second stage, the outranking relationships are analysed for identifying the dominant set of alternatives.

Key features of the ELECTRE III algorithm are [105]:

The outranking relationship *aSb*;

The outranking degree *S(a,b): S(a,b)* measures the credibility of *aSb*. The numerical value of *S(a,b)* is between [0, 1], it approaches 1 as the credibility of *aSb* is higher. The value of *S(a,b)* depends on *concordance* and *discordance* of the criteria to the *aSb* statement.

The indifference threshold q_i: it is the greatest difference on performances on a criterion that makes two options indifferent for the decision-maker's point of view.

The preference threshold p_i: it is the smallest performance difference on a criterion that makes an option preferred to the other for the decision-maker's point of view [144].

The veto threshold v_i: it is the smallest performance difference on a criterion which leads to the rejection of the proposed outranking relationship, albeit the other criteria agrees with it [144].

Indifference, preference, and veto thresholds can be defined as absolute values, or as functions of the values of performances. In general, (3.4) has to be verified [105].

$$qi \leq pi \leq v_i \tag{3.4}$$

3.2.5.3.2.1 First stage: computation of the dominance degrees

The dominance degree *S(a,b)* is evaluated by means of the concordance and discordance indices ($c_j(a,b)$ and $d_j(a,b)$, respectively). Firstly, those indices are evaluated for each criterion (partial indices), then the global concordance index (*C(a,b)*) is obtained. Finally, the outranking degree *S(a,b)* of the alternative a on the alternative b is computed by aggregating the discordance indices and the global concordance index.

The partial concordance index cj(a,b) measures the credibility of the outranking relationship *aSb* with respect to the j-th criterion. cj(a,b) is evaluated by means of (3.5), (3.6), and (3.7) [144].

$$c_j(a,b) = 1 \quad if\ f_j(b) - f_j(a) \leq q_j \tag{3.5}$$

$$c_j(a,b) = \frac{p_j - [f_j(b) - f_j(a)]}{p_j - q_j} \quad if\ q_j < f_j(b) - f_j(a) < p_j \tag{3.6}$$

$$c_j(a,b) = 0 \quad if\ f_j(b) - f_j(a) \geq p_j \tag{3.7}$$

The partial discordance index $d_j(a,b)$ measures the degree of discordance on the outranking relationship *aSb* of each criterion. $d_j(a,b)$ is evaluated by means of (3.8), (3.9), and (3.10) [144].

$$d_j(a,b) = 1 \quad if\ f_j(b) - f_j(a) \geq v_j \tag{3.8}$$

$$d_j(a,b) = \frac{[f_j(b) - f_j(a)] - p_j}{v_j - p_j} \quad if\ p_j < f_j(b) - f_j(a) < v_j \tag{3.9}$$

$$d_j(a,b) = 0 \quad if\ f_j(b) - f_j(a) \leq p_j \tag{3.10}$$

The global concordance index *C(a,b)* aggregates the partial concordance indexes obtained for each criterion, taking into account the weights of criteria. *C(a,b)* is evaluated by means of (3.11) [144].

$$C(a,b) = \frac{\sum_{j=1}^{q} w_j \cdot c_j(a,b)}{\sum_{j=1}^{q} w_j} \tag{3.11}$$

Finally, the outranking degree *S(a,b)* aggregates the global concordance index *C(a,b)* and the partial discordance index $d_j(a,b)$. Therefore, *S(a,b)* measures the strength of the outranking relationship *aSb*. *S(a,b)* is evaluated by means of (3.12) and (3.13) [144].

$$S(a,b) = C(a,b)\ se\ d_j(a,b) \leq C(a,b)\ \ \forall j \tag{3.12}$$

Otherwise:

$$S(a,b) = C(a,b) \cdot \prod_{V} \left[\frac{1 - d_j(a,b)}{1 - C(a,b)} \right] \tag{3.13}$$

Where V represents the set of criteria which $d_j(a,b) > C(a,b)$.

To avoid that a single criterion would be the only responsible of the final decision on the outranking relationship when the veto threshold is not exceeded, the *non-dictatorship* condition (3.14) has to be respected [144].

$$w_j \leq \sum_{\substack{k=1 \\ k \neq j}}^{q} w_k \tag{3.14}$$

3.2.5.3.2.2 Second stage: distillation

The second stage of ELECTRE III is called *distillation*; the previously obtained outranking degrees are exploited by two iterative procedures that identify the dominant set. Each iterative procedure provides a partial ranking of the alternatives, the intersection between the partial rankings is the final ranking of the alternative according to the ELECTRE III method [105].

Before the distillation procedure, a worthiness score is assigned to each alternative according to its outranking behaviour. The worthiness score of an alternative is unitarily increased each time it dominates another. Conversely, the worthiness score is unitarily decreased each time the alternative is dominated.

In each iteration of the descending distillation procedure, the set with the highest worthiness score is extracted from the whole set of the alternatives under analysis. Therefore, a ranking of the alternatives is built by iteratively considering sets having a decreased value of worthiness score. O_1 is the partial ranking obtained using the descending distillation procedure. Similarly, the ascending procedure provides a partial ranking of the alternatives (O_2) built according to the increasing values of the worthiness score. Once the partial rankings O_1 and O_2 are obtained, the intersection between these sets is evaluated. The intersection set is found according to the following global relationships [105]:

- $a\ is\ globally\ better\ than\ b\ (a \succ b), if\ and\ only\ if$:
  - *a* is *better* than *b* in O_1 and O_2, or
  - *a* is *indifferent* to *b* in O_1 but *better* than *b* in O_2, or
  - *a* is *better* than *b* in O_2 and *indifferent* to *b* in O_1.
- $a\ and\ b\ are\ globally\ indifferent\ (a \equiv b), if\ and\ only\ if$:
  - *a* and *b* are *indifferent* in O_1 and O_2.
  - $a\ and\ b\ are\ globally\ incomparable\ (a \boxtimes b), if\ and\ only\ if$:
  - *a* is *better* than *b* in O_1 but *b* is *better* than *a* O_2, or
  - *b* is *better* than *a* in O_1 but *a* is *better* than *b* O_2.
- $a\ is\ globally\ worse\ than\ b\ (a \prec b), if\ and\ only\ if$:
  - *b* is *better* than *a* in O_1 e O_2, or
  - *a* is *indifferent* to *b* in O_1 but *b* is *better* than *a* in O_2, or
  - *b* is *better* than *a* in O_2 and *indifferent* to *a* in O_1.

3.2.5.3.3 OA methods for qualitative input data

Frequently, decision-making problems involve qualitative judgments both for assessing the criteria relevance and the level of performances of the alternatives. Several MADM methods focused on qualitative data have been proposed in literature; among the OA methods, REGIME [145] is one of the most acknowledged. The main feature of REGIME is its capability to accept mixed input data both for alternatives score and criteria weights [143]. According to the OA, REGIME defines the dominance relationships between the alternatives by means of a pairwise comparison process; but REGIME involves an ordinal generalisation of this process [36].

3.2.5.4 Fuzzy MADM Methods

The use of the fuzzy set theory has been introduced in MCA to manage the imprecision of the input data of the decision-making problem. However, MCA methods based on fuzzy sets are not widely employed in practice; their use is limited to academic studies [36]. Fuzzy sets represent qualitative data and preferences employing membership functions with the aim to model the natural language imprecision [36]. Therefore, the attractiveness of an option can be quantified using a fuzzy number between [0, 1]. In fuzzy-MCA methods, performances and weights are expressed and managed in terms of fuzzy numbers, but the methodological framework is inherited from the corresponding MCA technique devised for crisp numbers. On the one hand, the strength of MCA fuzzy methods relies on the mathematical modelling of uncertainties of real decision-making problems. On the other hand, the high complexity and the choice of the most reliable membership functions are the main shortcomings [36].

4 TECHNIQUES FOR WEIGHTING THE EVALUATION CRITERIA

This chapter focuses on the techniques for weighting the evaluation criteria since the considerable relevance of criteria weights in the outcome of the multi-criteria analysis. Subjective, objective, and integrated methods for criteria weights are reviewed. Then, the most common aggregation strategies are described. The method for assessing the final global ranking stability in terms of criteria weight sensitivity is illustrated.

This chapter aims at answering the following questions:

- How can evaluation criteria weights be obtained?
- How can the criteria weights be obtained from subjective preferences?
- How can the criteria weights be obtained from objective information?
- How can the criteria weight be obtained from subjective and objective information?
- How much is the final outcome sensitive to the criteria weights changes?

4.1 Subjective methods for determining the criteria weights

In subjective methods for determining the weight of the criteria, stakeholders play a pivotal role. Stakeholders are all the individuals and organizations involved in the outcome of the planning process, or in general, of the decision-making. Identifying these actors and determining their involvement is part of the planning process. Decision-making processes addressed by means of the MCA are influenced by stakeholders since from the stage in which the evaluation criteria are identified and defined [36], [113]. The evaluation of the best alternative is based on the satisfaction of the stakeholders' goal and the compliance with the constraints imposed on the decision-making process. In cases in which subjective methods are used to determine the mutual relevance of the criteria, the importance of the role of stakeholders is augmented. In scientific literature, subjective methodologies able to determine the weight of the criteria starting from incomplete preference information have aroused considerable interest [113], [115].

The collection of stakeholders' perspectives is a critical element of the multi-criteria analysis of decision problems. In particular, determining criteria weights on the basis of the preferences expressed by the stakeholders shows relevant issues. The value assumed by the criteria weights is crucial for determining the result of the analysis; therefore, the concerns related to the definition of criteria weights from subjective judgments affect the reliability of the evaluation. Lack of time, insufficient information and awareness from stakeholders, the vagueness of language, and the particular method for collecting preferences influence the obtained result [113], [115].

Since the highlighted issues, a general consensus towards a procedure does not exist. Defining the relevance of evaluation criteria on the basis of stakeholders' preferences represents a complex activity, and it is susceptible to biases. The information provided by decision-maker and stakeholders are often imprecise, inconsistent, and influenced by personal biases. In conclusion, the aspects which influence the outcome of the MADM analysis are [113]:

- The procedure used for collecting the preferences;
- The vagueness of human language;
- The lack of information/awareness of stakeholders on the decision-making problem;
- The personal biases;
- The possible lack of rationality of stakeholders point of views;
- The procedure used for aggregating preferences from individuals.

These elements related to the use of subjective methods for determining the criteria weights undermine the reliability of the result obtained from the entire multi-criteria analysis. To obtain an effective and reliable procedure for solving decision-making problems without introducing unwanted conditioning, it is advisable to exploit strategies that include objectivity in defining the evaluation criteria relevance [113].

4.1.1 Subjective methods for collecting complete information

4.1.1.1 The trade-off method

The Trade-off method is based on the pairwise comparison of criteria [94], [120]. For each pair of criteria, two artificial alternatives that differ only in the performance level of those criteria are built. First, the stakeholders have to choose one of these two alternatives; then, their willingness to give up on one criterion to improve the other one is assessed. The behaviour of the stakeholders defines the trade-off weights between criteria. Drawbacks of the Trade-off method are its complexity and the high degree of inconsistency on collected preferences. In addition, the computational effort increases along with the number of criteria since the number of pairwise comparisons required grows.

4.1.1.2 The swing method

The Swing method is based on the analysis made by the stakeholders of two artificial options: option W has the worst level of performances on all criteria, and option B has the best level of performances on all criteria [94], [120]. The relative weights of criteria are obtained by an iterative process in which stakeholders have to decide which performance level of W swing to B level. The importance of criteria is related to the chronological order of these choices. In comparison to the Trade-off method, the Swing method is more straightforward and less sensitive to inconsistencies of preferences. Moreover, the number of criteria less influences its computational effort.

4.1.1.3 Resistance to Change Method

The resistance to Change method is mainly used for the preference elicitation on outranking methods [94], [120]. The resistance to Change method introduces elements of the Swing method within a criterion pairwise comparison framework.

4.1.2 Subjective methods for collecting incomplete information

In literature, a general consensus exists on the fact that it is easier for stakeholders defining a ranking of evaluation criteria based on their relevance than providing direct judgements [113], [115]. Among the subjective methods for criteria weighting from incomplete preference information, the methodologies that deal with ordinal information are the most investigated [113], [115]. To simplify the collection of information on criteria relevance, some approximate techniques allow determining the numerical value of the weights from criteria ordinal classification. For solving decision-making problems in which partial information about the relevance of the criteria is available, it is necessary to rely on the dominance relations defined by Weber [146]. The dominance relationships can be analysed through linear programming techniques. The method can be generalized to cases where there is incomplete information regarding both the relevance of the criteria and the values of the attributes of the alternatives. However, the dominance relationships obtained from incomplete information regarding the weight of the evaluation criteria are not always adequate for solving real decision-making problems [147].

In a decision-making problem characterised by a set of alternatives $A=\{A_1, A_2, \ldots, A_m\}$, each alternative is defined through a finite set of attributes which dimension is n (i.e. the decision-making problem presents n evaluation criteria). The value of the i-th attribute of the k-th alternative is $v_i(A_k) \in [0, 1]$; w_i is the numerical value of the weight of the i-th criterion. Then, the multi-attribute value function related to the k-th alternative is represented by (4.1).

$$V(A_k) = \sum_{i=1}^{n} w_i v_i(A_k) \tag{4.1}$$

Where $V(A_k) \in [0, 1]$ is the overall value of the k-th alternative and w_i is the numerical value of the weight of the i-th criterion, it follows (4.2).

$$\begin{cases} w_i \geq 0 \\ \sum_{i=1}^{n} w_i = 1 \end{cases} \tag{4.2}$$

By evaluating all the *m* alternatives of *A* by exploiting (4.1), the overall score (the value) for all the alternative is obtained.

The methods for determining the criteria weights from a list ordered are able to calculate the numerical values considering the position of each criterion and the total number of evaluation criteria. Each methodology has a different underlying hypothesis on the distribution of the relevance over the ordered elements.

If *n* is the number of evaluation criteria of the decision-making problem, the criteria are sorted according to $\{w_1 \geq w_2 \geq \ldots \geq w_n\}$, in which the index *i* is related to the relevance of the criteria and indicates the position in the sorted list.

The Rank Sum method evaluates the weight of the i-th criterion by exploiting (4.3) [146].

$$w_i = \frac{n - i + 1}{\sum_{j=1}^{n}(n - j + 1)} \tag{4.3}$$

The Rank Reciprocal method calculates the criterion weight using (4.4) [146].

$$w_i = \frac{1/i}{\sum_{j=1}^{n} 1/j} \tag{4.4}$$

The Rank Exponent method determines the weight of the i-th criterion using (4.5) [146].

$$w_i = \frac{(n - i + 1)^2}{\sum_{j=1}^{n}(n - j + 1)^2} \tag{4.5}$$

The Rank Order Centroid (ROC) method is based on (4.6) [146], [147].

$$w_i = \frac{1}{n} \sum_{j=i}^{n} \frac{1}{j} \tag{4.6}$$

The ROC method calculates the criteria weights by modelling a centre of mass. The set of ROC weights represent all the possible combination of permissible weight according to the linear inequality relationships which define the constraints [148]. The set of constraints defines the feasible region *K* for the criteria weights value, as defined by (4.7).

$$K = \left\{ w: w_1 \geq w_2 \geq \cdots \geq w_n \,; \sum_{i=1}^{n} w_i = 1 \,;\ w_i \geq 0 \,; i = 1,2, \ldots, n \right\} \tag{4.7}$$

The vertices of the set K are represented by the vector $E^{(i)}$ defined by (4.8).

$$E^{(i)} = \left(\frac{1}{i}, \frac{1}{i}, \ldots, \frac{1}{i}, 0, \ldots, 0 \right) \ con\ i = 1,2, \ldots, n \tag{4.8}$$

An *i-th* vertex $E^{(i)}$ is represented by a vector which firsts *i* entries are positive while the remaining are equal to zero. The centroid of the set *K* is defined by the mean of the vertices' coordinates, as defined by (4.9).

$$w_1^{(ROC)} = \frac{1 + \frac{1}{2} + \frac{1}{3} + \dots + \frac{1}{n}}{n}; w_2^{(ROC)} = \frac{0 + \frac{1}{2} + \frac{1}{3} + \dots + \frac{1}{n}}{n}; \dots; w_n^{(ROC)} = \frac{0 + 0 + \dots + 0 + \frac{1}{n}}{n} \tag{4.9}$$

$w_1^{(ROC)}$ represents the weight related to the most relevant criterion (the first ranked), $w_n^{(ROC)}$is the weight related to the less relevant criterion (the last ranked).

If no information on criteria relevance is available, the ranking is not consistent. In this case, an equal relevance to all criteria has to be assigned, the criteria weights are obtained by exploiting (4.10).

$$w_i = \frac{1}{n}\ ;\ i = 1,2, \dots, n \tag{4.10}$$

4.2 Objective methods for weighting the criteria

In multi-criteria decision-making problems, the relevance of the evaluation criteria is modelled by a numerical value (the weight). The objective methodologies for determining the weight of criteria do not consider the preferences expressed by the stakeholders but only exploit the information on the alternatives available in the DM.

Objective methods for determining the criteria weights analyse the distribution of attribute values among the alternatives and define the relevance of the criteria by quantifying the level of discrimination of the alternatives that each of them achieves. This concept is in line with the principle of multi-criteria analysis, which establishes that it is not of interest a criterion to which all the alternatives have the same performance.

This section describes some of the most used objective methods for calculating the weights of the evaluation criteria: the Shannon entropy-based method [148], [149], the variance method [150], the standard deviation method [122], and the CRITIC method [122].

4.2.1 The normalisation of the decision matrix

The objective methodologies for calculating the weights of the criteria are based on the value of the attributes of the alternatives in the DM. In general, the metrics for measuring attributes are heterogeneous; therefore, the performances of the alternatives are incommensurable. To be able to compare different evaluation criteria, it is necessary to normalise the numerical values of the attributes.

In general, the normalisation of the DM converts all the entries of the matrix to the interval [0, 1]. To obtain a generalized normalisation procedure, it is possible to exploit (4.11) and (4.12) [150]. If a KPI is related to a criterion that has to be maximised, (4.11) has to be used for normalisation, otherwise (4.12).

$$z_{i,j} = \frac{x_{i,j} - min\{x_{1,j}, \dots, x_{n,j}\}}{max\{x_{1,j}, \dots, x_{n,j}\} - min\{x_{1,j}, \dots, x_{n,j}\}} \tag{4.11}$$

$$z_{i,j} = \frac{max\{x_{1,j}, \dots, x_{n,j}\} - x_{i,j}}{max\{x_{1,j}, \dots, x_{n,j}\} - min\{x_{1,j}, \dots, x_{n,j}\}} \tag{4.12}$$

Where $z_{i,j}$ is the normalised value of the attribute $x_{i,j}$ of the i-th alternative and the j-th criterion.

The exploitation of (4.11) and (4.12) allows obtaining a normalised DM in which all criteria have to be maximised by considering the normalised value of the attributes.

4.2.2 Shannon’s entropy weighting method

Among objective methods for determining the criteria weights, the method based on Shannon’s entropy [149] focuses on the entropy of the information contained in the attributes’ value distribution. This method captures the share of information contained in the attribute values of evaluation criteria [148]. The entropy concept has been introduced in the information theory by Shannon [149]; in this context, entropy measures the amount of useful information contained in the analysed data. Then, the concept of Shannon’s entropy has been extended for defining a weighting method for MCA [150]. Considering an evaluation criterion, the entropy weight is the parameter that describes the extent to which the alternatives are different from each other. The entropy value and the related entropy weight are inversely proportional; therefore, the higher the entropy value, the lower the entropy weight. It occurs in cases in which the set of alternatives has small differences in the attribute value of the criterion considered. Consequently, the analysed attribute has a low value of information, then it has little relevance for the decision-making problem [148].

In the context of probability theory, Shannon's entropy measures the information contained in the available information. The concept of entropy derives from thermodynamics; it describes the irreversibility of the phenomena. The entropy of a set of observations can be expressed mathematically by (4.13), in which p_i represent the relative frequency of the i-th element [151].

$$H(p_1, p_2, \dots, p_n) = -\sum_{i=1}^{n} p_i \ln p_i \tag{4.13}$$

The entropy function is unique and (4.13) is valid if (4.14), (4.15) and (4.16) are satisfied.

$$H(p_1, p_2, \dots, p_n) \le H(1/n, 1/n, \dots, 1/n) \tag{4.14}$$

$$H(p_1, p_2, \dots, p_n) = H(p_1, p_2, \dots, p_n, 0) \tag{4.15}$$

$$H(AB) = H(A) + H(A|B) \tag{4.16}$$

Shannon’s entropy can be used in the context of multi-criteria analysis for defining the weights of the evaluation criteria [151]: given a DM $\underline{X}$ characterised by m rows (number of alternatives) and n columns (number of evaluation criteria), as represented by (4.17).

$$\underline{X} = \begin{bmatrix} x_{1,1} & \cdots & x_{1,n} \\ \vdots & \ddots & \vdots \\ x_{m,1} & \cdots & x_{m,n} \end{bmatrix} \tag{4.17}$$

Then, calculating S_j (j=1, 2, …, m) as the sum of the entries in the j-th column, the relative frequency $f_{i,j}$ of the entry in the i-th row and j-th column is calculated as (4.18).

$$f_{i,j} = \frac{x_{i,j}}{S_j} \tag{4.18}$$

The DM in terms of relative frequencies of the attributes represents the normalised matrix to be used for calculating the entropy related to the evaluation criteria, the (4.19) is exploited.

$$H_j = -\sum_{i=1}^{m} f_{i,j} \ln f_{i,j} \tag{4.19}$$

Where H_j is the entropy of the information contained in the j-th column of the matrix $\underline{X}$; $f_{i,j}$ is the relative frequency of the element in the i-th row and j-th column.

The entropy weights for the decision-making problem are obtained by normalising the values calculated through (4.19).

4.2.2.1 *Algorithm for calculating the Shannon's entropy weights*

Considering the decision-making problem characterised by *m* alternatives, described as A_i in which $i=1, 2, ..., m$, and *n* evaluation criteria, described as C_j in which $j=1, 2, ..., n$. Then, the DM of the decision-making problem is formed by *n* rows and *m* columns. The entry $x_{i,j}$ represents the attribute of the i-th alternative concerning the j-th criterion. The entropy weights of the *n* evaluation criteria are based on the values of the attributes described in the DM $\underline{X}$.

4.2.2.1.1 Step 1 - Normalisation of the X matrix

The method for calculating the criteria weights according to Shannon's entropy requires the DM to be in terms of relative frequency. Normalisation is addressed criterion by criterion according to the relationships (4.20) and (4.21).

$$\mathrm{p_{i,j}} = \frac{\mathrm{x_{i,j}}}{\sum_{\mathrm{i=1}}^{\mathrm{m}} \mathrm{x_{i,j}}} \tag{4.20}$$

$$\mathrm{p_{i,j}} = \frac{(\mathrm{x_{i,j}})^{-1}}{\sum_{\mathrm{i=1}}^{\mathrm{m}} (\mathrm{x_{i,j}})^{-1}} \; ; \mathrm{i} = 1,2, \dots, \mathrm{n} \tag{4.21}$$

Where $\mathrm{x_{i,j}}$ is the attribute of the i-th alternative with respect to the j-th criterion, $\mathrm{p_{i,j}}$ is the related normalised attribute in terms of relative frequency.

If a criterion has to be maximised, (4.20) is exploited; (4.21) otherwise. As a result, the normalised DM $\underline{P}$ is obtained. However, this methodology for normalising is not directly applicable in the cases in which a given criterion shows values of the attributes of the alternatives have values of different sign. In order to generalize the entropy weighting method, it is possible to exploit (4.20) and (4.21) on the previously normalised $\underline{Z}$ matrix obtained from $\underline{X}$ through the use of (4.11) and (4.12). Consequently, the normalising relationship useful for evaluating the entropy weights is (4.22) [128].

$$p_{i,j} = \frac{z_{i,j}}{\sum_{i=1}^{m} z_{i,j}} \; ; i = 1,2, \dots, n \, , j = 1,2, \dots, m \tag{4.22}$$

4.2.2.1.2 Step 2 – Evaluating the values of entropy

The entropy related to each criterion is calculated on the elements of the matrix $\underline{\mathrm{P}}$ using (4.23).

$$\mathrm{e_j} = -\frac{1}{\ln \mathrm{m}} \sum_{\mathrm{j=1}}^{\mathrm{n}} \mathrm{p_{i,j}} \ln \mathrm{p_{i,j}} \tag{4.23}$$

Where e_j is the entropy of the j-th criterion, $p_{i,j}$ is the relative value of the attribute of the alternative i-th with respect to the j-th criterion.

4.2.2.1.3 Step 3 – Evaluating the degree of divergence

The third step involves calculating the degree of divergence related to each criterion. The degree of divergence of a criterion measures the dispersion of the values that the alternatives show in terms of attributes. Therefore, as the degree of divergence increases, it also increases the relevance of the related criterion. The degree of divergence $\mathrm{d_j}$ of the j-th criterion is calculated according to (4.24).

$$\mathrm{d_j} = 1 - \mathrm{e_j} \tag{4.24}$$

4.2.2.1.4 Step 4 – Calculating the entropy weight

The entropy weight of a criterion depends on the value of the degree of divergence assumed by the set of criteria. The entropy weight $\mathrm{w_j}$ of the j-th criterion of the set formed by n criteria can be obtained by exploiting (4.25).

$$\mathrm{w_j} = \frac{\mathrm{d_j}}{\sum_{\mathrm{k}=1}^{\mathrm{n}} \mathrm{d_k}} \tag{4.25}$$

4.2.3 The statistical variance method

The method for calculating the weights of the evaluation criteria based on statistical variance exploits the dispersion of the attributes' numerical values of the alternatives [130]. Statistical variance measures the dispersion that the values of a set of observations show compared to the average value. The statistical variance takes into account all the points of the set and quantifies the distribution; this aspect gives the variance concept a great relevance in empirical and statistical applications [130]. Based on the concept of statistical variance, it is possible to define the objective weights for the evaluation criteria of a decision-making problem. The greater the variance of a given attribute, the greater the relevance that the related criterion has for discriminating the alternatives [113].

The statistical variance method has a lower computational burden than the method based on the Shannon entropy [130]. Similarly to the Shannon's entropy weights method, the variance method also requires the normalisation of the DM in terms of the relative frequency of attributes, as described for Shannon's method. The statistical variance of the attributes related to the j-th criterion is evaluated according to (4.26) [130].

$$\mathrm{v_j} = \frac{1}{\mathrm{n}} \sum_{\mathrm{i}=1}^{\mathrm{n}} \left(\mathrm{p_{i,j}} - \bar{\mathrm{p}}_\mathrm{j}\right)^2 \tag{4.26}$$

Where $\mathrm{v_j}$ is the statistical variance of the attributes related to the j-th criterion; n is the number of the alternatives; $\mathrm{p_{i,j}}$ is the normalised attribute of the i-th alternative with respect to the j-th criterion; $\bar{\mathrm{p}}_\mathrm{j}$ is the mean value of the normalised attributes related to the j-th criterion.

The objective weight related to each of the evaluation criteria is obtained through (4.27).

$$\mathrm{w_j} = \frac{\mathrm{v_j}}{\sum_{\mathrm{k}=1}^{\mathrm{m}} \mathrm{v_k}} \tag{4.27}$$

Where $\mathrm{w_j}$ is the objective weight of the j-th criterion; $\mathrm{v_j}$ is the statistical variance related to the j-th criterion; m is the number of evaluation criteria in the decision-making problem.

4.2.4 The standard deviation method

The objective method for weighting the evaluation criteria that exploits the standard deviation (SD) determines the weight of each criterion on the basis of the value of the standard deviation that the various alternatives show on each attribute [122]. Considering the j-th evaluation criterion, in the standard deviation method, the objective weights are obtained by using (4.28).

$$w_j = \frac{\sigma_j}{\sum_{k=1}^{m} \sigma_k} \; ; j = 1,2, \dots, m \tag{4.28}$$

Where $\mathrm{w_j}$ is the weight of the j-th criterion, σ_j is the standard deviation of the alternatives' attributes compared to the j-th criterion obtained as the squared statistical variance.

4.2.5 The CRITIC method

The CRITIC (Criteria Importance Through Intercriteria Correlation) method determines the criteria weights by considering the standard deviation related to each attribute and the correlation among attributes [122]. Therefore, the CRITIC method requires evaluating the correlation matrix among the attributes of the decision-making problem.

Considering a decision-making problem characterised by *m* evaluation criteria, the entries of the correlation matrix $\underline{R}$ of dimension (*m*,*m*) are calculated by using (4.29).

$$r_{j,k} = \frac{\sum_{i=1}^{n}\left(z_{i,j} - \bar{z}_j\right) \cdot \left(z_{i,j} - \bar{z}_j\right)}{\sqrt{\sum_{i=1}^{n}\left(z_{i,j} - \bar{z}_j\right)^2 \cdot \sum_{i=1}^{n}\left(z_{i,k} - \bar{z}_k\right)^2}} \ ; \ j,k = 1,2,\dots,m \tag{4.29}$$

Where $r_{j,k}$ is the correlation coefficient between the criteria j-th and k-th; $\bar{z}_j = \frac{1}{n}\sum_{i=1}^{n} z_{i,j} \ for \ j = 1,2,\dots,m$; and $z_{i,j}$ is the normalised attribute of the i-th alternative with respect to the j-th criterion.

The amount of information contained by the j-th criterion can be measured using the coefficient C_j evaluated on the correlation coefficients $r_{j,k}$ and the standard deviation σ_j as in (4.30).

$$C_j = \sigma_j \cdot \sum_{k=1}^{m}(1 - r_{j,k}) \ ; \ j = 1,2,\dots,m \tag{4.30}$$

The weight of the j-th criterion is evaluated according to (4.31).

$$w_j = \frac{C_j}{\sum_{k=1}^{m} C_k} \ ; j = 1,2,\dots,m \tag{4.31}$$

The CRITIC method considers the correlation between attributes rather than taking into account the impact that each attribute has on the decision-making problem.

4.3 Integrated weighting methods based on optimisation models

The integrated (or hybrid) methods for determining the weight of the evaluation criteria are based on optimisation models whose solution offers the optimal value of the criteria weights for the studied decision-making problem [113]. These methodologies can be defined as hybrid or integrated as they allow to include preference information in their model that constrains the values that can be assumed by criteria weights. In the case in which the subjective constraints on the criteria weight criteria are not included in the model, the method leads back to an objective approach. The use of optimisation methods to define the weights of evaluation criteria allows solving the decision-making problem even when only partial or incomplete information on the decision-making problem is available. Complete information on criteria relevance represents all the information that allows us to univocally determine the numerical value of the weight of each criterion. Partial or incomplete information is represented by the set of information expressed in verbal, sorting or numerical form that allows to deduce the relevance of the criteria and to determine the numerical value given a share of uncertainty [152]. In general, it is not guaranteed that the final ranking of alternatives remains unchanged within this uncertainty range.

When partial information on criteria relevance is available, regardless of the collection procedure, the partial information can be modelled in terms of linear inequalities, as shown in Table 4.1, where $0 \leq \alpha_i \leq \alpha_i + \varepsilon_i \leq 1$.

Table 4.1. Inequalities for ranking criteria according to relevance

Type	Relationship	Model
Form 1	Weak ranking	$w_i \geq w_j$
Form 2	Strict ranking	$w_i - w_j \geq \alpha_i$
Form 3	Ranking on differences	$w_i - w_j \geq w_k - w_l \ per \ j \neq k \neq l$
Form 4	Product ranking	$w_i \geq \alpha_i w_j$
Form 5	Value interval	$\alpha_i \leq w_i \leq \alpha_i + \varepsilon_i$

4.3.1 Ideal Point method

The Ideal Point method for evaluating criteria weights is based on an optimisation model which builds a virtual alternative. Weights are obtained by optimising the distance between each alternative and the virtual one [125].

Given the matrix $\underline{B}$ which dimension is (n, m) as the weighted DM of the decision-making problem characterised by n alternatives and m criteria. Each entry of the matrix $\underline{B}$ is obtained according to $b_{i,j}=z_{ij}w_j$ where i=1,2,…,n e j=1,2,…,m; w_j is the weight of the j-th criterion. The virtual alternative S^* is built by considering the maximum value of each attribute of the set of alternatives in the evaluation set, as described in (4.32).

$$\begin{gathered} S^* = \{b_1^*, \dots, b_m^*\} \\ \text{where } b_j^* = max\{b_{1,j}, \dots, b_{n,j}\} = z_j^* w_j \\ \text{and } z_j^* = max\{z_{1,j}, \dots, z_{n,j}\} \\ j = 1,2, \dots, m \end{gathered} \tag{4.32}$$

The distance g_i between the i-th alternative and the virtual one can be quantified according to (4.33).

$$g_i = \sum_{j=1}^{m} \left(b_j^* - b_{i,j}\right)^2 = \sum_{j=1}^{m} \left(z_j^* - z_{i,j}\right)^2 w_j^2 \;\; ; i = 1,2, \dots, n \tag{4.33}$$

By minimising the objective function formed by the sum of the distances g_i it is possible to obtain the weights for the evaluation criteria. The optimisation model is described by (4.34).

$$\begin{gathered} \min(J) = \min\left\{\sum_{j=1}^{n} g_i\right\} = \min\left\{\sum_{i=1}^{n}\sum_{j=1}^{m} \left(z_j^* - z_{i,j}\right)^2 w_j^2\right\} \\ s.t. \begin{cases} \sum_{j=1}^{m} w_j = 1 \\ w_j \geq 0 \; ; \; j = 1,2, \dots, m \end{cases} \end{gathered} \tag{4.34}$$

The optimisation model defined in (4.34) leads to a finite form if no constraints on criteria weights value are available, as shown is (4.35).

$$w_j^* = \frac{\left(\sum_{i=1}^{n} \left(z_j^* - z_{i,j}\right)^2\right)^{-1}}{\sum_{k=1}^{m} \left(\sum_{i=1}^{n} \left(z_k^* - z_{i,k}\right)^2\right)^{-1}} \;\; ; \; j, k = 1,2, \dots, m \tag{4.35}$$

Whereas, if the set of constraints Ω is not empty, a finite form for the optimisation model expressed by (4.36) does not exist.

$$\begin{gathered} \min(J) = \min\left\{\sum_{j=1}^{n} g_i\right\} = \min\left\{\sum_{i=1}^{n}\sum_{j=1}^{m} \left(z_j^* - z_{i,j}\right)^2 w_j^2\right\} \\ s.t. \begin{cases} w_j \in \Omega \\ \sum_{j=1}^{m} w_j = 1 \\ w_j \geq 0 \; ; \; j = 1,2, \dots, m \end{cases} \end{gathered} \tag{4.36}$$

The main disadvantage of the Ideal Point method is represented by the fact that a weight value equal to one may be assigned to a single criterion.

4.3.2 Method of maximising the deviation of attributes

The method of maximising the deviation of attributes has been proposed in the 1990s by Yingming [123]. By exploiting an objective procedure that involves an optimisation model, the method determines the weights for multi-criteria decision problems. Relative weights are calculated by exploiting a maximisation model that emphasizes the criteria to which the alternatives show a greater deviation in terms of values of attributes.

Given a set of alternatives A={A_1, A_2, …, A_n}, which dimension is n, and a set of evaluation criteria G ={G_1, G_2, …, G_m}, which dimension is m, the DM of the decision-making problem is $\underline{X}$, which dimension is (m, n).

The method of maximising the deviation of attributes requires normalising the DM according to (4.37), (4.38), (4.39), (4.40). If a criterion has to be maximised, (4.37) has to be exploited [123].

$$z_{i,j} = \frac{x_{i,j} - \min\{x_{1,j}, \dots, x_{n,j}\}}{\max\{x_{1,j}, \dots, x_{n,j}\} - \min\{x_{1,j}, \dots, x_{n,j}\}} \tag{4.37}$$

If a criterion has to be minimised, (4.38) has to be exploited [123].

$$z_{i,j} = \frac{\max\{x_{1,j}, \dots, x_{n,j}\} - x_{i,j}}{\max\{x_{1,j}, \dots, x_{n,j}\} - \min\{x_{1,j}, \dots, x_{n,j}\}} \tag{4.38}$$

Moreover, if a criterion is satisfied by an attribute that has to assume a reference value, (4.39) has to be exploited.

$$z_{i,j} = \frac{\left|x_{i,j} - x_j^{(ref)}\right|}{\max_i\left\{\left|x_{i,j} - x_j^{(ref)}\right|\right\}} \tag{4.39}$$

Where $x_j^{(ref)}$ is the reference value that fully satisfies the j-th criterion.

If the reference value is represented by an interval of values, (4.40) has to be used for normalising the related attributes.

$$z_{i,j} = \begin{cases} 1 - \dfrac{q_{1,j} - x_{i,j}}{\max\left\{q_{1,j} - x_j^{(min)}, x_j^{(max)} - q_{2,j}\right\}} & x_{i,j} < q_{1,j} \\ 1 & x_{i,j} \in [q_{1,j}, q_{2,j}] \\ 1 - \dfrac{x_{i,j} - q_{2,j}}{\max\left\{q_{1,j} - x_j^{(min)}, x_j^{(max)} - q_{2,j}\right\}} & x_{i,j} > q_{2,j} \end{cases} \tag{4.40}$$

Where $q_{1,j}, q_{2,j}$ are the lower and the higher values of the optimal attributes' value range; while: $x_j^{(\min)} = min\{x_{1,j}, \dots, x_{n,j}\}$ and $x_j^{(\max)} = max\{x_{1,j}, \dots, x_{n,j}\}$.

By the normalisation procedure, it is possible to obtain the matrix $\underline{Z}$, the normalised matrix of the attributes of the alternatives of the decision problem; this matrix is positive definite.

The underlying hypothesis of the method of maximising the deviation of attributes is that the weight of a criterion increases with the dispersion of the attribute values of the alternatives. Regarding the vector *W* of criteria weights, of size (1, m), such that the sum of the square of its elements is unitary. The deviation $v_{i,j}$ of the i-th alternative is defined by considering only the j-th criterion and the set of remaining alternatives. The deviation $v_{i,j}$ can be calculated according to (4.41).

$$v_{i,j} = \sum_{k=1}^{n} \left|w_j z_{i,j} - w_j z_{k,j}\right|; \quad i = 1,2, \dots, n\, ; j = 1,2, \dots, m \tag{4.41}$$

Where $v_{i,j}$ is the deviation of the i-th alternative concerning the remaining n-1 alternatives by considering the j-th criterion; w_j is the weight of the j-th criterion; $z_{i,j}$ is the normalised value of the attribute of the i-th alternative with respect to the j-th criterion.

The total deviation related to the j-th criterion is obtained as the sum of the deviations on the j-th criterion considering the n alternatives of the decision-making problem, as represented by (4.42).

$$v_j = \sum_{i=1}^{n} v_{i,j} = w_j \sum_{i=1}^{n} \sum_{k=1}^{n} \left| z_{i,j} - z_{k,j} \right| ;\ j = 1,2,\dots,m \tag{4.42}$$

The set of weights that allows maximising the deviation measured among the alternatives on the m criteria is obtained by solving the optimisation model (4.43).

$$\begin{gathered} \max\{F(W)\} = \max \left\{ \sum_{j=1}^{m} \sum_{i=1}^{n} \sum_{k=1}^{n} \left| z_{i,j} - z_{k,j} \right| w_j \right\} \\ \text{s.t.} \sum_{j=1}^{m} w_j^2 = 1 \end{gathered} \tag{4.43}$$

The solution to the optimisation model (4.43) is (4.44).

$$\widetilde{w}_j = \frac{\sum_{i=1}^{n} \sum_{k=1}^{n} \left| z_{i,j} - z_{k,j} \right|}{\sqrt{\sum_{j=1}^{m} \left[\sum_{i=1}^{n} \sum_{k=1}^{n} \left| z_{i,j} - z_{k,j} \right| \right]^2}} ;\ j = 1,2,\dots,m \tag{4.44}$$

By evaluating (4.44) for all the *m* criteria of the decision-making problem, the vector $\widetilde{W}$ is obtained. The normalised weight for the evaluation criteria can be calculated by exploiting (4.45) or (4.46).

$$W = \frac{\widetilde{W}}{\sum_{j=1}^{m} \widetilde{W}_j} ;\ j = 1,2,\dots,m \tag{4.45}$$

$$w_j = \frac{\sum_{i=1}^{n} \sum_{k=1}^{n} \left| z_{i,j} - z_{k,j} \right|}{\sum_{j=1}^{m} \sum_{i=1}^{n} \sum_{k=1}^{n} \left| z_{i,j} - z_{k,j} \right|} ;\ j = 1,2,\dots,m \tag{4.46}$$

The algorithm of the weighting method of maximising the deviation of attributes can be resumed in two steps:

i. Construction of the normalised preference matrix $\underline{Z}$, according to (4.37), (4.38), (4.39), and (4.40);
ii. Calculation of the normalised vector of criteria weights according to (4.46).

4.3.3 Method of maximising the generalized deviation of attributes

The method of Maximising the Generalized Deviation (MGD) of the attributes generalizes the method of maximising the deviation, and it allows determining the weights for a MADM type problem using a non-linear optimisation model [153]. This methodology can be used both in the cases in which partial information on the criteria weights is available and in cases in which there is no information.

Compared to the original method based on the measurement of the deviation, the generalized approach normalises the optimal solution obtained and allows better integration of objective and subjective information regarding the relevance of the criteria [153].

Furthermore, the non-linear optimisation model is solved exactly, and the obtained formula allows to obtain already normalised weights for the criteria.

Given the decision-making problem characterised by the set of n alternatives $A=\{A_1, A_2, \ldots, A_n\}$ and a set of m evaluation criteria $G=\{G_1, G_2, \ldots, G_m\}$. Then, the DM $\underline{X}$ dimension is (n,m). Moreover, the generic vector for criteria weight is $W=\{w_1, w_2, \ldots, w_m\}$, in which $w_j \in [0, 1]$ for j=1,2,…,m e $\sum_{j=1}^{m} w_j = 1$.

The generalized deviation of the attributes of two alternatives concerning a k-th criterion measures the difference between the values assumed by the two alternatives in the decision problem. The deviation can be measured in terms of distance, for example, using the Hamming, Euclidean, or Chebyshev distance. If we refer to the Euclidean distance, the deviation between the alternatives is defined by (4.47).

$$d_{i,j,k}^{(p)} = |x_{i,k} - x_{j,k}| \tag{4.47}$$

Where $d_{i,j,k}^{(p)}$ is the generalised deviation between the i-th and the j-th alternative considering the k-th criterion; $x_{i,k}$ and $x_{j,k}$ are the k-th attribute values of alternatives i-th and j-th; p>0 is the parameter which defines the generalized deviation (p=1 Hamming, p=2 Euclidean, p=∞ Chebyshev).

The deviation between two genric alternatives has to comply with (4.48) [153].

$$\begin{gathered} d_{i,j,k}^{(p)} \in [0,1] \\ d_{i,j,k}^{(p)} = 0 \; if \; and \; only \; if \; x_{i,k} = x_{j,k} \\ d_{i,j,k}^{(p)} = d_{j,i,k}^{(p)} \\ se \; x_{i,k} < x_{j,k} < x_{t,k} \;\; then \;\; d_{i,t,k}^{(p)} \geq d_{i,j,k}^{(p)} \; e \; d_{i,t,k}^{(p)} \geq d_{j,t,k}^{(p)} \end{gathered} \tag{4.48}$$

Given the alternatives A_i e A_j, considering all the evaluation criteria of the decision-making problem, the generalized deviation can be calculated as in (4.49).

$$\mathrm{d}_{\mathrm{i,j}}^{(\mathrm{p})} = \sum_{\mathrm{k=1}}^{\mathrm{m}} \mathrm{w}_{\mathrm{k}}^{\alpha} \cdot \mathrm{d}_{\mathrm{i,j,k}}^{(\mathrm{p})} \tag{4.49}$$

Where w_k^{α} is the weight of the k-th criterion, α ∈ [0, 1] is a parameter useful for avoiding extreme solution points, in general α=0.5 [153].

In multi-criteria decision problems, the information regarding the relevance of evaluation criteria can be totally or partially missing. In cases in which partial information is available, it is modelled in terms of linear inequalities, as in Table 4.1, where $0 \leq \alpha_i \leq \alpha_i + \varepsilon_i \leq 1$.

According to the method of maximisation of the deviation [123], the greater the total deviation related to the attribute j-th, the greater the relevance and the numerical value of the weight of the j-th criterion. This concept leads to the definition of a weighting scheme that emphasizes the discrimination between alternatives and that reduces the relevance of the less discriminating criteria of the decision-making problem. To determine the weighting scheme that maximises the generalised deviation between the alternatives, it is necessary to solve the optimisation problem presented by the model (4.50).

$$\begin{gathered} max\{F(W)\} = max\left\{\sum_{i=1}^{n}\sum_{j=1}^{n} d_{i,j}^{(p)}\right\} = max\left\{\sum_{i=1}^{n}\sum_{j=1}^{n}\sum_{k=1}^{m} d_{i,j,k}^{(p)} \cdot w_k^{\alpha}\right\} \\ s.t.\begin{cases} w_j \in \Omega_0 \\ \sum_{j=1}^{m} w_j = 1 \\ w_j \in [0,1] \; per \; j = 1,2,\ldots,m \end{cases} \end{gathered} \tag{4.50}$$

Where Ω_0 is the set of information on criteria relevance in terms of the relationships defined in Table 4.1. If this information is missing, Ω_0 is empty.

To illustrate, if Ω_0 is not empty and considering α=0.5 and $\overline{w}_k = w_k^{0.5}$, then $\Omega_0 \rightarrow \Omega$; criteria weights can be obtained by solving the non-linear model (4.51) [153].

$$max\{F(W)\} = max\left\{\sum_{i=1}^{n}\sum_{j=1}^{n}\sum_{k=1}^{m} d_{i,j,k}^{(p)} \cdot \overline{w}_k\right\}$$
$$s.t.\begin{cases} \overline{w}_k \in \Omega \\ \sum_{j=1}^{m} \overline{w}_k{}^2 = 1 \\ w_j \in [0,1]\ per\ j = 1,2,\dots,m \end{cases} \tag{4.51}$$

Once the optimisation problem is solved, the solution is defined by the vector $\overline{W}^*$. The weight of the k-th criterion can be obtained as $w_k^* = (\overline{w}_k^*)^2$.

Otherwise, if Ω_0 is empty and considering α=0.5 and $\overline{w}_k = w_k^{0.5}$, criteria weights can be obtained by solving the non-linear model (4.52).

$$max\{F(W)\} = max\left\{\sum_{i=1}^{n}\sum_{j=1}^{n}\sum_{k=1}^{m} d_{i,j,k}^{(p)} \cdot \overline{w}_k\right\}$$
$$s.t.\begin{cases} \sum_{j=1}^{m} \overline{w}_k{}^2 = 1 \\ w_j \in [0,1]\ per\ j = 1,2,\dots,m \end{cases} \tag{4.52}$$

The model (4.52) can be solved by exploiting the Lagrangian function, $L(w,\lambda)$ a finite form can be obtained (4.53).

$$\overline{\mathrm{w}}_\mathrm{k} = \frac{\sum_{\mathrm{i}=1}^{\mathrm{n}}\sum_{\mathrm{j}=1}^{\mathrm{n}} \mathrm{d}_{\mathrm{i,j,k}}^{(\mathrm{p})}}{\sqrt{\sum_{\mathrm{k}=1}^{\mathrm{m}}\left[\sum_{\mathrm{i}=1}^{\mathrm{n}}\sum_{\mathrm{j}=1}^{\mathrm{n}} \mathrm{d}_{\mathrm{i,j,k}}^{(\mathrm{p})}\right]^2}}\ \mathrm{con\ k} = 1,2,\dots,\mathrm{m} \tag{4.53}$$

Considering that $\overline{\mathrm{w}}_\mathrm{k} = \mathrm{w}_\mathrm{k}^{0.5}$, criteria weight can be obtained by (4.54).

$$\mathrm{w}_\mathrm{k} = \frac{\left(\sum_{\mathrm{i}=1}^{\mathrm{n}}\sum_{\mathrm{j}=1}^{\mathrm{n}} \mathrm{d}_{\mathrm{i,j,k}}^{(\mathrm{p})}\right)^2}{\sum_{\mathrm{k}=1}^{\mathrm{m}}\left[\sum_{\mathrm{i}=1}^{\mathrm{n}}\sum_{\mathrm{j}=1}^{\mathrm{n}} \mathrm{d}_{\mathrm{i,j,k}}^{(\mathrm{p})}\right]^2}\ \mathrm{con\ k} = 1,2,\dots,\mathrm{m} \tag{4.54}$$

The MGD method can be summarized in the following steps.

i. Defining the set Ω of constraints. If no information on criteria relevance is available, Ω is empty.
ii. Defining the parameter p for particularizing the measure of the generalized deviation.
iii. Calculation of the deviation among the alternatives for each criterion (4.47).
iv. If the set Ω is empty, the criteria weights are obtained through (4.54).
v. If the set Ω is not empty, the weights of criteria are obtained by solving the optimisation model (4.51). From the obtained $\overline{w}_k^*$ values, normalised criteria weights are calculated as $w_k^* = (\overline{w}_k^*)^2$ per *k*=1, 2, …, *m*.

4.3.4 CCSD weighting method

The weighting method based on the combination of the Correlation Coefficient and the Standard Deviation (CCSD) of attributes has been proposed by Wang and Luo in [128]. The CCSD method evaluates the criteria weights by combining the information given by the standard deviation of the attributes with the correlation coefficient that exists between each criterion and the overall result of the evaluation. The CCSD method is similar to the CRITIC method; however, it has some differences [128].

The CCSD method determines the weight of the evaluation criteria based on the standard deviation of the values of the attributes of the alternatives and considering the influence of each criterion on the result of the overall assessment of the decision-making problem. The impact of each criterion on the overall assessment is quantified using the correlation coefficient calculated by excluding the considered criterion. The greater the value of the CC of a given criterion, the lower the relevance of this criterion for the decision-making problem, as a consequence, the related weight is low.

Given a decision-making problem defined by a set of n alternatives $A=\{A_1, A_2, \dots, A_n\}$ and by a set of m evaluation criteria $O=\{O_1, O_2, \dots, O_m\}$. Each alternative is described by m attributes: x_{ij} is the attribute of the i-th alternative for the j-th criterion. The decision-making problem is, therefore, characterised by a decision matrix $\underline{X}$ which dimension is (n,m).

Attributes related to different criteria are incommensurable; therefore, $\underline{X}$ has to be normalised. For criteria that have to be maximised, attributes have to be normalised according to (4.55); while, the attributes related to criteria that have to be minimised have to be normalised according to (4.56).

$$z_{i,j} = \frac{x_{i,j} - min\{x_{1,j}, \dots, x_{n,j}\}}{max\{x_{1,j}, \dots, x_{n,j}\} - min\{x_{1,j}, \dots, x_{n,j}\}} \tag{4.55}$$

$$z_{i,j} = \frac{max\{x_{1,j}, \dots, x_{n,j}\} - x_{i,j}}{max\{x_{1,j}, \dots, x_{n,j}\} - min\{x_{1,j}, \dots, x_{n,j}\}} \tag{4.56}$$

Where $z_{i,j}$ is the normalised value of the attribute of the i-th alternative with respect to the j-th criterion.

The matrix $\underline{Z}$ represents the normalised DM of the decision-making problem.

Given the vector of criteria weights $W=\{w_1, w_2, \dots, w_m\}$, the entries of $\underline{W}$ respect the condition (4.57).

$$\begin{cases} w_j \geq 0 \ ; \ \mathrm{j} = 1,2,\dots,\mathrm{m} \\ \sum_{j=1}^{m} w_j = 1 \end{cases} \tag{4.57}$$

Where w_j is the weight related to the j-th criterion.

By considering that the MADM methodology exploited aggregates scores and weights according to a linear combination, as in (4.58), the greater the value of the overall score obtained from an alternative, the greater the preferability of this alternative compared to the remaining objects of the set A.

$$d_i = \sum_{j=1}^{m} z_{i,j} w_j \ ; \ i = 1,2,\dots,n \tag{4.58}$$

Where d_i represents the overall score obtained by the i-th alternative;

The CCSD procedure requires calculating the CC that links each criterion and the final result of the evaluation. By excluding from the analysis of the j-th criterion, the value of the overall score related to the alternatives of group A is calculated according to (4.59).

$$d_{i,j} = \sum_{\substack{k=1 \\ k \neq j}}^{m} z_{i,j} w_j \ ; \ i = 1,2,\dots,n \tag{4.59}$$

Where $d_{i,j}$ represents the overall score obtained by the i-th alternative when the j-th criterion is excluded.

The correlation coefficient of the j-th criterion concerning the overall score of the alternatives is obtained through (4.60), (4.61), and (4.62).

$$R_j = \frac{\sum_{i=1}^{n}\left(z_{i,j} - \bar{z}_j\right)\cdot\left(d_{i,j} - \bar{d}_j\right)}{\sqrt{\sum_{i=1}^{n}\left(z_{i,j} - \bar{z}_j\right)^2 \cdot \sum_{i=1}^{n}\left(d_{i,j} - \bar{d}_j\right)^2}} \; ; \; j = 1,2,\dots,n \tag{4.60}$$

where

$$\bar{z}_j = \frac{1}{n}\sum_{i=1}^{n} z_{i,j} \; ; \; j = 1,2,\dots,m \tag{4.61}$$

$$\bar{d}_j = \frac{1}{n}\sum_{i=1}^{n} d_{i,j} = \sum_{\substack{k=1 \\ k\neq j}}^{n} \bar{z}_k w_k \; ; \; j = 1,2,\dots,m \tag{4.62}$$

According to the value obtained for the correlation coefficient R_j:

If R_j is close to 1, then the j-th criterion has little influence on the result of the decision-making problem; hence, the numerical value of its weight is low.

If R_j is close to -1, then the j-th criterion has a significant influence on the result of the decision-making problem; thus, the numerical value of the corresponding weight is high.

Based on these considerations, if all the alternatives of set A have the same numerical value for a given attribute, then the related criterion can be removed from the analysis as it does not influence the final result. The distribution of the values of an attribute among the alternatives of set A is measurable through the calculation of the standard deviation. The evaluation criteria to which a high standard deviation value is associated have great relevance; thus, the related weight has to be high. The numerical value of the weight of the evaluation criterion can be calculated according to (4.63).

$$w_j = \frac{\sigma_j\sqrt{1-R_j}}{\sum_{k=1}^{m}\sigma_k\sqrt{1-R_k}} \; ; \; j = 1,2,\dots,m \tag{4.63}$$

Where σ_j is the standard deviation of the j-th criterion obtained from (4.64).

$$\sigma_j = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(z_{i,j} - \bar{z}_j\right)^2} \; ; \; j = 1,2,\dots,m \tag{4.64}$$

Obtaining the weights for all the criteria by exploiting (4.63) leads to a non-linear system of order *m*. The solution to this system of non-linear equation is obtained by solving the optimisation model (4.65).

$$\begin{gathered} min(J) = min\left\{\sum_{j=1}^{m}\left(w_j - \frac{\sigma_j\sqrt{1-R_j}}{\sum_{k=1}^{m}\sigma_k\sqrt{1-R_k}}\right)^2\right\} \\ s.t.\begin{cases} \sum_{j=1}^{m} w_j = 1 \\ w_j \geq 0 \; ; j = 1,2,\dots,m \end{cases} \end{gathered} \tag{4.65}$$

In the solution point, the value of the objective function of the model (4.65) is zero.

If information about the criteria relevance is available, it can be included in the model (4.65) as constraints on the weight values. The constraints in the set P_w can be described in terms of the forms presented in Table 4.1. In that case, the optimisation model of the CCSD method is defined by (4.66).

$$min(J) = min\left\{\sum_{j=1}^{m}\left(w_j - \frac{\sigma_j\sqrt{1-R_j}}{\sum_{k=1}^{m}\sigma_k\sqrt{1-R_k}}\right)^2\right\} \tag{4.66}$$

$$s.t.\begin{cases} e^T W = 1 \\ W \in P_W \\ W \geq 0 \end{cases}$$

Where e^T=(1,..,1), W=(w_1,w_2, …,w_m) is the criteria weight vector. If no information about the criteria relevance is available, the set P_w is empty.

By solving the optimisation model, the vector which contains all the criteria weights is obtained: $W^* = (w_1^*, w_2^*, \dots, w_m^*)$.

4.4 Aggregation strategies

The relevance assigned to the evaluation criteria influences the decision-making processes; therefore, the approach used for defining criteria weights plays a key role. In the context of the weighting methods, functional relationships have been proposed for aggregating the numerical value obtained independently through an objective and a subjective evaluation approach. In [154], subjective weights obtained through the AHP comparison process are combined with the objective weights determined by the Shannon entropy method. In [155], a similar procedure is used to assess the security offered by a set of smart grid initiatives. The combined use of objective and subjective methodologies for the calculation of the criteria weights can effectively contribute to reducing the influence of subjectivity on the analysis.

4.4.1 Aggregation by product

The weights of evaluation criteria can be obtained by combining the weights determined by objective methodologies and subjective methodologies. A possible combination approach is represented by (4.67) [129].

$$w_j^{(h)} = \frac{w_j^{(s)} w_j^{(o)}}{\sum_{k=1}^{n} w_k^{(s)} w_k^{(o)}} \tag{4.67}$$

Where $w_j^{(h)}$ is the aggregated weight of the j-th criterion; $w_j^{(s)}$ is the subjective weight of the j-th criterion; $w_j^{(o)}$ is the objective weight of the j-th criterion.

If the subjective weight $w_j^{(s)}$ is not assigned, the value of the aggregated weight coincides with the objective weight.

4.4.2 Aggregation by the linear combination

The aggregation of the criteria weights obtained with a subjective method and with an objective method is possible through a linear combination [130], as described in (4.68).

$$w_j^{(h)} = \alpha^{(s)} w_j^{(s)} + \alpha^{(o)} w_j^{(o)} \tag{4.68}$$

Where

$w_j^{(h)}$ is the aggregated weight of the j-th criterion;

$w_j^{(s)}$ is the subjective weight of the j-th criterion;

$w_j^{(o)}$ is the objective weight of the j-th criterion;

$\alpha^{(s)}$ is the relevance of the subjective approach over the objective;

$\alpha^{(o)}$ is the relevance of the objective approach over the subjective.

$\alpha^{(o)}$ and $\alpha^{(s)}$ have to comply with (4.69).

$$\begin{cases} \alpha^{(s)}, \alpha^{(o)} \in [0,1] \\ \alpha^{(s)} + \alpha^{(o)} = 1 \end{cases} \tag{4.69}$$

In each decision-making problem, the decision-maker can set the relevance of the subjective evaluation over the subjective one by defining the value of the parameters $\alpha^{(o)}$ and $\alpha^{(s)}$.

4.4.3 Aggregation by the exponential combination

The combination of the objective and subjective weights of the criteria can be obtained considering in exponential terms the mutual relevance of the two evaluation approaches [131]. The weight of the j-th criterion can be calculated according to (4.70).

$$w_j^{(h)} = \frac{\left(w_j^{(s)}\right)^{\alpha} \left(w_j^{(o)}\right)^{1-\alpha}}{\sum_{j=1}^{n}\left(\left(w_j^{(s)}\right)^{\alpha}\left(w_j^{(o)}\right)^{1-\alpha}\right)} \; ; j = 1,2,\dots,n \tag{4.70}$$

Where

$w_j^{(h)}$ is the aggregated weight of the j-th criterion;

$w_j^{(s)}$ is the subjective weight of the j-th criterion;

$w_j^{(o)}$ is the objective weight of the j-th criterion;

$\alpha \in [0, 1]$ is the coefficient that models the relevance assigned to the subjective weights over the objective weights.

4.5 Global ranking stability

If the MADM methodology used for solving the decision problem is based on an additive linear model for combining attributes and criteria weights, then the incomplete information regarding the relevance of the criteria can be mathematically expressed in terms of ranges of values in the weight-space. This information defines the constraints which determine a subspace in the weight-space in which the best solution of the set is to be sought; this subspace represents the feasible region for criteria weights [131]. Within the feasible region, a subspace within which the indication of the best alternative does not change can be considered as a criteria weight interval in which the solution of the method is stable. The global sensitivity analysis of the criteria weights is useful for analysing the stability of the result obtained from the multi-attribute analysis. The stability of the result can be understood in terms of invariance of the best alternative indication or terms of invariance of the entire final ordering. The identification of the range of values within which the weights can vary without involving a change in the final result allows estimating the stability and robustness of the solution suggested by a MADM method.

Given a ranking of alternatives $Q_i^* = \left(A_{i,1}^* \succ A_{i,2}^* \succ \; \dots \succ A_{i,n}^*\right)$ which has been obtained through an MCA; and considering the weight vector $W^* = (w_1^*, w_2^*, \dots, w_m^*)$ of the evaluation criteria. The goal of the global stability analysis is to identify the range of variation of criteria weights within which the ranking of alternatives is invariant. This range of variation ensures that the best alternative, or the entire ordering, is robust and stable considering the criteria weight [131]. This range of variation cannot be determined arbitrarily; therefore, the method of global stability analysis assumes that the weights of all criteria vary according to the same proportionality coefficient [131], [156].

Accordingly, the range of variation of the weight of the j-th criterion is defined by (4.71).

$$w_j = w_j^*(1 \pm \eta) \in \left[w_j^* - \eta w_j^*, w_j^* + \eta w_j^*\right] ; j = 1,2,\dots,m \tag{4.71}$$

Where w_j^* is the weight of the j-th criterion; η is the proportionality constant.

For determining η, is possible to consider the ranking of alternatives $Q_i^* = \left(A_{i,1}^* \succ A_{i,2}^* \succ \ldots \succ A_{i,n}^*\right)$ obtained by evaluating the values of the overall score received by each alternative: $d_{i,1}^* \geq d_{i,2}^* \geq \ldots \geq d_{i,n}^*$.

Two adjacent alternatives have an overall non-negative score difference, that is, for the generic s-th alternative, (4.72) holds.

$$d_{i,s}^* - d_{i,s+1}^* \geq 0\,; s = 1,2, \ldots, n-1 \tag{4.72}$$

Therefore, also (4.73) holds.

$$\begin{gathered} D_{k.l} = d_k - d_l = \sum_{j=1}^{m} \left(z_{k,j} - z_{l,j}\right) w_j \geq 0 \\ k = i_s\,, l = i_s + 1, s = 1,2, \ldots, n-1 \end{gathered} \tag{4.73}$$

Where $D_{k.l}$ is the difference between the overall score of the k-th and l-th adjacent alternatives evaluated by considering the initial values of criteria weights.

To guarantee compliance with (4.73) when w_j varies within the range $\left[w_j^* - \eta w_j^*, w_j^* + \eta w_j^*\right]$, then w_j has to comply with (4.74).

$$\begin{gathered} w_j = \begin{cases} w_j^* - \eta w_j^*\,; & if\ \left(z_{k,j} - z_{l,j}\right) \geq 0 \\ w_j^* + \eta w_j^*\,; & if\ \left(z_{k,j} - z_{l,j}\right) < 0 \end{cases} \\ j = 1,2, \ldots, m \end{gathered} \tag{4.74}$$

By substituting (4.74) in (4.73), (4.75) is obtained.

$$\begin{gathered} D_{k.l} = \sum_{j=1}^{m} \left(z_{k,j} - z_{l,j}\right) w_j^* - \eta \sum_{j=1}^{m} \left|z_{k,j} - z_{l,j}\right| w_j^* \geq 0 \\ k = i_s\,, l = i_s + 1, s = 1,2, \ldots, n-1 \end{gathered} \tag{4.75}$$

From (4.75), the calculation of the proportionality constant η is obtained by (4.76).

$$\begin{gathered} \eta \leq \frac{\sum_{j=1}^{m} \left(z_{k,j} - z_{l,j}\right) w_j^*}{\sum_{j=1}^{m} \left|z_{k,j} - z_{l,j}\right| w_j^*} \\ k = i_s\,, l = i_s + 1, s = 1,2, \ldots, n-1 \end{gathered} \tag{4.76}$$

The maximum value of η that does not produce a change in the ranking of the options is defined by (4.77).

$$\eta^* = min \left\{ \frac{\sum_{j=1}^{m} \left(z_{k,j} - z_{l,j}\right) w_j^*}{\sum_{j=1}^{m} \left|z_{k,j} - z_{l,j}\right| w_j^*}; k = i_s\,, l = i_s + 1, s = 1,2, \ldots, n-1 \right\} \tag{4.77}$$

Once the value of η^* is obtained, the acceptable range of variation for criteria weights is defined by (4.78).

$$w_j \in \left[w_j^* - \eta^* w_j^*\,,\ w_j^* + \eta^* w_j^*\right]; j = 1,2, \ldots, m \tag{4.78}$$

By considering the weight vector $W = (w_1, w_2, \ldots, w_1)$ where $w_j \in \left[w_j^L\,,\ w_j^U\right]$ and $0 \leq w_j^L \leq\ w_j^U$ for $j = 1,2, \ldots, m$. If the vector W satisfies (4.79) and (4.80), then it is normalised.

$$\sum_{j=1}^{m} w_j^L + max\left(w_i^U - w_i^L\right) \leq 1 \tag{4.79}$$

$$\sum_{j=1}^{m} w_j^U + max\left(w_i^U - w_i^L\right) \geq 1 \tag{4.80}$$

The weighs obtained by means of (4.78) are normalised if (4.81) is true.

$$max\left\{w_j^* \mid j = 1,2, \dots, m\right\} \leq 0.5 \tag{4.81}$$

If (4.81) is not satisfied, the vector W can be normalised by solving for each m entry the linear programming problem defined by (4.82).

$$\begin{gathered} min\left(\widehat{w}_j\right) ; max\left(\widehat{w}_j\right) \\ s.t. \begin{cases} w_j^L \leq \widehat{w}_j \leq w_j^U \; j = 1,2, \dots, m \\ \sum_{j=1}^{m} \widehat{w}_j = 1 \end{cases} \end{gathered} \tag{4.82}$$

The linear programming problem defined by (4.82) leads to (4.83) and (4.84).

$$\widehat{w}_j^L = max\left\{w_j^L , 1 - \textstyle\sum_{i \neq j} w_j^U\right\} ; j = 1,2, \dots, m \tag{4.83}$$

$$\widehat{w}_j^U = min\left\{w_i^U , 1 - \textstyle\sum_{i \neq j} w_j^L\right\} ; j = 1,2, \dots, m \tag{4.84}$$

The range of weights for the stability of the best alternative of the set can be obtained by particularizing the expressions presented in this section. Assuming that the best alternative of the set is A_{i_1} to which the rank index i_1 is related, the maximum value of η can be calculated utilizing (4.77) considering k=i_1 and l=1, 2, …, n with $l \neq i_1$.

$$\eta^* = min\left\{\frac{\sum_{j=1}^{m}\left(z_{i_1,j} - z_{l,j}\right) w_j^*}{\sum_{j=1}^{m}\left|z_{i_1,j} - z_{l,j}\right| w_j^*} ; \; l = 1,2, \dots, n ; l \neq \; i1\right\} \tag{4.85}$$

Once the parameter η^* has been obtained, the acceptable range for criteria weights can be obtained through (4.78).

5 DECISION THEORY APPROACHES FOR MULTI-CRITERIA ANALYSIS

This chapter discusses the application of Decision Theory rules to multi-criteria analysis. Since both approaches concern decision-making, the most acknowledged Decision Theory rules are reviewed in light of their combination with the multi-criteria analysis. The potential use of the decision rules reviewed is studied and discussed. Finally, the chapter ends by proposing a multi-criteria approach that combines the minimax regret rule. This approach does not require to express criteria weights since the exploitation of an optimisation model. This approach represents one of the contributions of the present dissertation.

This chapter aims at answering the following questions:

- Which are the most acknowledged decision rules of Decision Theory?
- Can Decision Theory and multi-criteria analysis work together?
- Which decision rules fit with multi-criteria analysis?
- How is it structured the proposed approach which combines multi-criteria analysis with the minimax regret decision rule?

5.1 Introduction

The MCA-type approaches require defining the relevance of criteria considering the overall objective of the decision-making problem. This step is crucial for the evaluation process; the distribution of weights between the criteria strongly influences the analysis outcome. As described in section 4, various methodologies have been proposed in the literature for criteria weighting.

Subjective methods determine the criteria weights on the preferences expressed directly or indirectly by the stakeholders. Objective methodologies calculate the weights of the criteria from the available information on the alternatives under analysis, and integrated methodologies merge subjective and objective elements.

Both the theoretical analysis illustrated in section 4 and the application described in section 7.3 of the most established methods for determining the weights of the criteria have shown that there is no technique of absolute validity. The various techniques are based on different primary hypotheses, each of which is reasonable; applying different techniques to the same decision-making problem may lead to the indication of discordant results. In decision-making problems, no general law is evident that would lead to prefer one technique over the others. Therefore, the choice to use a particular technique to determine the criteria weights is an arbitrary choice of the analyst.

Moreover, the reviewed criteria weighting methods indicate the best alternative considering only a particular condition. In fact, the analysed methods define a specific scheme of weights useful for identifying the dominant alternative; however, the validity of the solution obtained can be evaluated only afterwards.

In the context of project selection problems in the smart grid sector, this approach may be ineffective. It does not consider the different relevance that impacts assume considering different sectors of society. To identify the alternative capable of achieving the highest consensus within the entire audience of stakeholders affected by the decision-making problem, approaches that consider stakeholder expectations beforehand and model the typical dynamics of decision-making processes sound more convincing.

To overcome the issues related to the determination of the criteria weights, the use of an optimisation technique combined with Decision Theory rules is proposed in this section. The methodology aims to indicate the best alternative by eliminating the need for criteria weight determination. The result provided by the optimisation model built on a decision rule can consider the multiplicity of the possible points of view; partial information on the relevance of the criteria can be provided to limit the eligible region for the evaluation of the alternatives.

To identify the most suitable decision rule to be encompassed within an MCA framework, a literature review on Decision Theory rules is provided in this section. The analysis examines the decision-making rules proposed in the literature and assesses their application in the context of the decision-making problem for the smart grid sector. In combination with optimisation techniques, decision rules allow overcoming the decision-makers subjectivity in assessing the relevance of the impacts. The research activity presented formalises an evaluation approach that eliminates the cognitive burden and personal biases introduced by the decision-maker and indicates the option characterised by the highest acceptance considering the entire audience of stakeholders of the decision-making problem.

5.2 Decision-making problems modelled for Decision Theory

According to the Decision Theory, the consequences determined by a given action depend on the specific action taken and on a set of external factors that may or may not be known to the decision-maker [157]. These external factors may or may not be under the control of the decision-maker. A state of nature (or state) is defined as the comprehensive description of the external factors of the decision-making problem [157].

The complete knowledge of the state of nature makes it possible to predict the consequences of an action. In general, the actual state of nature is not known to the decision-maker at the time when the decision is to be made [157].

According to the Decision Theory, the elementary form for modelling decision-making problems is the decision table [157]. For a generic decision problem, the decision table shows the possible actions and the associated consequences for each of the possible states of nature of interest for the analysis.

Considering a decision-making problem characterised by a finite set of *n* states [θ_1, …, θ_n] and a finite set of feasible actions *m* [a_1, …, a_m]. Only one of the *m* actions can be chosen, x_{ij} represents the consequence of the action a_i when θ_j is the actual state of nature [157].

In general, the consequences x_{ij} can be described with quantitative or qualitative values; in the latter case, the numerical value can be obtained considering a real function $v(\cdot)$ which measures the consequence's value. The greatest the value $v_{ij}= v(x_{ij})$ of a consequence x_{ij}, the highest the preference which the decision-maker has for the generating action a_i.

Based on the model described, the decision table for a generic problem is represented by Table 5.1 [157].

Table 5.1. Decision table for a generic decision-making problem [157]

Values		**States**			
		θ_1	θ_2	…	θ_n
Actions	a_1	v_{11}	v_{12}	…	v_{1n}
	a_2	v_{21}	v_{22}	…	v_{2n}
	…	…	…	…	…
	a_m	v_{m1}	v_{m2}	…	v_{mn}

Based on the level of knowledge of the state of nature which the decision-maker has, decision-making problems can be divided into three categories: decision-making problems under conditions of certainty, risk, and uncertainty [157].

In decision-making problems under conditions of certainty, the decision-maker knows the actual state of nature when making the decision. Therefore, the consequences of the action taken are predictable with certainty. A general decision-making problem under conditions of certainty is when only one possible state exists [157].

In decision-making problems under conditions of risk, the actual state of nature is not known with certainty to the decision-maker; however, the uncertainty regarding the knowledge of states is modelled by probability distributions [P(θ1), P(θ2), ..., P(θn)]. Below conditions of rationality, the decision-maker resolves the decision-making problem by taking the generic action to which the maximum expected utility value is associated, calculated according to (5.1) [157].

$$U = \sum_{j=1}^{n} P(\theta_j) \cdot v_{ij} \tag{5.1}$$

In decision-making problems under uncertainty, the decision-maker does not know the actual state and is unable to quantify the uncertainty of his estimation of the state of nature [157]. However, the decision-maker knows the set of states in terms of possible feasible representations [157].

5.3 Decision-making rules for problems in conditions of uncertainty

The decision-making rules proposed by the Decision Theory are based on different hypotheses and model a different attitude of making choices. Individually, each decision-making rule provides a reasonable result, but different results can be obtained if applied to the same decision-making problem [157]. Therefore, it is necessary to identify the decision rule that best suits the characteristics of the decision problem under analysis [157]–[159].

5.3.1 Maximin rule

The maximin rule (Wald's maximin return) is a conservative choice criterion as it leads to the choice of the action that determines the maximum utility value in the worst-case scenario. For each action, the minimum value of utility obtainable in the various scenarios is identified, and the action with the maximum value is selected, as described by (5.2) [157].

$$choose\ a_k : s_k = \max_{i=1\ldots m}\{s_i\} = \max_{i=1\ldots m}\{\min_{i=1\ldots n}\{v_{ij}\}\} \tag{5.2}$$

The value $s_i = \min_{i=1\ldots n}\{v_{ij}\}$ is defined as the security level of the action a_i.

The choice made using the *maximin* criterion has characteristics of being overly pessimistic as it assumes the worst possible scenario.

5.3.2 Maximax rule

The maximax rule is an optimistic choice criterion as it leads to the choice of the action that determines the maximum utility in the best possible scenario. For each action, the maximum value of utility obtained in the different scenarios is identified, the action that achieves the maximum value is selected, as described by (5.3) [157].

$$choose\ a_k : o_k = \max_{i=1\ldots m}\{o_i\} = \max_{i=1\ldots m}\{\max_{i=1\ldots n}\{v_{ij}\}\} \tag{5.3}$$

The maximax rule produces overly optimistic choices as it assumes the best possible scenario.

5.3.3 Hurwicz rule

The maximin and maximax criteria represent two extreme rules in terms of pessimism and optimism as they assume, respectively, the worst-case scenario and the best-case scenario. Hurwicz's optimism-pessimism rule fits between the two extreme rules by introducing a measure of the optimism/pessimism attitude of the decision-maker. Through the α optimism-pessimism index, the actions are classified on the basis of the weighted average of security and optimism, defined as in (5.4) [157].

$$as_i + (1-a)o_i \qquad where\ 0 \le a \le 1 \tag{5.4}$$

Hurwicz's decision rule is defined as in (5.5).

$$choose\ a_k\colon\ as_k + (1-a)o_k = \max_{i=1\ldots m}\{\,as_i + (1-a)o_i\} \tag{5.5}$$

The value of a is specific for each decision-maker and applies to all decision-making problems in which he or she is involved. The determination of this value is possible through the iterative solution of a simple decision-making problem characterised by two actions and two states, as represented in Table 5.2 [157].

Table 5.2. Decision table for determining the Hurwicz parameter [157]

	θ_1	θ_2	…	s_i	o_i	$as_i + (1-a)o_i$
a_1	1	0	…	0	1	$(1-a)$
a_2	v	v	…	v	v	v

The value of the Hurwicz parameter is determined as $a = (1-v)$ at the iteration corresponding to the indication of indifference given by the decision-maker [157]. This condition is obtained starting from a low v value that is increased at each iteration until indifference is reached.

5.3.4 Minimax regret rule

The maximin, maximax, and Hurwicz decision rules are based on the direct use of utility values v_{ij} and comparing the different possible actions according to an evaluation made considering different states of nature [48], [157]. However, the occurrence of a given state is beyond the control of the decision-maker; therefore, the different actions should be compared considering at the same time the same state of nature [48], [157]. The comparison of the actions considering the same state of nature is implemented by Savage's minimax regret rule [48]. The regret determined by selecting one action compared to another is defined mathematically by (4.1) [157].

$$r_{ij} = \max_{l=1\ldots m}\{v_{lj}\} - v_{ij} \tag{5.6}$$

Considering the state θ_j, the regret r_{ij} is the difference between the utility related to the best possible action and the utility caused by the *i-th* action a_i.

By evaluating all possible scenarios, for each action, the maximum value of regret is calculated as in (5.7) [157].

$$\rho_i = \max_{j=1\ldots m}\{r_{lj}\} \tag{5.7}$$

The decision rule based on the minimax regret criterion is defined by (5.8).

$$choose\ a_k\colon\ \rho_k = \min_{i=1\ldots m}\{\rho_i\} = \min_{i=1\ldots m}\left\{\max_{i=1\ldots m}\{r_{lj}\}\right\} \tag{5.8}$$

The minimax regret rule leads to the choice of the alternative that causes the minimum value of maximum regret. In other words, the solution to the decision problem is the alternative that can determine the minimum regret in case the most unfavourable state of nature for this alternative occurs.

5.3.5 Laplace's rule of insufficient reason

Laplace's principle of insufficient reason assumes that the lack of knowledge of the state of nature corresponds to the assignment of a fair probability to all possible states [157]. Based on this assumption, the rule of decision is defined mathematically using (5.9) [157].

$$choose\ a_k:\ \rho_k = \sum_{j=1}^{n} \frac{1}{n} v_{kj} = \max_{i=1\dots m} \left\{ \sum_{j=1}^{n} \frac{1}{n} v_{ij} \right\} \tag{5.9}$$

Laplace's principle of insufficient reason leads to the choice of the action that, considering all possible states, has the highest average value of utility [157].

5.3.6 Discussion on the described decision-making rules

The decision-making rules described in Section 5.3 are based on different assumptions, so if applied to the same decision-making problem, the provision of the same outcome is not guaranteed. This behaviour has been demonstrated in [160], where an elementary problem shows that different decision-making rules lead to different choices [157].

This behaviour does not prove the unreliability of the decision-making rules, which are reasonable in themselves [157]. Indeed, each decision-making rule shapes a rational approach to solving decision-making problems under conditions of uncertainty [160]. On the contrary, the result obtained indicates that the decision-making rule to be used must be established on the characteristics of the decision-making problem and the attitude of the decision-maker. In this context, it is preferable to identify the conditions that limit the applicability of each of the rules rather than aspire to define a decision rule of universal validity [160].

In absolute terms, each decision-making rule presents critical issues arising from the assumptions on which it is based. The maximin rule leads to highly conservative choices; in cases where the worst state does not often occur, the choice made can be highly unsatisfactory [159]. The minimax regret rule shows a similar behaviour; it can lead to considerable regrets for a significant share of the scenarios [159]. At the same time, the maximax rule being highly optimistic may lead to an extremely unsatisfactory choice for all those cases where the most favourable scenario for this alternative does not occur with a reasonable frequency. The Hurwicz rule is based on the use of the pessimism-optimism parameter, whose definition is arbitrary [159]. Finally, the principle of insufficient reason is based on the unjustified hypothesis of fair probability of states [158], [159].

To overcome the problem of the choice of the rule to adopt, several criteria have been proposed in the literature [157]–[159].

One of the proposed criteria is represented by the application of all the rules to the decision-making but considering the possible actions in pairs. In some cases, this approach leads to inconsistent results (intransitive order of preference, voting paradox) [158], [159].

The condition of the mixture is based on the hypothesis that indifference between two actions implies the subsistence of indifference for any of their probabilistic combinations [158], [159]. The Hurwicz rule does not satisfy this condition [158], [159].

The condition of irrelevant expansion states that introducing a new action that it is not better than the initial actions must not lead to changes in the order previously determined for such actions [158], [159]. The minimax regret rule does not satisfy this condition [158], [159].

The literature analysis underlines that even considering the conditions described above, it is not possible to identify a decision-making rule of general validity[158], [159]. A preliminary study of the decision-making problem and its context is indispensable to identify the most suitable decision-making rule [158], [159]. In cases in which extreme consequences are possible, it might be preferable to adopt conservative approaches, while for repeated decisions, it might be profitable to maximise the average usefulness of possible actions [152].

5.3.7 Decision theory applied to the problem of multi-criteria analysis

The decision-making model defined according to the MADM methods requires the definition of the relevance of the evaluation criteria for formulating the final choice suggested [26], [27]. Each distinct weighting scheme defines a different scenario that models a particular point of view expressed by stakeholders.

Based on the definitions described in sections 3.2.2 and 5.3.6, it is possible to formulate the multi-criteria analysis problem in terms of the Decision Theory model. It is assumed that the unknown variables of the multi-criteria problem are the criteria weights; therefore, the set of possible weight schemes represents the set of possible states of the decision-making problem. In the context of the multi-criteria analysis applied to the smart-grid area, it is of greater interest to identify the alternative that achieves satisfactory performance considering all possible states. On the contrary, identifying an alternative that is valid only under particular conditions represents an activity of little interest.

Considering a decision-making problem characterised by a set Θ of q states [$\underline{\theta_1}$, …, $\underline{\theta_q}$] and a finite set A of m feasible actions [$\underline{A_1}$,…, $\underline{A_m}$]. The *j-th* state represents the vector $\underline{\theta_j}$=$\underline{W_j}$=[w_1, …, w_n] of criteria weights for the decision-making problem, each weight vector has to satisfy (5.10).

$$\begin{cases} w_i \geq 0 \\ \sum_{i=1}^{n} w_i = 1 \end{cases} \tag{5.10}$$

The set A of feasible actions coincides with the set of alternatives of the multi-criteria problem, the generic *i-th* action is represented by the vector $\underline{A_i}$=[a_1, …, a_n] of the attributes that the *i-th* alternative have concerning the criteria of the multi-criteria problem.

The overall evaluation of each of the alternatives in set A is obtained employing (5.11). It coincides with the utility value caused by the related alternative, as described in section 5.2.

$$V(A_k) = \sum_{i=1}^{n} w_i a_{i,k} \tag{5.11}$$

Based on the assumptions made, the decision table for the decision problem of multi-criteria analysis takes the form shown in Table 5.3

Table 5.3. Decision table for the decision problem of multi-criteria analysis

Values		**States**			
		$\underline{W_1}$	$\underline{W_2}$	.	$\underline{W_q}$
Alternatives	A_1	V_{11}	V_{12}	.	V_{1q}
	A_2	V_{21}	V_{22}	.	V_{2q}
	.	.		.	.
	A_m	V_{m1}	V_{m2}	.	V_{mq}

Assuming that none of the techniques for calculating the criteria weights is used, so the set Θ of the criteria weights is not explicitly known. The lack of knowledge of the actual state of nature leads the decision-making problem in analysis back to the condition of uncertainty. In this context, the decision-making rules described in section 5.3 are applicable to solve the decision-making problem.

5.3.7.1 Application of the maximin rule

The application of the maximin rule to the problem of multi-criteria analysis results in the selection of the alternative of the set that presents the maximum utility value considering the weight scheme that determines the minimum possible value.

For each alternative, the method requires searching in the weights space for the point to which the utility value is minimum (minimum utility). Once the minimum utility value has been obtained for all the alternatives, the alternative of the set with the maximum-minimum utility value is selected as the solution of the decisional problem. The process of solution of the decisional problem can be synthesized by (5.12).

$$choose\ A_k: V_k = \max_{k=1\ldots m}\{\min_{j=1\ldots q}\{V_{ij}\}\} = \max_{k=1\ldots m}\{\min_{j=1\ldots q}\{\sum_{i=1}^{n} w_{i,j} a_{i,k}\}\} \tag{5.12}$$

If the set Θ of possible states coincides with the infinite set of weights space, the decisional problem characterised by the maximin rule is solvable by using optimisation techniques. For each alternative, the optimisation problem characterised by the minimisation of the utility function is solved. For the generic alternative k-th (5.13) is valid.

$$U_k = \min\left\{\sum_{i=1}^{n} w_i a_{i,k}\right\} \qquad for\ k = 1, \ldots, m$$
$$\text{s.}t. \begin{cases} \sum_{i=1}^{m} w_i = 1 \\ w_i \in [w_{i,L}, w_{i,H}] \end{cases} \tag{5.13}$$

Where $w_{i,L}$ e $w_{i,H}$ the lower end and the upper end for the permissible values for the weight of the i-th criterion; if specific information is missing, the following values have to be considered $w_{i,L} = 0$ e $w_{i,H} = 1$.

Once the minimum utility values U have been obtained for each of the *m* alternatives of the set, the decision problem is solved by selecting the alternative with the maximum-minimum utility value.

The application of the maximin rule to the problem of multi-criteria analysis is led back to the solution of a series of minimisation problems and the subsequent resolution of the resulting selection problem.

The application to the problem of multi-criteria analysis of the maximin rule leads to extreme pessimistic choices. In the context of the multi-criteria problem analysed in this thesis, this aspect coincides with the selection of the alternative that receives the maximum value of minimum consensus from the stakeholders concerned. Therefore, rather than a compromise alternative, the suggested solution is an overly conservative option that may not produce sufficient satisfaction considering the entire audience of stakeholders.

5.3.7.2 Application of the maximax rule

The maximax rule applied to the problem of multi-criteria analysis corresponds to the identification of the alternative of the set that achieves the maximum utility value considering all possible weight schemes.

For each alternative, the method requires searching in the weights space for the point to which the utility value is maximum (maximum utility). Once the maximum utility value has been obtained for each of the alternatives, the alternative of the set that has the maximum utility value is selected as the solution to the decision-making problem. The process of solution of the decisional problem can be summarized by (5.14).

$$choose\ A_k: V_k = \max_{k=1\dots m}\{\max_{j=1\dots q}\{V_{ij}\}\} = \max_{k=1\dots m}\{\max_{j=1\dots q}\{\sum_{i=1}^{n} w_{i,j}a_{i,k}\}\} \quad (5.14)$$

Suppose Θ, the set of possible states, coincides with the infinite set determined by the weights space. In that case, the decisional problem faced by the maximax rule can be solved using optimisation techniques. For each alternative, the optimisation problem characterised by the maximisation of the utility function is solved. For the generic alternative k-th (5.15) is valid.

$$U_k = \max\left\{\sum_{i=1}^{n} w_i a_{i,k}\right\} \qquad for\ k = 1, \dots, m$$
$$\text{s.}t.\begin{cases} \sum_{i=1}^{m} w_i = 1 \\ w_i \in [w_{i,L}, w_{i,H}] \end{cases} \quad (5.15)$$

Where $w_{i,L}$ and $w_{i,H}$ are the lower end and the upper end for the permissible values for the weight of the i-th criterion; in the absence of information, the values are $w_{i,L} = 0$ e $w_{i,H} = 1$.

Once the maximum utility values U have been obtained for each of the *m* alternatives of the set, the decision problem is resolved by selecting the alternative with the maximum utility value.

Applying the maximax rule to the multi-criteria analysis problem leads to the solution of a series of *m* maximisation problems and the subsequent resolution of the resulting selection problem.

The application to the problem of multi-criteria analysis of the maximax rule leads to an extreme optimistic choice. In the context of the multi-criteria problem analysed in this thesis, this aspect coincides with the selection of the alternative that receives the maximum preference from a particular stakeholder. Therefore, the alternative indicated as the solution to the decision-making problem may not satisfy the entire audience of stakeholders.

5.3.7.3 Application of the Hurwicz rule

The Hurwicz rule through the introduction of the α optimism-pessimism index is an intermediate decision criterion to the maximin and maximax rules. For each alternative, the application of the Hurwicz rule requires the evaluation of the maximum and minimum value of utility for all the states of the decision problem.

For each alternative, the minimisation problem associated with the pessimistic assessment of the rule has to be solved as defined by (5.16).

$$S_k = \min\left\{\sum_{i=1}^{n} w_i a_{i,k}\right\} \qquad for\ k = 1, \dots, m$$
$$\text{s.}t.\begin{cases} \sum_{i=1}^{m} w_i = 1 \\ w_i \in [w_{i,L}, w_{i,H}] \end{cases} \quad (5.16)$$

Besides, for each alternative, the maximisation problem associated with the optimistic assessment of the rule, as defined in (5.17), have to be solved.

$$O_k = \max\left\{\sum_{i=1}^{n} w_i a_{i,k}\right\} \qquad for\ k = 1, \dots, m$$
$$\text{s.}t.\begin{cases} \sum_{i=1}^{m} w_i = 1 \\ w_i \in [w_{i,L}, w_{i,H}] \end{cases} \quad (5.17)$$

The models (5.16) and (5.17) are respectively the lower end and the upper end for the permissible values for the weight of the i-th criterion; in the absence of any information, these values are $w_{i,L} = 0$ e $w_{i,H} = 1$.

In (5.16) and (5.17), the values of S_k e O_k are defined, relation (5.18) applies.

$$S_k \leq O_k \quad per \quad \forall k \in [1, m] \tag{5.18}$$

Subsequently, the solution of the decision-making problem is identified by solving the selection problem defined by (5.19).

$$choose\ A\colon\ H_k = aS_k + (1-a)O_k = \max_{i=1\ldots m}\{\,aS_i + (1-a)O_i\} \tag{5.19}$$

Where the α optimism-pessimism index has a unique value defined by the range 0≤ α ≤1.

Suppose the value of the α index is univocal. In that case, the decision problem solved by Hurwicz rule requires the solution of *m* minimisation problems, *m* maximisation problems, and the subsequent solution of the problem of selecting the alternative that presents the maximum value of the linear combination of pessimistic and optimistic evaluation.

The parameter α is unique for the system of *m* equations defined by the Hurwicz rule. Considering (5.19), for each alternative, the maximum possible value of H_k is the minimum value of parameter α. For α =0 we obtain $H_k \equiv O_i$, the Hurwicz rule is reduced to the maximax rule.

5.3.7.4 Application of the MiniMax Regret rule

The MiniMax Regret decisional rule compares all possible actions considering the same state of nature [48], [157]. This aspect is of interest in the application of the minimax regret rule to the problem of multi-criteria analysis that is the subject of the thesis. In fact, this rule allows the comparison of alternatives in homogeneous terms considering the different possible points of view of stakeholders. The minimax regret rule leads to the identification of an alternative that is accepted by the stakeholder audience; the proposed solution consists of the alternative that least of all displeases the stakeholder with the most critical point of view.

In the context of the application of the minimax regret rule to the problem of multi-criteria analysis, the regret determined by the selection of a generic i-th alternative to the j-th state is defined by (5.20).

$$R_{ij} = \max_{l=1\ldots m}\left\{\sum_{k=1}^{n} w_{k,j}a_{l,k}\right\} - \sum_{k=1}^{n} w_{k,j}a_{i,k} \tag{5.20}$$

Given the generic j-th state, the regret R_{ij} generated by the i-th alternative is defined as the difference between the utility produced by the best possible alternative and the utility produced by the generic alternative A_i.

Considering the set of all the possible states, which can coincide with the whole space of the weights, the maximum value of regret ρ_i generated by the i-th alternative is defined by (5.21).

$$\rho_i = \max_{j=1\ldots q}\{R_{ij}\} = \max_{j=1\ldots q}\left\{\max_{l=1\ldots m}\left\{\sum_{k=1}^{n} w_{k,j}a_{l,k}\right\} - \sum_{k=1}^{n} w_{k,j}a_{i,k}\right\} \tag{5.21}$$

The decision rule based on the minimax regret criterion determines the choice of the alternative of the set that achieves the minimum value of the maximum regret, as described in the report (5.22).

$$choose\ A_k\colon\ \rho_k = \min_{i=1\ldots m}\{\rho_i\} = \min_{i=1\ldots m}\left\{\max_{j=1\ldots q}\left\{\max_{l=1\ldots m}\left\{\sum_{k=1}^{n} w_{k,j}a_{l,k}\right\} - \sum_{k=1}^{n} w_{k,j}a_{i,k}\right\}\right\} \tag{5.22}$$

The application of optimisation techniques to the multi-criteria decision making problem solved by the minimax regret rule is possible through a procedure consisting of a series of steps.

The first step consists of solving m maximisation problems to identify the maximum regret value for each of the alternatives in the evaluation set. The maximisation problem is described by (5.23).

$$\rho_k = \max_{j=1\ldots q}\left\{\max_{l=1\ldots m}\left\{\sum_{k=1}^{n} w_{k,j}a_{l,k}\right\} - \sum_{k=1}^{n} w_{k,j}a_{i,k}\right\} \qquad for\ k = 1,\ldots,m$$
$$\text{s.}t.\begin{cases} \sum_{i=1}^{m} w_i = 1 \\ w_i \in [w_{i,L}, w_{i,H}] \end{cases} \tag{5.23}$$

Where $w_{i,L}$ and $w_{i,H}$ are the lower end and the upper end for the weight of the i-th criterion; in the absence of any information, the values are $w_{i,L} = 0$ e $w_{i,H} = 1$.

Having obtained the values of maximum regret ρ_k for all the m alternatives of the set, the solution of the decision-making problem is obtained by solving the selection problem that leads to the identification of the alternative that has achieved the minimum value of maximum regret, as represented by (5.22).

5.3.7.5 Application of Laplace's insufficient reason rule

The application of the Laplace rule of insufficient reason to decision-making problems leads to the choice of the alternative with the highest average utility value considering all possible states [157]. In the case of the solution of the multi-criteria problem on which this document is focused, the application of the insufficient reason principle identifies the alternative that presents the highest average value of utility calculated considering all possible points of the weight space. This corresponds to the identification of the alternative that brings an average level of satisfaction to the whole audience of stakeholders, to whom equal importance is assigned.

Laplace's insufficient reason principle applied to the problem of multi-criteria analysis is described by (5.24).

$$choose\ A_k{:}\ L_k = \max_{k=1\ldots m}\left\{\frac{1}{q}\sum_{j=1}^{q} v_{kj}\right\} = \max_{k=1\ldots m}\left\{\frac{1}{q}\sum_{j=1}^{q}\sum_{i=1}^{n} w_{i,j}a_{i,k}\right\}$$
$$s.t.\begin{cases} \sum_{i=1}^{m} w_i = 1 \\ w_i \in [w_{i,L}, w_{i,H}] \end{cases} \tag{5.24}$$

Where $w_{i,L}$ and $w_{i,H}$ represent respectively the lower end and the upper end for the permissible values for the weight of the i-th criterion; in the absence of specific information there are the following values $w_{i,L} = 0$ e $w_{i,H} = 1$.

Given the form of the decision rule of the insufficient reason principle, optimisation techniques are not applicable. The application of the insufficient reason principle to the described multi-criteria problem requires a tremendous computational burden as it requires the calculation of the utility value for the whole weights space to derive the overall average value.

The overall decision-making problem is solved through the problem of selecting the alternative of the set that has achieved the highest average utility value.

5.3.7.6 Discussion on decision-making rules applied to the problem of multi-criteria analysis solved by optimisation techniques

As highlighted by the scientific literature and described in section 5.3.6, none of the proposed decision-making rules is generally valid. Therefore, it is necessary to identify the decision rule best suited to the peculiarities of the decision-making problem under analysis [157]–[159].

The multi-criteria decision-making problem of interest for this thesis is characterised by a linear relationship for combining the attributes of the alternatives and the criteria weights (5.11). The attributes of the alternatives are known with certainty and represent the coefficients of the linear combination. In contrast, the criterion weights are the independent variables.

The objective of the decision-making problem is to identify the alternative that, considering the whole weight space, meets stakeholders' expectations. The use of the decision-making rules of decision theory aims at defining the satisfaction criterion mathematically. The use of optimisation techniques is useful to analyse the weight space in search of the solution point that optimises the value of the objective function defined by the particular decision rule considered.

The maximin rule applied to the multi-criteria problem under analysis admits the use of optimisation techniques. This rule has the disadvantage of leading to an extremely conservative choice as it identifies the alternative that achieves the highest utility value considering the most unfavourable weight scheme. In the context of the evaluation of planning alternatives in the smart grid sector, implementing an alternative selected according to an excessively conservative criterion may prove to be highly disadvantageous.

The MaxiMax Rule leads to the alternative that achieves the highest value of maximum utility, evaluated according to all points of the weight space. The choice of such an alternative would bring a high degree of satisfaction to a specific category of stakeholders, potentially displeasing the rest of the audience. The maximax rule does not lead to the definition of shared choices; therefore, its application to evaluate planning activities of collective interest is of little interest.

The Hurwicz rule allows compromise choices to be made in between an overly pessimistic vision (maximin rule) and an overly optimistic vision (maximax rule). The fulcrum of the compromise depends on the value imposed on the parameter of optimism-pessimism whose determination is arbitrary. In the planning of initiatives of collective interest, the decision-maker would, therefore, have the burden of establishing the orientation of the evaluation. This intervention introduces subjectivity into the valuation activity. Moreover, the burden of calculating the problem is high as it requires the solution of many optimisation problems as two times the number of alternatives under analysis.

The minimax regret rule leads to the identification of an alternative shared by all stakeholders. The level of sharing is expressed in terms of regret determined by making a collective choice different from the alternative preferred by each of the individual stakeholders. Exits the possibility which the alternative indicated by the method differs from any of the alternatives preferred by each of the stakeholders; however, the solution indicated is the alternative that least of all causes dissatisfaction to the most critical stakeholder. In addition, the assessment based on the MiniMax Regret rule allows the comparison of alternatives under homogeneous conditions in terms of weight scheme. This aspect differs from the other decisional rules that compare the various alternatives on evaluations made considering different weight schemes. The minimax regret rule admits the use of optimisation techniques; however, the optimisation model is non-linear. Finally, the issue related to the non-respect of the condition of irrelevant expansion does not influence the validity of the solution obtained for the decisional problem of the multi-criteria analysis since it is possible to assume that a variation of the set of alternatives is such that a new decisional problem is faced.

The decisional rule based on the principle of insufficient reason does not allow the application of optimisation techniques and is therefore of little interest for a practical application to the multi-criteria problem. Furthermore, in planning activities, there may be a need to assign greater or lesser importance to the point of view associated with a particular stakeholder category in planning activities.

Based on the characteristics of the decision-making the selection of the planning initiative in the smart grid sector, and taking into account the characteristics of each of the decisional rules proposed by the scientific literature of the Decision Theory, the comparison described in this section highlights how the minimax regret rule is the most suitable criterion for carrying out the evaluation activities.

In practical cases, the problem of selecting the best smart grid initiative is characterised by a small number of alternatives, generally less than 10, and the evaluation criteria are no more than 20. The size of the problem is compatible with the complexity of the algorithm proposed in section 5.3.7.4.

5.4 The optimisation method based on decision theory

In planning activities, the goal of the decision-making problem is the selection of the alternative that leads to the optimal allocation of available resources. Typically, this choice is made under risk or uncertainty; therefore, it is of interest the selection of the option able to ensure the highest utility considering all possible scenarios. The identification of the alternative to be implemented have to be based on a process that ensures a rational choice.

In this document, the selection problem of the best planning alternative for smart grids is addressed through a decision support tool that includes economic analysis within a multi-criteria approach. This evaluation framework considers the performances achieved by each alternative according to various criteria and produces an overall assessment. Considering the overall score obtained by the alternatives, the best alternative of the set is selected. This approach requires the definition of the relevance of evaluation criteria; the obtained result is influenced by the weighting scheme used. As highlighted in the previous sections, the decision-making problems are not under certainty, nor in terms of performance of the alternatives, nor terms of relevance assigned to evaluation criteria. Therefore, the methodologies used to calculate the numerical value of the criteria weights have a crucial role. Subjective methods directly involve stakeholders but are affected by the vagueness of the language; furthermore, the methodology used influences the obtained result. Objective methodologies calculate the weight of the criteria considering the attributes of the alternatives. These methodologies reject the subjectivity on criteria weights; consequently, the result obtained may be far from the expectations of the stakeholders. In the context of decision-making problems, no general law appears to ensure the absolute validity of the result obtained by exploiting objective methodologies. A large number of methods available in the literature, thus choosing to use a technique over the others, represent an arbitrary choice. The integrated methodologies are a compromise between the use of subjective and objective methodologies. By exploiting an optimisation model, these methods combine objective information on attributes with partial information on the relevance of the criteria. The result offered represents a compromising weight scheme that depends on the optimisation model used and the features of the decision-making problem under analysis. The methods analysed in this document aim at defining a specific weighting scheme that leads to the identification of the dominant alternative. The stability of the solution obtained can be assessed ex-post.

When a decision-making problem under uncertainty is addressed, the decision-maker may be interested in identifying an alternative that achieves satisfactory performances in all possible scenarios. Unlike an approach that suggests the best alternative under particular conditions, it can be more effective a strategy that identifies a valid compromising option even in the worst scenario. However, choosing the best alternative in the worst possible scenario can be excessively cautious. To avoid sub-optimal choices, the approach of minimising the maximum regret (MinMax Regret - MMR) allows identifying the alternative that leads to the least maximum regret for the stakeholders considering the worst possible scenario [161]–[163]. Over time, this approach has been widely applied in industrial decision-making processes. Recently, an approach based on the least regret assessment has been exploited to identify the target capacity value for the Italian transmission system [164].

In decision-making problems, regret occurs when, given a scenario, the selected action leads to fewer benefits than those that an alternative action would have produced. The regret between two options can be quantified in terms of the difference of their utilities. The MinMaxRegret approach consists of selecting the alternative with the minimum-maximum regret value; the maximum regret is calculated with respect to the best alternative of each possible scenario.

Considering the multi-criteria framework for evaluating the alternatives in the smart grid sector, it is of interest to identify alternatives that bring an adequate degree of satisfaction for all categories of stakeholders. The impacts produced by smart grids affect various sectors of society; therefore, synthesizing the point of view of the various categories of stakeholders assumes relevance for the success of the initiatives. In this context, the MinMaxRegret approach is presented to identify the alternative able to bring the least disappointment to all possible categories of stakeholders. Instead of synthesizing the various points of view of stakeholders in terms of a unique scheme of weights, this section proposes an optimisation model based on the MinMaxRegret approach that identifies the best compromising alternative based on the analysis of all possible points of view available for the decision-making problem. This approach allows for a conservative but not pessimistic choice to be made.

Given the decision-making problem characterised by the set of alternatives $A=(A_1, A_2, \dots, A_n)$ and by the set of criteria $C=(C_1, C_2, \dots, C_m)$. Each alternative A_i is described by a vector X_i which each entry x_{ij} is the attribute of the i-th alternative concerning the j-th criterion. The DM $\underline{X}$ is then normalised using the procedure described in section 4.2.1 employing (4.11) and (4.12). Therefore, the decision-making problem is described by the normalised decision-matrix $\underline{Z}$ in which the entry z_{ij} is the normalised attribute of the i-th alternative concerning the j-th criterion and the vector W_k of criteria weights. W_k models the k-th scenario in terms of the evaluation criteria relevance. The entries of the vector W_k are in terms of $w_{j,k}$ that represents the weight of the j-th criterion in the k-th scenario. In each scenario, the weight vector has to comply with (5.25) and (5.26).

$$\sum_{j=1}^{m} w_{k,j} = 1 \tag{5.25}$$

$$w_{k,j} \in [0,1] \; ; \; j = 1, \dots, m \tag{5.26}$$

The utility $U_{i,k}$ of the i-th alternative evaluated in the k-th scenario represents the overall score obtained by the linear combination of weights and normalised attributes (5.27).

$$U_{i,k} = \sum_{j=1}^{m} w_{k,j} z_{i,j} \tag{5.27}$$

The maximum regret related to the i-th alternative in the k-th scenario is evaluated through (5.28).

$$R_{i,k} = \left[\max_{t}\left(U_{t,k}\right) - U_{i,k}\right] \; ; \; t = 1, \dots, n \tag{5.28}$$

Where $R_{i,k}$ is the maximum regret of the i-th alternative in the k-th scenario calculated as the difference of the maximum utility value among the alternatives in the k-th scenario and the utility value achieved by the i-th alternative.

By considering the set Q of the scenarios defined by (5.25) and (5.26), the optimisation model for identifying the alternative which shows the minimum value of the maximum regret is defined by (5.29).

$$\begin{gathered} \min_{i} \max_{k} \left\{R_{i,k} \cdot P_k\right\} \\ i = 1, \dots, n \\ k = 1, \dots, m \\ P_k \in [0,1] \end{gathered} \tag{5.29}$$

Where P_k is the probability related to the k-th scenario. This probability models the attitude of the stakeholders to focus their opinion on a limited number of criteria. To decrease the probability of the scenarios in which few criteria have a large share of the relevance, P_k can be defined as in (5.30).

$$\begin{gathered} P_k = \left(1 - \varepsilon \cdot \|W_k\|_2{}^2\right) \; ; \; t = 1, \dots, n \\ \varepsilon \in [0,1] \end{gathered} \tag{5.30}$$

Where $||W_k||_2$ is the Euclidean norm of the weight vector related to the k-th criterion, ε represents the attitude of the decision-maker of considering irrelevant the extreme scenarios. An example of the impact of the coefficients $||W_k||_2$ and ε on the value of the probability P_k for several weight scenarios is given in Table 5.4.

Table 5.4. Example of the probability values for several scenarios

$\boldsymbol{W_k}$	$\boldsymbol{\|W_k\|_2}^2$	$\boldsymbol{\varepsilon}$	$\boldsymbol{P_k}$
[1 0 0 0]	1	1	0
[0.5 0.5, 0, 0]	0.5	1	0.5
[0.25 0.25 0.25 0.25]	0.2	1	0.8
[1 0 0 0]	1	0.5	0.5
[0.5 0.5, 0, 0]	0.5	0.5	0.75
[0.25 0.25 0.25 0.25]	0.2	0.5	0.9
[1 0 0 0]	1	0	1
[0.5 0.5, 0, 0]	0.5	0	1

The optimisation model represented by (5.31) identifies the alternative of the set that achieves the minimum value of the maximum regret by considering all possible weight schemes.

$$\min_{\substack{i \\ i=1,\dots,n}} \max_{\substack{k \\ k=1,\dots,m}} \left\{ \left[\max_{\substack{t \\ t=1,\dots,n}} \left(\sum_{j=1}^{m} w_{k,j} z_{t,j} \right) - \sum_{j=1}^{m} w_{k,j} z_{i,j} \right] \cdot \left(1 - \varepsilon ||W_k||_2{}^2\right) \right\} \tag{5.31}$$

$$s.t. \begin{cases} w_j \in \Omega_0 \\ \sum_{j=1}^{m} w_{k,j} = 1 \\ w_j \in [0,1] \end{cases}$$

Where Ω_0 is the set of constraints of the value of the weights expressed in terms of the relationships described in Table 4.1. Besides, the non-dominance condition is considered (5.32). It avoids that a single criterion assumes a weight greater than the sum of the weights of the remaining *n*-1 criteria.

$$w_{k,s} < \sum_{\substack{j=1 \\ j \neq s}}^{m} w_{k,j} \tag{5.32}$$

The model described by (5.31) identifies the alternative, which achieves the highest consensus among the stakeholders by considering all possible points of view. The best alternatives represent the option that leads to the least regret to the most sceptical stakeholder.

The objective function of the model (5.31) is nonlinear because of the term $\max_{\substack{t \\ t=1,\dots,n}} \left(\sum_{j=1}^{m} w_{k,j} z_{t,j}\right)$. When the weights vary within the feasible region, also varies the value of utility related to the best alternative. Therefore, a discontinuity exists for all weight values in which the option with the greatest utility changes. However, the objective function is continuous in the weight intervals in which the alternative which achieves the highest utility score does not change. Within these subspaces, the objective function is linear if ε is equal to zero; otherwise non-linear due to the quadratic term of the probability function. The constraints of the optimisation model are linear.

To solve the optimisation model described by (5.31), an analytic algorithm is exploited. The non-linearity of the objective function is addressed by an initialization procedure that restricts the weight-space search region.

The algorithm is formed by three steps:

- Initialization, the starting point for the maximisation process is identified;
- For each alternative of the set, the objective function $\{R_{i,k} \cdot P_k\}$ is maximised;
- The alternative that achieves the minimum value of the maximised objective function in the solution point of the maximisation process is selected as the best alternative.

The initialization process identifies the region in the weight-space that contains the solution point for the objective function. The initial point is identified employing a brute force solution approach characterised by a large evaluation step. Then, for each alternative, the optimisation model is solved for identifying the point in the weight-space in which the maximum regret is achieved. In practice, the maximisation problem is converted to a minimisation problem by changing the sign of the objective function. The independent variables of the optimisation problem are the entries of the weight vector. By considering the objective function in the initial point neighbourhood, the Interior Point method has been selected for solving the minimisation problem. The solution to the problem is the weight vector to which the maximum value of regret is achieved. The value of the objective function in this solution point represents the maximum regret achieved by the considered alternative. Once the maximising problem is solved for each alternative, the alternative which achieved the minimum value of the maximum regret is selected as the suggested solution for the decision-making problem.

The computational burden of the model described by (5.31) increases with the size of the decision-making problem defined by the number of alternatives and criteria. As the computational burden increases, the convergence of the model on the solution point is not guaranteed in a reasonable amount of time. Therefore, to improve the computational algorithm efficiency, including the evaluation of uncertainties, the development of an analytical and heuristic resolution approach will be addressed in future studies.

6 MC-CBA COMBINED APPROACH

In this chapter, the proposal of an approach for appraising smart grid initiatives characterised by a joint multi-criteria analysis and cost-benefit analysis is described. First, a general overview of the compatibility of the two decision-making tool is provided. Then, one of the most acknowledged international guidelines for smart grid project appraisal is reviewed. On the basis of the lesson learnt, the MCA-CBA approach for the appraisal of smart grid initiative is described, the mathematical procedure is described in detail. The formalisation of the assessment procedure represents one of the contributions of this dissertation.

This chapter aims at answering the following questions:

- Are CBA and MCA compatible tools?
- Which is the state of the art of international guidelines for smart grid project appraisal?
- Which decision rules fit with multi-criteria analysis?
- Which are the main features of the proposed MC-CBA approach for the appraisal of smart grid initiatives?
- Which is the mathematical process that formalises the MC-CBA approach for the appraisal of smart grid initiatives?

6.1 Are CBA and MCA compatible tools?

As described, both CBA and MCA are relevant tools for appraising investment initiatives; both approaches allow for a comparative appraisal of the different options.

CBA shows some fundamental lack if employed to evaluate decision-making problems that involve a significant share of intangible impacts and externalities. If the quota of those elements is considered negligible, a CBA limited to tangible impacts can be addressed. Intangible impacts and externalities can be mentioned alongside the CBA results to provide additional information [94]. Conversely, if intangible impacts and externalities are majoritarian, it is necessary to include them within a structured assessment framework.

MCA allows to evaluate conflicting criteria; the main advantage of MCA is that it does not require expressing all impacts in monetary terms; therefore, all intangible impacts and externalities can be directly assessed. Therefore, MCA outclasses the highlighted shortcomings of the monetisation techniques exploited for intangible impacts.

In conclusion, the flexibility of the approach based on MCA allows to include the results of a rigorous CBA carried on monetary impacts. Therefore, a structured appraisal of the decision-making problem that includes the largest number of impacts is possible.

To devise an approach that combines CBA and MCA it is of interest since the individual peculiarities of each methodology can be transferred to the joined approach. In Table 6.1, the strengths and weaknesses of MCA and CBA are summarised [31].

Generally in CBA, the preferences are collected from individuals using indirect methods based on market paradigms. Conversely, in MCA, stakeholders are involved in the decision-making process, the stakeholders' point of view is directly collected. Accordingly, these preferences are doubly specific because associated with the actual stakeholders of the initiative and the actual decision-making problem under analysis. As a result, the preferences collected in MCA are a more reliable picture of the stakeholders' point of view than the CBA money values. In addition, a sensitivity assessment about preferences is difficult in CBA because they are not input parameters of the analysis. The role of stakeholders is passive in CBA; contrariwise, stakeholders are actively part of the MCA procedure.

Moreover, the participation of stakeholders in CBA is limited by the use of monetisation techniques. More than one stakeholder's point of view can be investigated in MCA considering different patterns of weights that can be combined or used for distinct MCAs. Furthermore, unlike CBA, MCA does not deal with the discounting of future impacts. This gives flexibility to MCA because the relevance of future impacts can be directly collected from stakeholders.

Table 6.1. Comparison of MCA and CBA [31], [94]

	CBA	**MCA**
Strengths	Rigours and rational Formalised Transparent Widely acknowledged Independent from judgement Potentially participative Easy communication of the results	Flexible Not strictly formalised Democratic The monetisation of impacts is not mandatory It assures participation and legitimacy
Weaknesses	Difficult and expensive technique It needs a large amount of data, often hardly obtainable Impossible to assess "soft effects" The equity achieved depends on the DM	Potentially ambiguous and subjective Some components of arbitrariness, especially in the perception of public costs vs private benefits Double counting Lack of clarity, consistency, accountability

Considering that planning activities have a limited budget; therefore, the efficient use of resources is mandatory [94]. In the public sector, it is crucial to identify the investment option that maximises the societal benefits. Moreover, in recent years have been characterised by an enhanced environmental and social awareness; thus, the demand from public opinion for novel planning approaches that better considers social and ecological impacts is increased [97].

CBA is an acknowledged and reliable tool for appraising the profitability of investments in the private sector. Conversely, CBA shows some fundamental shortcomings if used in the public sector or in decision-making problems that involve a significant share of intangible impacts. In this context, MCA can play a crucial role by outclassing the drawbacks of CBA. In fact, CBA is focused on expense efficiency, while MCA focuses on expense effectiveness by identifying the best alternative for achieving a particular target [38]. Therefore, the result provided by these tools applied independently on the same decision-making problem is complementary [38].

Regardless of the differences between CBA and MCA, these two approaches are not mutually exclusive; the joint use can be useful to relieve the respective lacks. Basically, the CBA can be considered as an element of an overlying MCA. To maximise the effectiveness of the joint use, CBA and MCA can interact according to two frameworks [38]:

a. CBA focused only on tangible impacts while the MCA only on intangible impacts;

b. first, MCA is used to select a subset of interesting investment options; then, each selected option's economic viability is assessed through the CBA.

In general, to avoid misleading results, the boundary of the appraisal made by each evaluation tool has to be clearly defined.

The overall assessment quality is improved since the joint MC-CBA use ensures a more in-depth and comprehensive analysis of impacts and priorities related to the decision-making problem. Despite its potential advantages, the joint use MC-CBA is not yet widely diffused in real applications; in the scientific literature, the joint analysis has been introduced with the aim to [38]:

- outclass the lack of CBA on the stakeholders' preference modelling;
- outclass the lack of MCA on the economic assessment;
- outclass the weaknesses of CBA in the evaluation of the intangible impacts;
- promote the active participation of stakeholders in the decision-making.

6.2 The JRC guidelines for smart grid project assessment

As reviewed in section 1.2, the European Union (EU) strategic view in terms of energy policy considers the smart grids as a critical component for achieving a low carbon energy sector [165]–[168]. In fact, the European Commission (EC) considers the smart grids as a means to achieve several strategic objectives, such as promoting renewable energy sources, enhancing the security of the network, promoting energy efficiency and energy savings, and increasing the active role of consumers in a liberalized energy market [32], [33], [165].

However, the transformation of the electricity sector requires huge investments; therefore, it is seen as of utmost interest to define a fair allocation of short-term costs and long-term benefits among the stakeholders [169]–[172]. Since smart grids are capital intensive and capable of generating high benefits for the whole society, a tailored approach for estimating the costs and benefits of smart grid initiatives is desirable [32]. In the context of appraisal approaches, the European policymakers ask for the adoption of frameworks based on CBA for assessing smart grid initiatives, as specified in Annex 1 of the Directive 2009/72/EC [64]. Moreover, the European Commission (EC) requires as eligibility criteria for the smart grid projects their economic, social and environmental viability. Hence, the appraisal of the viability in these areas requires a comprehensive impact assessment methodology that encompasses the CBA [32].

Following the EC proposals, JRC developed methodological guidelines for a CBA of smart grid initiatives to provide a common appraisal framework for all Member States [32]–[35]. The JRC guidelines have been developed on the data collected from smart grid pilot projects; the result is a comprehensive assessment framework whose core is the CBA [168]. The guidelines help tailor the analysis to the local conditions, identifying and monetising costs and benefits, performing the sensitivity analysis [32]. The JRC approach is considered comprehensive because, besides the CBA, the guidelines provide support for identifying externalities and social impacts that can result from the implementation of smart grid projects but cannot be easily monetised and included in the CBA [32].

According to JRC, the CBA guidelines have to be considered as a structured set of suggestions and a checklist of essential elements to consider in the analysis of smart grid initiatives [32], [33]. The JRC assessment framework involves the CBA of monetary impacts and the qualitative analysis of non-monetary impacts. Namely, JRC suggests a CBA focused only on tangible impacts, while intangible impacts have to be evaluated aside with a qualitative appraisal tool (Figure 6.1).

The JRC's assessment framework is formed by an economic-oriented CBA tailored for smart grid initiatives that aim to appraise costs, benefits, and externalities [32]. The economic evaluation is undertaken from the societal perspective through a Social Cost-Benefit Analysis (SCBA). Not only the impacts related to the companies directly involved in the smart grid planning option are considered but are also included all the project's impact on the entire value chain and society at large [32]. In particular, the JRC CBA approach recognises that the smart grid impact goes beyond what can be captured in monetary terms. Therefore, the economic analysis (monetary appraisal of costs and benefits on behalf of society) is accompanied by a qualitative impact analysis (non-monetary appraisal of non-quantifiable impacts and externalities, e.g. social impacts, contribution to policy goals) [32].

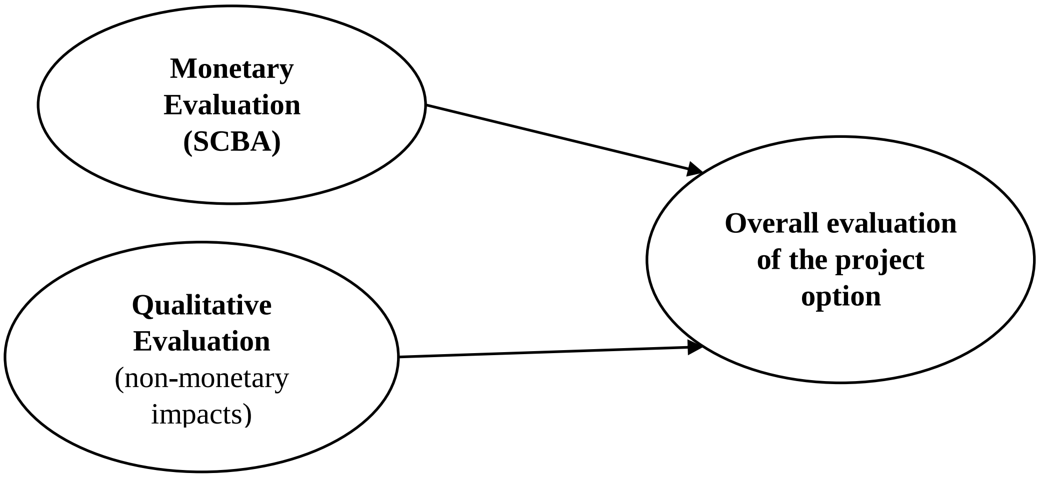

Figure 6.1.Project option assessment according to JRC

6.2.1 The JRC CBA approach

6.2.1.1 The economic analysis: the appraisal of monetary impacts

The economic analysis is undertaken from the societal perspective and considers all costs and benefits that can be expressed in monetary terms. The economic analysis aims to include the impacts generated by the smart grid initiative that pass on the electricity system (e.g., enabling the future integration of distributed energy resources, impact on electricity prices and tariffs) and society at large (e.g. environmental costs). However, to what extent these additional impacts might be included in the CBA depends on the reliability of the monetisation process.

The approach proposed by JRC for the CBA of smart grid initiatives comprises several steps [32], [173]:

1. Definition of the boundary conditions (e.g. demand forecast, discount rate, local grid characteristics, time horizon, regulatory framework, fuel prices);
2. Definition of the implementation choices (e.g. roll-out time, chosen functionalities);
3. Review of and description of technologies, elements and goals of the project;
4. Map assets onto functionalities;
5. Map functionalities onto benefits;
6. Establish the baseline;
7. Monetise the benefits and identify the beneficiaries;
8. Identify and quantify the costs;
9. Compare costs and benefits;
10. Discuss the results;
11. Sensitivity analysis of the CBA outcome to variations in key variables and parameters.

The economic analysis goal is to identify the parameter values that enable a positive outcome of the CBA. According to the JRC framework, the outputs provided by the CBA are the indicators: NPV, IRR, and CBR [32], [33].

In addition to the methodological procedure for carrying on the CBA, the JRC guidelines provide [32] support for choosing the key parameters, for linking deployed assets with benefits, formulas for monetising benefits, the indication of the most relevant cost categories, and support for identifying the critical variables to be investigated in the sensitivity analysis.

6.2.1.2 The qualitative analysis: the appraisal of non-monetary impacts

In the JRC assessment framework, the qualitative analysis is deputed for considering all impacts and externalities that cannot be expressed in monetary terms. This includes broad social costs and benefits like the security of supply, consumer participation and improvements to market functioning [32]. To this end, it is necessary to identify project impacts and externalities and assess them in physical terms or through a qualitative description to give decision-makers enough elements for conducting the non-monetary appraisal [32].

The qualitative analysis is formed by the assessment of the initiatives in terms of the contribution towards the smart grid realization and the externalities, such as social and environmental impacts. Therefore, two steps form the qualitative assessment of additional impact caused by the initiatives: the evaluation of the contribution of projects to the achievement of the different policies and the evaluation of the impacts on society (e.g. environmental impact, social impact, job creation, consumer inclusion). To guarantee the reliable appraisal of non-monetary impacts, the assessment has to be based as much as possible on quantitative information, hence, on quantitative indicators. The JRC guidelines suggest presenting a detailed description of the expected impacts when not quantifiable [32].

Considering the appraisal of the contribution towards the smart grid transition, in [174] the European Commission (EC) defined a list of benefits for the energetic sector related to the smart grid development. Starting from the EC document, the Joint Research Centre (JRC) devised a list of Policy Criteria (PCs) to provide a common assessment framework for smart grid projects [32]–[35].

The policy criteria are:

i. Level of sustainability;

ii. Capacity of transmission and distribution grids;

iii. Network connectivity;

iv. Security and quality of supply;

v. Efficiency and service quality;

vi. Contribution to cross-border electricity markets.

Moreover, the fulfilment of the PCs is appraised through Key Performance Indicators (KPIs) [32]–[35]. The formulas useful for computing most of the KPIs have also been proposed by the JRC [34], [35]. Generally, each evaluated KPI refers to a baseline scenario. It is worth highlighting that the evaluation of the project options through KPIs is outcome-oriented. In other words, utilizing the KPIs are not evaluated the technical features of the infrastructure but the produced effects.

The assessment of the externalities of the smart grid initiatives has to identify all costs and benefits that spillover from the project into society and that cannot be monetised and included in the economic analysis (externalities). All externalities should be listed and expressed in physical terms (e.g. use decibels to quantify noise reduction benefit). For each impact, an indicator has to be defined to make the appraisal as objective, rigorous, and transparent as possible. Where the calculation of an indicator is not feasible, a detailed description of the estimated impacts of the project should be provided to give decision-makers the whole range of elements for the appraisal.

The proposed externalities are [32]:

i. Job impact;
ii. Safety;
iii. Environmental impact;
iv. Social acceptance;
v. Time lost/saved by the consumers;
vi. Enabling new services and applications and market entry for third parties;
vii. Reduction of the gap in skills and personnel;
viii. Privacy and security.

6.2.1.3 Combining monetary and non-monetary appraisals

Once the economic and qualitative analyses have been accomplished, the obtained outcomes have to be combined [32]. To this aim, suitable weighting factors have to be defined according to the characteristics of the assessment.

6.2.2 Discussion on the JRC guidelines for smart grid project assessment

The JRC guidelines for the appraisal of smart grid initiative provide a methodology that combines a societal CBA with a qualitative analysis of non-monetary impacts. This approach allows capturing the impacts that go beyond the costs and benefits incurred by the actors carrying out the smart grid initiative and cannot be expressed in monetary terms. The combined assessment provides a comprehensive project appraisal.

The guidelines provide a systematic approach for identifying the local peculiarities which influence the effectiveness of the initiatives. The regional context plays a pivotal role since the same smart grid initiative would not fit with different boundary conditions; therefore, it is necessary to tailor the appraisal accordingly.

Moreover, the JRC guidelines illustrate a methodical procedure for mapping the technological features of the smart grid initiative into functionalities and then into impacts. This activity is crucial for achieving an understanding of the scale of the initiative.

In addition, for the calculation of costs and benefits, several formulas are proposed both for monetary and non-monetary impacts. Within a common assessment framework, the exploitation of a standardised set of formulas for quantifying the impacts enables the comparability of different initiatives.

However, the JRC guidelines lack in providing a clear methodology for addressing the combination of the monetary and non-monetary assessment. Therefore, besides a well-structured CBA, the analysis of non-monetary impacts appears not well defined. As enclosed to the main CBA, the outcome of the qualitative analyses is likely to be underestimated by the final decision-maker.

Moreover, the JRC guidelines are not self-explanatory about the methodology to be used for weighting the criteria of the qualitative analysis as well as for devising the combined monetary-quantitative-qualitative assessment. Decision-making processes characterised by more criteria require assigning them weights; furthermore, their values significantly influence the obtained outcome. The criteria weights play a crucial role since they represent the stakeholders' perspective; hence their values have to be carefully defined. Privileging a criterion over the others represents a strategic decision that is modelled in the decision-making problem through criteria weights.

Finally, the formulas proposed to quantify the impacts require a considerable amount of information and undertake burdensome network studies. Therefore, to reduce the burden of the analysis, the exploitation of the JRC guidelines requires to be decided since the early stages of the project appraisal and be correlated with the initiatives' design procedure.

The approach proposed by JRC is mainly focused on CBA. The JRC guidelines provide support in choosing the context parameters, mapping assets with benefits. Moreover, it is proposed a possible (non-exhaustive) set of formulae to monetise benefits. Recommendations are also given for addressing a sensitivity analysis to identify critical variables affecting the CBA outcome [32], [33].

Furthermore, the JRC guidelines also concern the evaluation of the intangible impacts. The project options should have assessed in terms of the expected outcome on policy objectives and externalities (e.g., new services enabled, job creation, consumer inclusion) [32], [33]. The JRC guidelines suggest quantifying non-monetary impacts through a physical unit of measurements or, if not quantifiable, to appraise them using qualitative indicators [32]. By combining quantitative and qualitative indicators, it is possible to appraise the effects of non-monetary impacts. In addition, a weight vector can be introduced to weight each impact according to its relevance to the decision-making problem.

6.3 The proposed MC-CBA approach for the appraisal of smart grid initiatives

In this section, a joint methodology that combines MCA and CBA is proposed. The methodology has been devised for the appraisal of smart grid development initiatives. The assessment has a time horizon that encompasses the whole life cycle of the project alternative. The proposed approach relies on the assessment guidelines for smart grid projects developed by the JRC and the Italian Regulator (ARERA, Autorità di Regolazione per Energia Reti e Ambiente). These fundamentals grant validity to the proposed approach whose scientific novelty is the formalisation of the assessment procedure.

The JRC assessment framework corroborates the need for a structured evaluation procedure that simultaneously manages monetary and non-monetary impacts. Therefore, an MCA approach can be suitable. In fact, MCA is a decision-making tool that helps the decision-maker in identifying the best alternative among a given set without requiring to express all impact in monetary terms.

As described in section 3.2, MCA is a structured approach that helps to solve complex decision-making problems. In the proposed MC-CBA approach, as depicted in Figure 6.2, CBA constitutes an input to the MCA. As previously argued, the joint use of these evaluation tools guarantees a better analysis of complex decision-making problems that involve a significant share of intangible impacts and externalities.

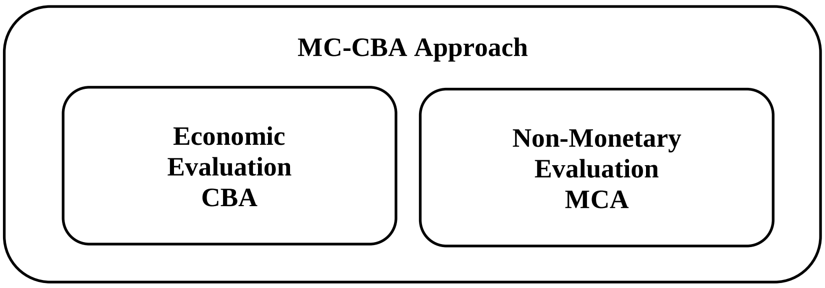

Figure 6.2. General representation of the MC-CBA model

According to the JRC guidelines, the proposed approach decomposes the decision-making problem by using a hierarchical structure. In addition, the concepts of the JRC guidelines are formalised and integrated within an MCA framework. The hierarchical structure of criteria has to reflect the way of achieving the main goal according to the core values of the company (or the organisation) which aims at it. Therefore, each impact has its relative relevance concerning the main goal that is modelled through criteria weights. Each impact is evaluated qualitatively or quantitatively considering the terminal criteria of the hierarchical structure. The magnitude of the impacts generated by a project option represents its performances on the evaluation criteria. Combining performances and criteria weights through a MADM technique is possible to obtain the MC-CBA framework's outcome. As a result, the project option that better satisfies the decision-makers expectations is identified as the solution to the decision-making problem.

The hierarchical structure is organised according to the principle of abstraction. Therefore, the main goal at the head of the hierarchy is related to the strategic objectives defined by the EC and linked to the vision for the future of the energy system and society. The intermediate objectives placed in the first level of the hierarchy represent general goals on specific sectors related to the main goal of the decision problem. The second level hosts criteria which describe specific objectives of the sector which each criterion belongs. The last level of the hierarchy is represented by terminal criteria whose fulfilment is directly measurable utilizing the performance indices. The satisfaction of terminal criteria leads to the fulfilment of the criteria of the upper levels of the hierarchy; hence the performances on terminal criteria determine how much a project option contributes to the achievement of the primary goal. Therefore, the DM of the decision-making problem is defined by the performances of the project options on terminal criteria.

The proposed approach aims at investigating three different areas of interest: economic effects, enhanced smartness of the grid, and externalities. A different hierarchical structure branch evaluates the performances of the project options in each area. In Table 6.5, the generalised structure of the DM is depicted; the terminal criteria related to each sector under analysis is highlighted.

Table 6.2. The general structure for the DM

	CBA indicator (1)	…	CBA indicator (Z)	Smart grid impact (1)	…	Smart grid impact (S)	External impact (1)	…	External impact (H)
Option 1	Score (1,1)	…	Score (1,Z)	Score (1,Z+1)	…	Score (1,Z+S)	Score (1,Z+S+1)	…	Score (1,Z+S+H)
Option 2	Score (2,1)	…	Score (2,Z)	Score (2,Z+1)	…	Score (2,Z+S)	Score (2,Z+S+1)	…	Score (2,Z+S+H)
…	…	…	…	…	…	…	…	…	…
Option R	Score (R,1)	…	Score (R,Z)	Score (R,Z+1)	…	Score (R,Z+S)	Score (R,Z+S+1)	…	Score (R,Z+S+H)

Once the DM is built and weights of criteria are obtained, the best alternative in achieving the main goal can be identified employing a MADM technique (Figure 6.3).

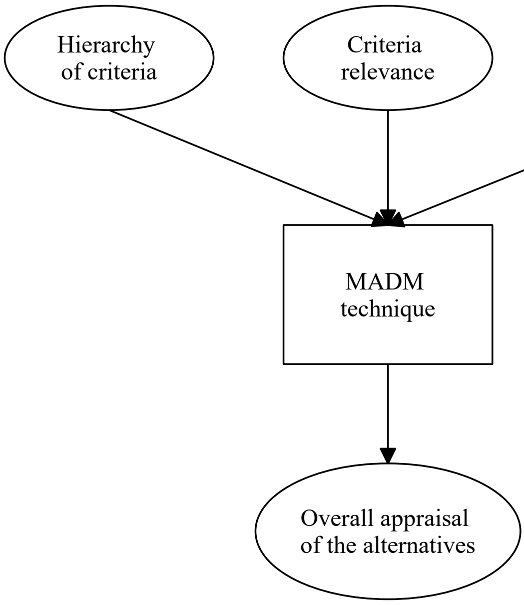

Figure 6.3. General representation of the MADM assessment framework

6.3.1.1 The hierarchical structure of the evaluation criteria

The proposed approach for smart-grid project selection generalises the concepts of JRC guidelines by formalising the decision-making problem according to an MCA framework.

Three independent branches form the hierarchical tree of criteria to evaluate the impacts of the project options on three areas of interest. Each branch starts from a first-level criterion, and it is directly linked to the main goal of the hierarchy. Therefore, the overall evaluation of project options is obtained by combining the result of the evaluation of each branch. The first branch is focused on the economic assessment, the second branch evaluates the contribution towards the smart grid realization, the third branch evaluates the effects of the project option in terms of externalities (Figure 6.4). The three branches are independent; therefore, an impact can be evaluated through its effects on each area of interest. Conversely, each impact has to be considered only on one of the branches to avoid double counting.

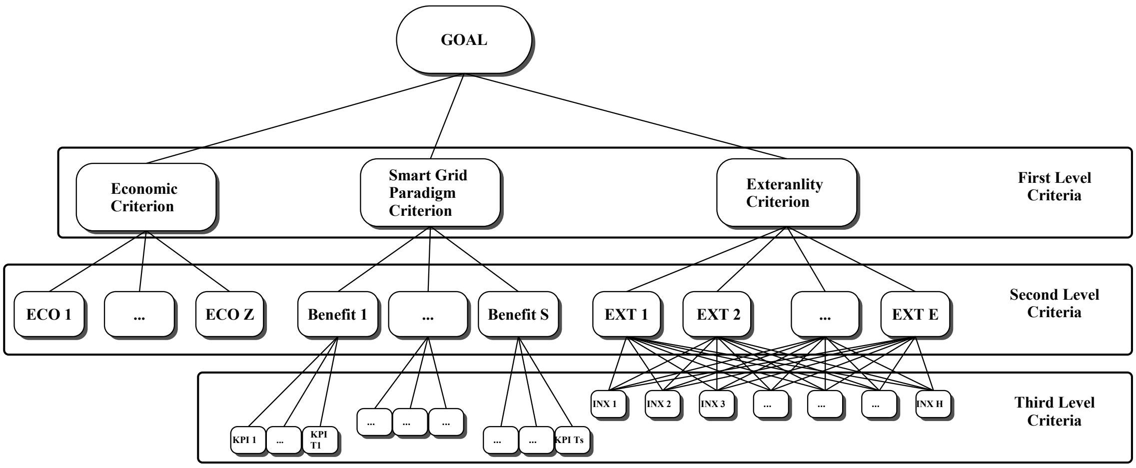

Figure 6.4. The hierarchical structure of criteria for the MC-CB approach

6.3.1.2 First level criteria

The overall evaluation of the project options is obtained by combining the results of the assessment on the three different branches. Each branch starts from a first-level criterion:

- the economic criterion;
- the smart grid deployment merit criterion (smart grid paradigm criterion);
- the externality criterion.

6.3.1.3 The economic evaluation branch

The economic criterion is the head node of the economic evaluation branch that aims at assessing the economic performance of the project options. The proposed approach involves a CBA of monetary impacts that can be run according to the procedure defined by JRC in [32], [33]. The economic assessment of a project option aims at evaluating its monetary costs and benefits. These economic performances can be represented by the indices computed by the CBA or explicitly considering the monetary cost and benefits. In the first case, the economic branch has three criteria in the second hierarchy level (Figure 6.5).

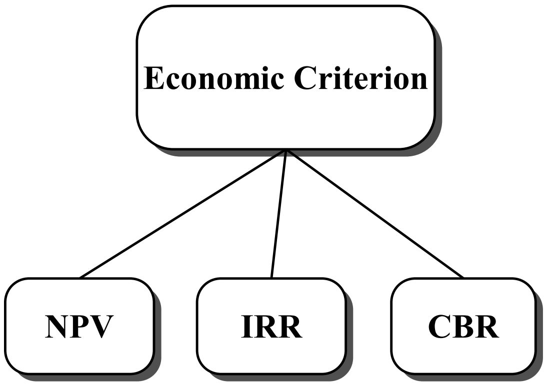

Figure 6.5. Economic branch based on the CBA output indices

Each criterion is related to a CBA outcome index:

- the NPV criterion measures the project profitability in terms of the net benefit. In general, an investment option is economically viable if NPV is positive. The profitability of the investment increases as the related NPV grows.
- The IRR criterion measures the quality of the investment option. An alternative is positively evaluated if its IRR is higher than the reference social discount rate.
- The CBR criterion measures the efficiency of the investment option. An alternative is positively evaluated if its CBR is greater than one.

Those criteria are fulfilled according to the increasing values of the related indices.

In the second case, the economic branch shows more than one hierarchical level whose criteria are the cost and benefit items related to the project impacts. Figure 6.6 depicts a generalised economic branch with elementary cost and benefits.

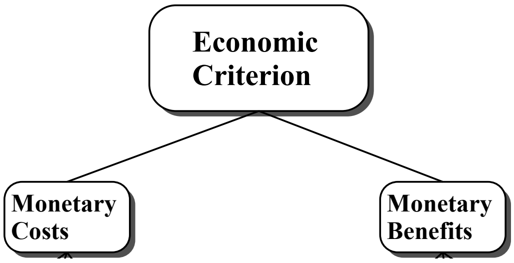

Figure 6.6. The economic branch with elementary cost and benefits

The criteria on the higher hierarchical levels aggregate the elementary monetary criteria of lower levels. In general, two sub-branches can be defined: the cost branch and the benefit branch. The performances on all criteria are measured in terms of currency; therefore, criteria are fulfilled by performances that minimise costs and maximise monetary benefits.

6.3.1.4 The smart grid deployment merit branch

The second branch of the hierarchy tree evaluates the contribution towards the smart grid realization given by the project options. The importance of this evaluation arises from the role of smart grids in government policies. In [174], the European Commission (EC) defined a list of benefits for the energy sector related to smart grid development. Starting from the EC document, the Joint Research Centre (JRC) devised a list of Policy Criteria (PCs) to provide common assessment guidelines for smart grid projects [32]–[35]. Moreover, the fulfilment of the PCs is appraised utilizing Key Performance Indicators (KPIs) [32]–[35]. The formulas useful for computing most of the KPIs have also been proposed by the JRC [34], [35]. Generally, each evaluated KPI is related to the baseline scenario. It is worth highlighting that the evaluation of the project options through KPIs is outcome-oriented. In other words, KPIs are not defined to evaluate the technical features of the infrastructure but the effects that the deployment of such infrastructure produces.

The structure of the “smart grid paradigm branch” reflects the JRC approach; therefore, the second level criteria are the PCs, the terminal criteria are the related KPIs. The performances of the project options are measured through the KPIs. According to the JRC guidelines, PCs are mutually independent. Furthermore, KPIs related to the same PC have the same relevance [32]–[35]. In Table 6.3, the list of PCs and related KPIs proposed by JRC and included in the are presented.

Table 6.3: List of Policy criteria and related KPIs defined by JRC [32]–[35]

Policy Criterion	KPI
1. Level of sustainability	**a.** Reduction of greenhouse gas emissions (GHG)
	b. Environmental impact of electricity grid infrastructure
2. Capacity of transmission and distribution grids	**a.** Installed capacity of distributed energy resources in distribution networks
	b. Allowable maximum injection of power without congestion risks in transmission networks
	c. Energy not withdrawn from renewable sources due to congestion or security risks
3. Network connectivity	**a.** Methods adopted to calculate charges and tariffs, as well as their structure, for generators, consumers and those that do both
	b. Operational flexibility provided for dynamic balancing of electricity in the network
4. Security and quality of supply	**a.** Ratio of reliably available generation capacity and peak demand
	b. Share of electricity generated from renewable sources
	c. Stability of the electricity system
	d. Duration and frequency of interruptions per customer, including climate-related disruptions
	e. Voltage quality performance
5. Efficiency and service quality	**a.** Level of losses in transmission and distribution networks
	b. Ratio between the minimum and maximum electricity demand within a defined period
	c. Demand-side participation in electricity markets and energy efficiency measures
	d. Percentage utilisation (i.e. average loading) of electricity network components
	e. Availability of network components (related to planned and unplanned maintenance) and its impact on network performances
	f. Actual availability of network capacity with respect to its standard value
6. Contribution to cross-border electricity markets	**a.** Ratio between interconnection capacity of a Member State and its electricity demand
	b. Exploitation of interconnection capacities
	c. Congestion rents across interconnections

6.3.1.5 The externality impacts assessment

The third branch concerns the assessment of the project options in terms of externalities. To aggregate impacts, it is possible to define thematic areas for evaluating the effects under analysis. Single impacts are related to the terminal criteria, while the second level criteria are the thematic areas. To illustrate, a thematic area can be the social area, whereas a related terminal criterion can be consumer satisfaction. Each impact has to be measured employing a quantitative or qualitative index. Those indices measure the fulfilment of the terminal criteria. Unlike the "smart grid paradigm" branch, it is assumed that the second level criteria are mutually dependent. In fact, an impact related to a thematic area can also influence the other areas.

6.4 The mathematical procedure of the MC-CBA approach

The approach which has been proposed relies on AHP. In the following, the key features of the mathematical procedure are described.

6.4.1 The pairwise comparison

The key moment of the assessment based on AHP is the pairwise comparison procedure of criteria and alternatives [136]. According to this procedure, the criteria relevance and the performances of the alternatives are converted to a standard numerical scale. In classical AHP, the subjectivity of the decision-makers influences both the scoring and weighting stage. In the scoring stage, the normalised scores are obtained from the preferences expressed by the decision-maker about the alternatives considering their performances contained in the DM. In the weighting stage, the criteria weights are obtained from the stakeholders' preferences and reflect the criteria relevance. In this section, the mathematical model behind these stages is described.

The criteria relevance depends on stakeholders' view; the criteria weights are defined accordingly. Each criterion has a local weight (or local priority) referred to the parent criterion and defined in comparison with the other criteria which belong to the same level of the hierarchy. In fact, the local weight represents the relevance of one criterion over the others in the same level of the considered sub-branch; the relevance is in terms of the fulfilment of the parent criterion. Conversely, the global weight (or global priority) of each criterion measures its relevance concerning the main goal at the head of the hierarchy. The global weight is computed from the local weights according to the hierarchical composition principle [132]. Once the global weights of all terminal criteria have been obtained, the overall scores of the alternatives are computed by multiplying the matrix of normalised scores of the alternatives and the vector of global weights of the terminal criteria.

6.4.1.1 Pairwise comparison for weighting the criteria

As already introduced, in AHP the weighting stage is based on the pairwise comparison procedure of criteria. This procedure allows to determine the local weight of each criterion in reference to the parent. According to the decision-maker's view, the local weight is the numerical value that represents the relevance of a criterion on another to fulfil the parent criterion.

The pairwise comparison procedure for determining the criteria weights regards two levels of the hierarchical structure. In a generic hierarchical structure, by considering:

- level $l=L-1$ the upper level, which hosts n criteria;
- level $l=L$ the lower level, which hosts m criteria (defined here as sub-criteria).

For each criterion that belongs to the level $L-1$ it is necessary to address a pairwise comparison procedure of the m sub-criteria. This process produces n preference matrixes which dimension is (m,m).

As already introduced, the pairwise comparison requires the decision-makers' view, which is collected using Saaty's judgement verbal scale (Table 3.3). In the weighting stage, the question for collecting the decision-makers' preference in the pairwise comparison procedure is structured as: "To fulfil the criterion $C_i^{(L-1)}$, how the criterion $C_j^{(L)}$ is important with respect to the criterion $C_{j+1}^{(L)}$?". Where $C_j^{(L)}$, $C_{j+1}^{(L)}$ are the *j-th* and the *j+1-th* criteria of the level L and $C_i^{(L-1)}$ is the parent criterion, the *i-th* criterion of the level $L-1$.

The preferences collected in the pairwise comparison procedure are converted into numerical values by using the equivalence defined by the Saaty's scale (Table 3.3). These numerical values are the entries of the preference matrix of the sub-criteria in reference to the parent criterion. Table 6.4 represents the preference matrix obtained from the pairwise comparison of the m sub-criteria of the level L considering the *i-th* parent criterion of the level $L-1$.

Table 6.4. Preference matrix of criteria

$C_i^{(L-1)}$	$C_1^{(L)}$	$C_2^{(L)}$	…	$C_m^{(L)}$
$C_1^{(L)}$	1	$a_{1,2}^{(i)}$	…	$a_{1,m}^{(i)}$
$C_2^{(L)}$	$\left(a_{1,2}^{(i)}\right)^{-1}$	1	…	$a_{2,m}^{(i)}$
…	…	…	1	…
$C_m^{(L)}$	$\left(a_{1,m}^{(i)}\right)^{-1}$	$\left(a_{2,m}^{(i)}\right)^{-1}$	…	1

Where $a_{j,k}^{(i)}$ is the intensity of relevance of the *j-th* criterion over the *k-th* criterion, both of level *L*, with respect to the *i-th* parent criterion of level *L-1*. The numerical value of $a_{j,k}^{(i)}$ is in terms of the Saaty's rational scale.

The local weights (or local priorities) of the sub-criteria with respect to the parent criterion are obtained from the preference matrix by evaluating the normalised eigenvector related to the maximum eigenvalue. The generic entry of this eigenvector is $v_{j,i}^{(L)}$ which represents the local weight of the *j-th* sub-criteria of level *L* referred to the *i-th* parent criterion of level *L-1*. The vector $\overline{V_i^{(L)}}$ of the local weights of the *m* sub-criteria in level *L* referred to the *i-th* parent criterion of level *L-1* is represented by (6.1).

$$\overline{V_i^{(L)}} = \begin{bmatrix} v_{1,i}^{(L)} \\ \vdots \\ v_{m,i}^{(L)} \end{bmatrix} \tag{6.1}$$

Once the pairwise comparison of the *m* sub-criteria has been accomplished for all the *n* parent criteria of level *L-1*, it is possible to build the matrix of local weights $\underline{V^{(L)}}$ of criteria of the level *L* with respect to the criteria of level *L-1* (6.2).

$$\underline{V^{(L)}} = \left[\overline{V_1^{(L)}}, \dots, \overline{V_n^{(L)}}\right] = \begin{bmatrix} v_{1,1}^{(L)} & \cdots & v_{1,n}^{(L)} \\ \vdots & \ddots & \vdots \\ v_{m,1}^{(L)} & \cdots & v_{m,n}^{(L)} \end{bmatrix} \tag{6.2}$$

6.4.1.2 Pairwise comparison for scoring the alternatives

In MCA methods, the scoring stage allows for converting all performance indexes towards a common normalised scale. In AHP the scoring stage relies on the pairwise comparison procedure of the alternatives. In this procedure, the decision-maker has to express his preferences on the alternatives with respect to each terminal criterion of the hierarchy. The preferences are collected employing the Saaty's judgement verbal scale (Table 3.3). For each terminal criterion, a preference matrix of alternatives is obtained.

In a generic hierarchical structure, by considering *h* terminal criteria and a set of *R* alternatives, the scoring stage produces *h* preference matrixes which dimension is (*R*,*R*). The generic preference matrix of the alternatives concerning the *i-th* terminal criterion is represented in Table 6.5.

Table 6.5. Preference matrix of the alternatives

Criterion i-th	**Alternative 1**	**Alternative 2**	**…**	**Alternative R**
Alternative 1	1	$q_{1,2}^{(i)}$	…	$q_{1,R}^{(i)}$
Alternative 2	$\left(q_{1,2}^{(i)}\right)^{-1}$	1	…	$q_{2,R}^{(i)}$
…	…	…	1	…
Alternative R	$\left(q_{1,R}^{(i)}\right)^{-1}$	$\left(q_{2,R}^{(i)}\right)^{-1}$	…	1

By considering the *i-the* terminal criterion, the entry $q_{j,k}^{(i)}$ represents the ratio between the level of fulfilment achieved by the alternative *j-th* and the level of fulfilment achieved by the alternative *k-th.*

The entries of the preference matrix can be obtained according to two different approaches:

- as in the classical AHP, from the stakeholders' view employing the Saaty's judgement scale;
- by calculating the ratio of the performance indexes reported in the DM.

The first approach involves the decision-makers' and stakeholders' view; therefore, subjectivity is introduced in the scoring stage. Conversely, the second approach the elements $q_{j,k}^{(i)}$ are obtained through a mathematical procedure that can be automated.

By considering two generic alternatives A_j and A_k, their pairwise comparison procedure concerning the *i-th* terminal criterion involves their performance indexes: $d_j^{(i)}$ for alternative *j-th* and $d_k^{(i)}$ for the alternative *k-th*. The verbal judgement from the decision-makers are collected through a question which can be structured as: "Considering the respective performances $d_j^{(i)}$ and $d_k^{(i)}$, how the alternative A_j is preferred to the alternative A_k to fulfil the *i-th* criterion?". The answer of the decision-makers has to be collected according to the Saaty's judgement scale, the numerical value $q_{j,k}^{(i)}$ is defined employing the correspondence defined by the judgement scale.

Otherwise, if the preference matrices are obtained according to the mathematical approach, their entries are evaluated as in (6.3).

$$q_{j,k}^{(i)} = \frac{d_j^{(i)}}{d_k^{(i)}} \tag{6.3}$$

In which:

$q_{j,k}^{(i)}$ represents the preference on the alternative *j-th* over the alternative *k-th* with respect to the criterion *i-th*.

$d_j^{(i)}$ is the value of the performance indicator of the alternative *j-th* with respect to the *i-th* criterion;

$d_k^{(i)}$ is the value of the performance indicator of the alternative *k-th* with respect to the *i-th* criterion;

According to AHP postulates, the value of the entries $q_{j,k}^{(i)}$ has to be bounded [137].

The preference matrix related to the *i-th* terminal criterion is obtained once when the pairwise comparison of the *R* alternatives have been completed.

Regardless of the approach which has been exploited for evaluating the entries of the preference matrix, the normalised score $s_{r,i}$ of the *r-th* alternative with respect to the *i-th* terminal criterion is the *r-th* element of the normalised eigenvector of the maximum eigenvalue of the preference matrix. The normalised scores of the *R* alternatives concerning the *i-th* criterion are represented by the vector $\overline{S_i}$ (6.4).

$$\overline{S_i} = \begin{bmatrix} s_{1,i} \\ \vdots \\ s_{R,i} \end{bmatrix} \tag{6.4}$$

For calculating all normalised scores, the described procedure has to be repeated for all *h* terminal criterion of the hierarchy. As a result, *h* preference matrices of alternative which dimension is (*R*,*R*) are obtained. Each matrix provides a vector of normalised scores, by aggregating those vectors is possible to obtain the matrix $\underline{S}$ of normalised scores of the *R* alternatives (6.5).

$$\underline{S} = \left[\overline{S_1}, \overline{S_2}, \dots, \overline{S_h}\,\right] = \begin{bmatrix} s_{1,1} & \cdots & s_{1,h} \\ \vdots & \ddots & \vdots \\ s_{R,1} & \cdots & s_{R,h} \end{bmatrix} \tag{6.5}$$

6.4.2 The hierarchical composition principle

6.4.2.1 How to calculate the global weights

Each criterion has its relevance concerning the primary goal of the hierarchical structure to which it belongs. The global weight (or global priority) is the numerical value that measures the global relevance of each criterion. Conversely, the local weight (or local priority) is the numerical value that represents the relevance of a criterion with respect to the other criteria that belong to the same level of the sub-branch. The global weight of terminal criteria is fundamental to evaluate the overall scores of the alternatives.

The evaluation of global weights is a *top-bottom* procedure, by considering a hierarchical structure formed by *L* levels, such that *l*=1, 2, …, *L*. Each level *l* holds a finite number of criteria. In the first level, the global weight of the criteria is equal to their local weight since the main goal of the hierarchy is the only criteria in the upper level. The local weights of the first level criteria are represented by the vector $\bar{V}^{(1)}$ which dimension is (*n*, 1), as in (6.6).

$$\overline{V^{(1)}} = \begin{bmatrix} v_1^{(1)} \\ \vdots \\ v_n^{(1)} \end{bmatrix} \tag{6.6}$$

Where *n* is the number of criteria in the level *l*=1, and $v_i^{(1)}$is the global weight of the *i-th* criterion of the level *l*=1.

Assuming that the level *l*=2 of the hierarchical structure hosts *m* criteria, each of them is characterised by *n* local weights. Therefore, for each criterion of the level *l*=2 exists a row vector $\bar{V}_i^{(2)}$which entries are the local weights of the *i-th* criterion, as in (6.7).

$$\overline{V_i^{(2)}} = [v_{i,1}^{(2)}, v_{i,2}^{(2)}, \dots, v_{i,n}^{(2)}] \tag{6.7}$$

In which:

$\overline{V_i^{(2)}}$ is a row vector of local weights of the *i-th* criterion of level *l*=2, which dimension is (1,*n*);

$v_{i,j}^{(2)}$ is the local weight of the *i-th* criterion of the level *l*=2 referred to the parent criterion *j-th* of level *l*=1.

Since *m* is the number of criteria in level *l*=2, *m* row vectors as in (6.7) exist. The matrix of the local weights of the criteria in level *l*=2 is obtained by aggregating the row vectors as in (6.8).

$$\underline{V^{(2)}} = \begin{bmatrix} v_{1,1}^{(2)} & \cdots & v_{1,n}^{(2)} \\ \vdots & \ddots & \vdots \\ v_{m,1}^{(2)} & \cdots & v_{m,n}^{(2)} \end{bmatrix} \tag{6.8}$$

Where $\underline{V^{(2)}}$ is the matrix of local weights in the level *l*=2, which dimension is (*m*,*n*).

The global weights of the criteria in level *l*=2 are evaluated by multiplying $\underline{V^{(2)}}$, the matrix of the local weights of the criteria in level *l*=2, and $\overline{V^{(1)}}$, the vector of global weights of the criteria in level *l*=1, as in (6.9).

$$\overline{W^{(2)}} = \underline{V^{(2)}} \cdot \overline{V^{(1)}} = \begin{bmatrix} w_1^{(2)} \\ \vdots \\ w_m^{(2)} \end{bmatrix} \tag{6.9}$$

In which:

$\overline{W^{(2)}}$ is the vector of global weights of criteria in level *l*=2, which dimension is (*m*,*1*);

$w_i^{(2)}$ is the global weight of the *i-th* criterion of level *l*=2.

Assuming that the level *l*=3 of the hierarchy hosts *p* criteria, each of them is characterised by *m* local weights, since *m* are the parent criterion in level *l*=2. For each criterion of level *l*=3 a vector of local weights as in (6.10) exists.

$$\overline{V_i^{(3)}} = [v_{i,1}^{(3)}, v_{i,2}^{(3)}, \dots, v_{i,m}^{(3)}] \tag{6.10}$$

In which:

$\overline{V_i^{(3)}}$ is the row vector of local weights of the *i-th* criterion of level *l*=3, which dimension is (*1*, *m*);

$v_{i,j}^{(3)}$ is the local weight of the *i-th* criterion of the level *l*=3 with respect to the *j-th* parent criterion of level *l*=2.

The matrix $\underline{V^{(3)}}$ of the local weights of the criteria in the level *l*=3 is obtained by composing the *p* row vectors as in (6.11).

$$\underline{V^{(3)}} = \begin{bmatrix} v_{1,1}^{(3)} & \cdots & v_{1,m}^{(3)} \\ \vdots & \ddots & \vdots \\ v_{p,1}^{(3)} & \cdots & v_{p,m}^{(3)} \end{bmatrix} \tag{6.11}$$

Where $\underline{V^{(3)}}$ is the matrix of the local weights of the criteria that belong to the level *l*=3, the dimension of the matrix $\underline{V^{(3)}}$ is (*p*, *m*).

The global weights of the criteria in level *l*=3 are obtained by multiplying the matrix $\underline{V^{(3)}}$ and the vector $\overline{W^{(2)}}$, as in (6.12).

$$\overline{W^{(3)}} = \underline{V^{(3)}} \cdot \overline{W^{(2)}} = \underline{V^{(3)}} \cdot \underline{V^{(2)}} \cdot \overline{V^{(1)}} = \begin{bmatrix} w_1^{(3)} \\ \vdots \\ w_p^{(3)} \end{bmatrix} \tag{6.12}$$

Where:

$\overline{W^{(3)}}$ is the vector of global weights of the criteria in level l=3, which dimension is (p,1);

$w_i^{(3)}$ is the global weight of the *i-th* criterion of level l=3.

As one can see in (6.12), the vector of global weights of the criteria in level l=3 is obtained as the product of the matrix of the local weights of the level l=3 and the matrixes of the local weight of upper levels. Generalising the procedure, if the hierarchical structure of criteria has L levels and h terminal criteria, the global weights of the terminal criteria are evaluated as in (6.13).

$$\overline{W^{(L)}} = \prod_{i=1}^{L} \underline{V^{(i)}} \tag{6.13}$$

Where:

$\overline{W^{(L)}}$ is the vector of global weights of the criteria in level l=L, which dimension is (h, 1);

$\underline{V^{(i)}}$ is the matrix of local weights of the criteria of the *i-th* level of the hierarchy.

Similarly, the global weights of the intermediate *j-th* level of the hierarchical structure are obtained as the product of the matrix of local weights of the criteria in level *j-th* and the matrixes of the local weight of the criteria in the levels above.

6.4.2.2 How to calculate the overall score of the alternatives

Once the vector $W^{(L)}$ of the global weights of the h terminal criteria and the matrix $\underline{S}$ of normalised scores of the R alternatives are obtained, the overall score of each alternative is obtained as in (6.14).

$$\overline{P} = \underline{S} \cdot \overline{W^{(L)}} = \begin{bmatrix} s_{1,1} & \cdots & s_{1,h} \\ \vdots & \ddots & \vdots \\ s_{R,1} & \cdots & s_{R,h} \end{bmatrix} \cdot \begin{bmatrix} w_1^{(L)} \\ \vdots \\ w_h^{(L)} \end{bmatrix} = \begin{bmatrix} p_1 \\ \vdots \\ p_R \end{bmatrix} \tag{6.14}$$

In which:

$\overline{P}$ is the vector of the overall score of the alternatives, its dimension is (R, 1);

$\underline{S}$ is the matrix of normalised scores of the alternatives with respect to each terminal criterion, its dimension is (R,h);

$s_{i,j}$ is the normalised score of the *i-th* alternative with respect to the *j-th* criterion;

$w_k^{(L)}$ is the global weight of the *k-th* terminal criterion;

p_i is the overall score of the *i-th* alternative.

6.4.3 The scoring stage

6.4.3.1 Qualitative pairwise comparison of the alternatives

Basically, in the scoring stage, the DM data are converted into normalised scores by using the preference matrices obtained in the pairwise comparison procedure. As illustrated, in the original AHP scoring procedure, the numerical values of the entries of the preference matrices are based on a subjective assessment of the performance in DM made by the decision-maker [47], [132]. The main advantage of this approach is that the verbal judgments allow for a qualitative appraisal of intangible impacts. Conversely, the main disadvantage is related to the subjectivity introduced in the assessment, even if quantitative data is available.

6.4.3.2 Quantitative pairwise comparison of the alternatives

An alternative approach to the qualitative pairwise comparison is to evaluate the entries of the preference matrices as the ratio of the quantitative performance indicators. According to AHP postulates, the values obtained have to be bounded [137]. The main advantage of this approach is the objectivity of the assessment; furthermore, since the decision-maker is not directly involved, the whole procedure can be automated. However, the obtained values are not in terms of the Saaty's ratio scale.

6.4.3.3 Automatized scaling for the quantitative pairwise comparison of the alternatives

To automate the pairwise comparison process by preserving the use of the Saaty's ratio scale, the values obtained as the ratio of quantitative indexes are converted employing a scaling function. The automated scoring procedure exploited by the MC-CBA toolkit generalises the methodology proposed in [175]. The scaling function *S* converts the ratio value in terms of the Saaty's ratio scale (Table 3.3). The algorithm used by the *MC-CBA toolkit* for the automated pairwise comparison is represented in Figure 6.7 [27].

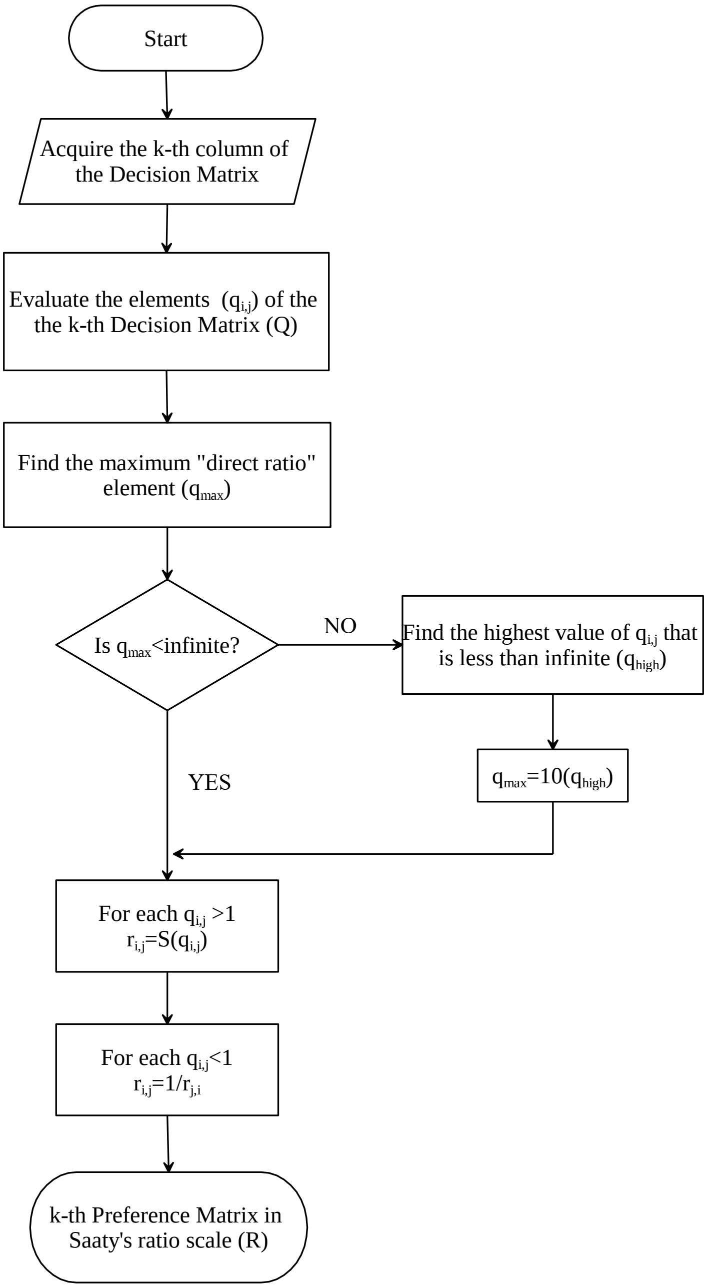

Figure 6.7. Flux diagram of the automated pairwise comparison procedure [27]

Firstly, for each *k-th* criterion is evaluated a "direct ratio" preference matrix $Q^{(k)}$ whose entries are $q_{i,j}^{(k)} = a_i^{(k)}/a_j^{(k)}$, where $a_i^{(k)}$ and $a_j^{(k)}$ are, respectively, the performances of the *i-th* and the *j-th* alternative on the *k-th* criterion. According to the straightforward use of the Saaty's ratio scale, the value of $q_{i,j}^{(k)}$ expresses how much the *i-th* alternative is preferred than the *j-th* one. To exploit the AHP methodology for the analysis, the obtained $q_{i,j}^{(k)}$ values have to be converted in terms of the Saaty's scale. Therefore, the scaling function *S* in (6.15) is employed.

$$r_{i,j}^{(k)} = S\left(q_{i,j}^{(k)}\right) = round\left(1 + \frac{(R_{max} - R_{min}) \cdot \left(q_{i,j}^{(k)} - 1\right)}{q_{max}^{(k)} - 1}\right) \tag{6.15}$$

In which:

$r_{i,j}^{(k)}$ is the image of the element $q_{i,j}^{(k)}$ in the new scale;

$q_{max}^{(k)}$ is the maximum value among all the $q_{i,j}^{(k)}$;

R_{max} and R_{min} are the maximum and the minimum value of the preferences in the destination scale; if the destination scale is the Saaty's ratio scale: $R_{max} = 9$ and $R_{min} = 1$.

The preferences in terms of the Saaty's ratio scale are integer values; therefore, the values obtained from the scaling function are rounded.

If all performance values of the alternatives are different from zero, the value of $q_{max}^{(k)}$ is finite thus, the scaling function S can be applied. Conversely, if at least one alternative has a performance equal to zero, the value of $q_{i,j}^{(k)}$ is a division by zero. In this case, if $q_{i,j}^{(k)}$ is evaluated as a mathematical limit, the value of $q_{max}^{(k)}$ tends to infinity. In addition to the model in [175], to avoid this event without losing the generality of the scaling process, the proposed automatic pairwise comparison algorithm finds $q_{high}^{(k)}$ which is the highest $q_{i,j}^{(k)}$ less than infinite. Once the $q_{max}^{(k)}$ value is obtained, the scaling function S is applied to the modified "direct ratio" preference matrix $Q^{(k)}$. The scaling function S is applied on all the entries of $Q^{(k)}$ greater than 1; the related elements on the other side of the diagonal of the matrix are obtained by evaluating the reciprocal value. Finally, the preference matrix $R^{(k)}$ related to the *k-th* criterion is obtained, it represents the image of the matrix $Q^{(k)}$ in terms of the Saaty's scale.

The described automated pairwise comparison procedure is exploited for each column of the DM. Suppose the sign of elements of the considered column of the DM differs. In that case, the values have to be shifted to obtain a column of elements with the same sign and exploit the automated pairwise comparison procedure described. The shift coefficient added to all the column elements is equal to the difference between the highest and the lower value.

The automated pairwise comparison procedure assumes that all terminal criteria of the hierarchy are satisfied by increasing the values of performance indicators. To consider terminal criteria which have to be minimised, the sign of the related column of the DM has to be changed.

6.4.3.4 Calculation of the normalised scores for the alternatives

Once all the preference matrix entries have been obtained, the related normalised scores of the alternative can be calculated according to different approaches.

i. The normalised score $s_{(r,i)}$ of the *r-th* alternative with respect to the *i-th* terminal criterion is the *r-th* element of the normalised eigenvector of the maximum eigenvalue of the preference matrix.

ii. The normalised score $s_{(r,i)}$ of the *r-th* alternative with respect to the *i-th* terminal criterion is the normalised geometric mean calculated by rows, as follows:

    a. Considering the preference matrix of *N* rows;
    b. For each *r-th* row, the geometric mean of each row is calculated;
    c. The *N* geometric means are normalised according to a factor equals to the sum of all *N* geometric means.

7 CASE STUDIES

In this chapter, the case studies developed for presenting the use of the multi-criteria analysis and the MC-CBA approach for project appraisal in the smart grid context are described. Four case studies are presented to illustrate four different realisations of the combined appraisal approach proposed in this dissertation. In all case studies, the planning alternatives include flexibility measures that compete with traditional network reinforcement.

The first case study concerns the application of the multi-criteria analysis the decision-making problem in which the options based on the flexible distribution system planning belong to a vast Pareto set. Flexibility providers are distributed energy storage devices.

The second case study concerns the application of the MC-CBA approach to a similar case study in which flexibility is provided by distributed energy storage devices and compete with network reinforcement. The aim is to present the appraisal procedure formalised in sections 6.3 and 6.4.

The third case study represents an evolution of the second one. The third case study aims to investigate the influence of the weighting technique in the result of the MC-CBA approach. Moreover, the third case study presents the application of the MC-CBA approach based on the minimax regret rule proposed in section 6.

The fourth case study concerns the analysis of distribution planning initiatives in which several planning approaches are compared. The traditional *fit and forget* approach is compared with a probabilistic *fit and forget*, the use of storage flexibility, the use of flexibility from generators and loads. The comparative analysis is made using the proposed MC-CBA approach based on the minimax regret rule, as proposed in section 6.

7.1 Case study one: MCA for multi-objective flexible distribution system planning

7.1.1 Introduction

The case study proposed for presenting the proposed MC-CBA approach is focused on the project selection of a reinforcement plan of a Medium Voltage (MV) distribution network. The alternative planning options under analysis are a set of plans based on the flexible distribution system approach, as described in section 2.5. Siting, sizing, and managing Distributed Energy Storage (DES) devices is considered a no-network solution and line and substation upgrading. The DSO is the promotor of the planning process; monetary impacts with service performance indicators are exploited for enlarging the monetary analysis by considering the societal perspective. The DSO owns the DES devices which are used for network operation; conversely, their use for energy price arbitrage is forbidden [176], [177].

7.1.2 The grid under analysis

The planning alternatives regard the typical distribution network scenario of rural areas [27]. As represented in Figure 7.1, the studied network is weakly meshed with emergency tie connections and radially operated [178]. Two primary substations feed 22 MV nodes (9 trunk nodes and 13 lateral nodes) that deliver power to MV and LV customers. The urban area (zone A1) consists of two underground feeders (95 mm^2 MV underground cables are used). The zone B1 is a rural area fed by an overhead feeder and characterised by photovoltaic generators and a passive lateral branch (zone C1). The second rural area (zone B2) shows a high density of distributed generation. In the rural areas, trunk feeders and lateral branches are made by overhead lines with sections of 35 mm^2 and 16 mm^2 respectively.

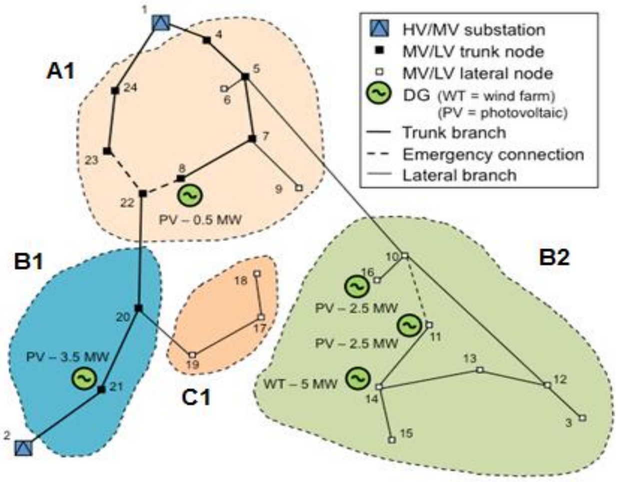

Figure 7.1. Distribution Network of the case study [27], [178]

7.1.3 How the planning options have been devised

The scope of the thesis is to present an MCA based approach for distribution network planning project selection; hence the procedure used for obtaining the set of planning alternatives is not discussed in detail. The information required by the presented MC-CBA approach is only related to the performance achieved by each planning option; at this stage, the assessment does not require information about how a reinforcement plan has been devised. However, for the sake of completeness, a brief description of the process which devised the alternatives is given. The planning options of the case study presented in this section has been devised according to the multi-objective optimisation planning, which procedure is described in [179]. It allows obtaining Pareto front initiatives that include both network reinforcement and flexibility solutions, as illustrated in section 2.5.

As described in section 2.5, the flexible distribution system planning approach differs from traditional *fit and forget* since it combines network solutions and active management strategies to maximise the exploitation of the existing infrastructure. The active management strategies are also known as *no-network* solutions*;* they involve, e.g., reactive power management, system reconfiguration, generator dispatch, demand-side management. In this case study, along with line and substation upgrading, the siting, sizing, and management of Distributed Energy Storage (DES) devices is considered as the *no-network* solution which provides flexibility to the system.

Each plan has a time horizon of 10 years, the topology of the MV network is fixed for the whole planning period [27], [179]. For each MV/LV node, a constant load growth rate of 3% per year has been assumed. Each load and generator have been modelled with typical daily profiles that consider the uncertainties by a normal probabilistic distribution function. Network calculations are based on a probabilistic load flow which evaluates for each hour of day types the steady-state and the emergency network configurations. The resulting probability distribution of nodal voltages and branch currents are used for checking the technical constraints violation risk. If the risk is considered not acceptable, several development plans based on a combination of network and *no-network* solutions are assessed. The devised planning options involve lines and substations upgrading (as traditional network solutions) and DES siting, sizing, and management (as the no-network solution). Amongst the no-network planning solutions, DESs optimally allocated can provide to the Distribution System Operator (DSO) numerous technical and economic benefits such as voltage support, losses reductions, enhanced reliability and quality of service, improved hosting capacity, deferral of network investments, and OPEX reduction [180]. Those benefits are not mutually exclusive because a single storage device can be used to offer different services. Therefore, to understand the multiplicity of benefits, it is obvious to analyse DESs planning alternatives trough a multi-criteria methodology. In this case study, Li-Ion batteries have been employed as DES technology, with a lifespan of 10 years, a nominal power range of 100kW ÷ 3MW, and a nominal duration from 1 to 10 hours. The unitary costs of related to this technology are 200€/kW and 400€/kWh [179]. All nodes have been considered eligible for hosting a DES device; each planning option can host 0 to 2 devices. The present study considered the same scenario as in [180], i.e., the DSO has the ownership of DES used for network operation, energy price arbitrage is not allowed. This thesis describes an output-based procedure for the appraisal of the planning option involving traditional network reinforcement measures and the exploitation of the flexibility offered by the connected resources. Therefore, is it out of the focus of the dissertation how the planning options have been obtained and, in this case, the particular control used for the management of the storage devices. It reflects a black-box analysis approach; any control technic can be exploited for devising the planning options; in the context of the output-based appraisal, only the Key Performance Indicators corresponding to each option are of interest. The active control of loads and generators has not been involved as a planning solution. The baseline scenario considered for planning does not employ DES devices; it only includes traditional network solutions for facing operational issues. When the whole network configuration satisfies the technical compliance in the planning horizon, the solution is memorised in the iterative planning process.

Since the set of the alternative under analysis contains the reference scenario, for the sake of clarity is defined:

- Business as Usual (BaU) scenario: reference scenario in which no smart grid solutions are developed [34], [35]. In the case study, no DES devices are installed in the distribution network in the BaU scenario. Thus, load growth is faced only by traditional network reinforcement solutions.
- Smart grid (SG) scenario: scenarios in which also smart grid solutions are developed [34], [35]. In the case study, the SG scenario concerns the DES devices as no-network solutions to provide flexibility. Each option belonging to the SG scenario is characterised by a different site, size, and device location.

In the described case study, the obtained Pareto set consists of 1200 different planning alternatives. The alternative A4 is the planning option that represents the BaU scenario; all the other options of the Pareto set under appraisal are based on the SG scenario.

7.1.4 Selection of the evaluation criteria

Since the MC-CBA approach is of general purpose for smart grid assets, it is required a preliminary stage for identifying the relevant criteria for the particular decision-making problem at hand [36].

A flat structure formalises the decision-making problem addressed in this case study. The hierarchy consists of three layers: the primary goal, the evaluation criteria, and the design options under analysis. The alternatives under analysis belong to a Pareto front provided as output from the multi-objective planning optimisation. To undertake an output-based analysis, the evaluation criteria identified for the MADM appraisal match with the objectives of the multi-objective planning; therefore, the performance indicators of the alternatives are evaluated as the objective function values [27]. As a consequence, these values are the entries of the DM. The hierarchy of evaluation criteria selected for the assessment in the present case study is depicted in Figure 7.2.

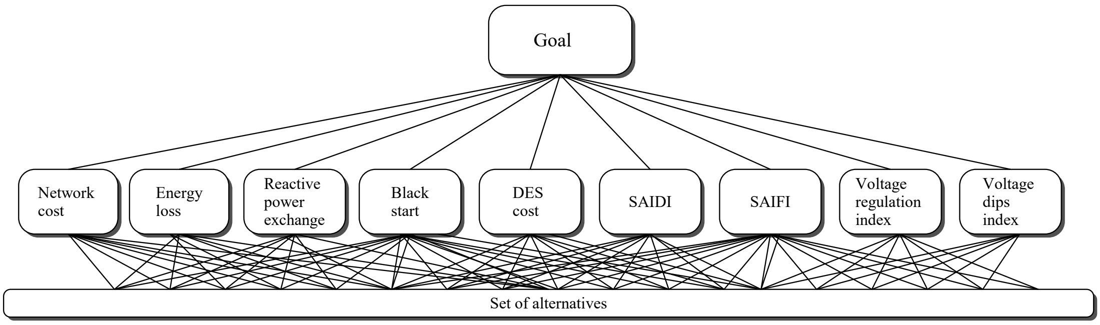

Figure 7.2. Overview of the hierarchy of evaluation criteria (flat case)

An overview of the impact metrics is provided by the formulas of the objective function described in this section. Decision-making problems aim to identify the best planning option; to this end, the black start support criterion is considered fulfilled by the alternatives which have a higher value of the related indicator, while the remaining eight criteria are fulfilled by the alternatives which exhibit lower values in the related objective functions [27].

Network investment cost

The network investment objective evaluates the economic value of the traditional network investment. This cost, C_{inv}, encompasses only the investment in new and upgraded lines and substations, it is evaluated by (7.1) [27].

$$C_{inv} = \sum_{j=1}^{N_{branches}} C_{0j} = \sum_{j=1}^{N_{branches}} (B_{0j} + M_{0j} - R_{0j}) \tag{7.1}$$

Where $N_{branches}$ is the number of network branches, C_{0j} is the present cost of the j^{th} branch, and B_{0j}, M_{0j}, and R_{0j} are respectively building, management and residual costs actualised at the beginning of the planning period by considering a prefixed discount rate.

Energy losses

The Joule energy losses for the j^{th} branch in the k^{th} sub-period are evaluated according to (7.2) [27].

$$E_{Ljk} = 8760 \cdot 3 \cdot R_j \cdot N_k \cdot (I^2{}_{fjk} + I^2{}_{0jk} + I_{fjk} \cdot I_{0jk}) \tag{7.2}$$

Where I_{0jk} and I_{fjk} are the branch current at the beginning and the end of the sub-period respectively, N_k is the sub-period duration in years, and R_j is the branch resistance. 8760 is the number of hours per year, 3 is the number of conductors. The total energy losses, E_L, are then obtained by summing the contributions of all branches in each sub-period.

Reactive power exchange with the Transmission System Operator

The interface inverter of DES devices can be used to separate the exchange of active and reactive power. This aspect can be used to manage the flows of reactive power in the high voltage side of the primary substations and to limit the costs that the distributors have to pay [27]. In this case study, that cost is calculated according to the Italian regulation framework (resolution 654/2015/R/EEL [181]).

Black start support

DES devices can be used to run the black start of a share of the whole grid. The metric P_{BS} of the black start support of each DES device consists of the sum of all the available power in each time slot. A greater P_{BS} value implies a higher black start capability; it is evaluated as in (7.3) [27].

$$P_{BS} = \sum_{h=1}^{N_h} min(SoC_h \cdot \eta_{sch}, P_n) \tag{7.3}$$

Where SoC_h is the state of charge in the h-th time slot, N_h is the number of the time slots, P_n is the nominal power rate of the storage device, whereas η_{sch} is the discharging efficiency.

Cost of the Energy Storage System

The cost of the DESs is evaluated by their CAPEX related to voltage installation in the planning period. The CAPEX is evaluated as by means of (7.4) [27].

$$C_{CAPEX}^{DES} = k_{pcs} \cdot c_p \cdot P_n + c_e \cdot P_n \cdot d_n \tag{7.4}$$

Where k_{pcs} is the oversizing factor of the power conversion system, P_n is the nominal power rating of the device, d_n is the nominal duration. c_p and c_e are the specific costs, their value is respectively 200 €/kW and 400 €/kWh. The residual value is assessed by considering a lifetime of 10 years. The maintenance cost and the OPEX related to the charge/discharge losses has been disregarded.

Quality of service – duration of interruptions

The quality of service guaranteed by each planning alternative depends on the duration of the interruptions that each costumer observes. This impact is measured by the *System Average Interruption Duration Index* (SAIDI), which is calculated as in (7.5) [27].

$$SAIDI = \frac{\sum_{i=1}^{n} U_i \cdot NC_i}{\sum_{i=1}^{n} NC_i} \tag{7.5}$$

Where NC_i is the number of customers in the i-th bus, U_i is the annual outage for customers in the i-th bus, whereas *n* is the overall number of busses of the network. This objective aims to evaluate the improvement of the reliability offered by the DES system. In fact, thanks to islanding operation, it is possible to avoid the outage effects to the set of costumers involved.

Quality of service – frequency of interruptions

The quality of service also is measured by the *System Average Interruption Frequency Index* (SAIFI), which is calculated as in (7.6) [27].

$$SAIFI = \frac{\sum_{i=1}^{n} \lambda_i \cdot NC_i}{\sum_{i=1}^{n} NC_i} \tag{7.6}$$

Where λ_i is the failure rate, NC_i is the number of customers in the i-th bus, whereas *n* is the overall number of busses of the network.

Voltage regulation

DES devices can contribute to voltage regulation with suitable injections of reactive and active power. The metric for the voltage regulation objective measures the difference between the maximum and the minimum bus voltage in the last year of the planning period. It is evaluated as in (7.7) [27].

$$regV_{index} = \sum_{i=1}^{N_{nodes}} \sum_{h=1}^{N_f} \left| V_{max.i}^h - V_{min.i}^h \right| \tag{7.7}$$

$V_{max.i}^h$ and $V_{min.i}^h$ are the maximum and minimum voltage of the i-th bus in the h-th time interval. N_{nodes} is the overall number of buses whereas N_f is the sub-period duration used for the evaluation of the daily profile of loads and generators. To avoid double-counting, this objective measures the contribution of DES to the quality of voltage; the contribution on avoiding voltage constraints violation is already accounted as a deferral of network upgrading investment.

Quality of services – voltage dips

DES can improve the quality of service by decreasing voltage dips occurrence and transient interruptions caused by short-circuits. The voltage dips objective metric measures the annual cumulative frequency of the voltage dips considering all the busses of the MV grid [27].

7.1.5 The Pareto front, the set of planning alternatives

Each element of the obtained Pareto front is a different planning *non-dominated* solution that involves the use of DESs for providing flexibility. Each alternative is different by another for the number, position in the grid, power rating, daily energy scheduling of the DES devices, and the traditional network upgrading solutions deployed. Since the obtained Pareto front consists of 1200 different planning alternatives, only a general description of the set is given in this section [27]. Each planning alternative in the Pareto front involves 2 DES devices at most. 1042 alternatives include 2 DES devices, 157 involves one only device; the baseline alternative (the option A4) has no DES installed. In Figure 7.3, the occurrence of DES devices in terms of power rating, duration, and on the installed busses considering all the alternatives of the Pareto front is provided.

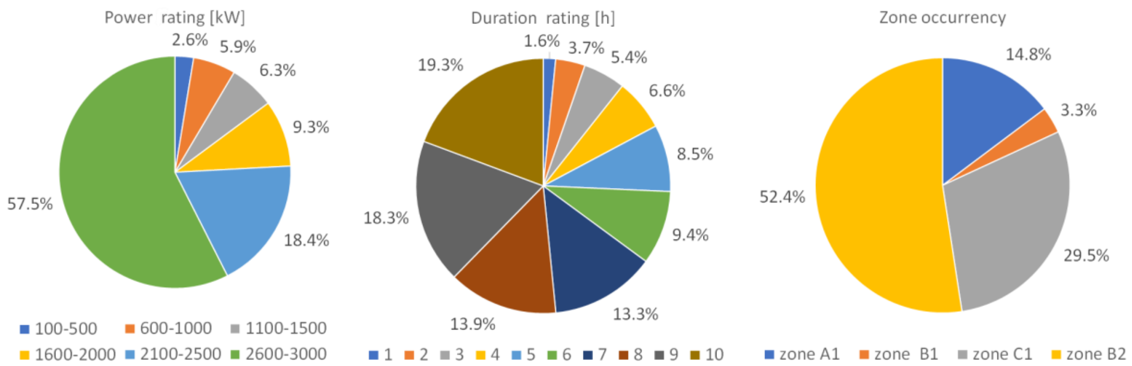

Figure 7.3. The occurrence of DES devices characteristics among the planning options [27]

Since the Pareto front contains the alternatives under analysis, it defines the DM, which is the input of the MADM method. The DM has N_a rows and N_c columns, where N_a is the number of planning alternatives, while N_c is the number of the criteria. In the present case study, the chosen evaluation criteria are the 9 objectives of the multi-objective planning; therefore, the Pareto front feature values are the entries of the DM; hence: N_a=1200 and N_c=9. Due to the large number of alternatives, the full DM is not reported. However, the performances of the alternatives on the 9 criteria are depicted in Figure 7.4 in relative terms to the baseline scenario. For each objective function, the difference between the performance value of each alternative and the baseline scenario has been calculated. Then, the obtained figures have been scaled according to the maximum absolute difference value. For the sake of clarity, the minimum and the maximum values of performance on each criterion are resumed in Table 7.1, along with the objective function values of the baseline scenario. The appraisal procedure proposed in this dissertation follows an output-based approach that does not investigate the particular assets and control strategies adopted; therefore, only the values obtained for the key performance indicators are of interest for each option. Nevertheless, with this black box approach, it is worth highlighting that the increased network losses observed for some of the SG options are related to the current intensity that flows on branches which section has not been oversized with respect to the baseline scenario. Considering this aspect, it is possible to observe that the final value of network losses can be not reduced by the presence of storage devices [179].

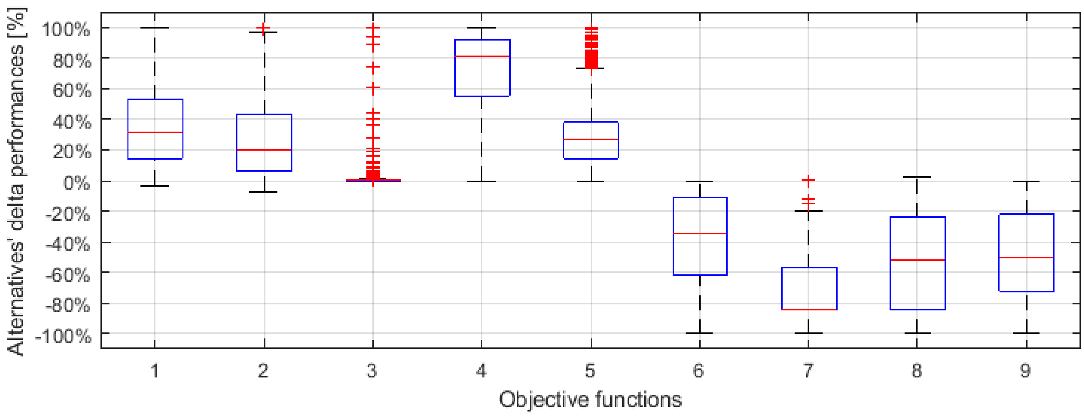

Figure 7.4. Relative performances of the alternatives compared to the baseline scenario

Table 7.1. Minimum and Maximum Values of Performances in the DM

Index		Minimum value	Maximum value	Baseline scenario
Network Costs	[k€]	2,174.2	3,208.2	2,205.0
Energy Losses	[MWh]	9,664.2	32,732.6	11,216.1
Reactive Power Exchange	[k€]	0	43,282.0	973.9
Black Start	[MW]	144.00	0	0
DES Cost	[k€]	0	115,200.0	0
SAIDI	[hr/yr]	1.630	2.026	2.026
SAIFI	[occurrences/yr]	0.735	0.837	0.837
Voltage Regulation Index	[p.u.]	5.258	11.636	11.483
Voltage Dips Index	$[Vdips/year]$	83.22	100.43	100.43

7.1.6 Automatized scoring from quantitative DM

Once the DM is built, the automatized scoring assessment follows the procedure described in section 6.4.3. The automatic scoring algorithm produces N_c=9 squared preference matrices, whose dimension is N_a=1200 [27]. The obtained preference matrices are consistent; the related Consistency Ratio is less than 0.03. The normalised scores of the alternatives are evaluated from each preference matrix by using the eigenvector method described in section 6.4.3. The procedure is repeated N_c=9 times, it leads to a normalised DM which dimension is (N_a,N_c)=(1200,9).

7.1.7 Overall score calculation

Once that the normalised DM has been obtained, the overall score is calculated for each alternative utilizing (7.8) [94].

$$OS_i = \sum_{j=1}^{n_c} p_{i,j} \cdot v_j \tag{7.8}$$

Where OS_i is the overall score of the *i-th* alternative; $p_{i,j}$ is the normalised partial score of the *i-th* alternative with respect to the *j-th* criterion; v_j is the global priority of the *j-th* criterion; n_c is the number of the terminal criteria of the hierarchy. The alternative that achieves the highest overall score *OS* is the one that the AHP indicates as the best alternative of the analysed set. The overall scores obtained by (7.8) are related to a single decision maker's point of view, which is accounted as evaluation criteria relevance modelled by the assigned relative weights. Thereby, a different decision-maker's point of view is modelled by different weights; hence the obtained ranking of alternatives may change. To find a robust result, in this case study, an approach for accounting all possible points of view of the decision-makers is proposed. The aim is to identify the alternative which is identified as the best considering all possible criteria weights values. To assess all perspectives of the decision-maker, the proposed approach repeats of (7.8) for each pattern of weight that respects (7.9) [27].

$$\begin{cases} \sum_{k=1}^{9} v_k = 1 \\ 0 \le v_k \le 1 \end{cases} \tag{7.9}$$

Where v_k is the weight of the k-th criterion.

7.1.8 The final score evaluation

From each evaluation of (7.8), the higher overall score and the label of the related alternative are collected. This final score is calculated as the sum of the overall score obtained by the best alternative on each AHP evaluation, as shown in (7.10).

$$FS_i = \sum_{j=1}^{n_{best,i}} OS_{i,j} \tag{7.10}$$

Where FS_i is the final score of the i-th alternative, $OS_{i,j}$is the overall score of the i-th alternative obtained in the j-th AHP evaluation, $n_{best,i}$ is the number of AHP evaluations in which the i-th alternatives obtained the highest overall score. Namely, for each alternative, its final score is related to the sum of the overall scores obtained only when it results as the best of the set for a particular criteria weight scheme. This approach emphasises the option that is labelled as best more times and collects the highest overall scores. The planning option that achieves the highest final score is identified as the best of the set under analysis.

Hence in this case study, the calculation (7.8) for obtaining the overall scores has been repeated for each weighting scheme defined by (7.9) [27]. A step size of $\Delta v_k = 0.05$ is considered among each evaluation point. The final score of each alternative is evaluated as defined by (7.10) [27].

7.1.9 Results and discussion

Table 7.2, Table 7.3, and Table 7.4 present the results of the MADM evaluations. Only the top 5 alternatives are described. In Table 7.2, the overall scores obtained after all the evaluations are shown (normalised in thousandths). In addition, the row “Hits” represents how many times the corresponding alternative has been pointed out as the best considering all pattern of weights. Table 7.3 shows the DM of the top 5 alternatives. The left pie chart in Figure 7.5 represents the distribution in relative terms of final score values among the alternatives; similarly, the right pie chart in Figure 7.5 resumes the distribution of “hits” obtained by the alternative on each AHP assessment. Table 7.4 presents the DES topological information of each top 5 alternatives. As highlighted in Table 7.2 and Figure 7.5, the alternative A1069 achieves the highest final score and is labelled as best most of the times; therefore, it is the best alternative identified by the method. Figure 7.5 shows that the first three alternatives obtain a final score higher than the sum of the final score of the remaining alternatives. This result is also obtained by considering the first position distribution depicted in the right pie chart. Accordingly, the alternatives A1069, A4, and A110 outclass all remaining alternatives belonging to the Pareto front.

Table 7.2. Final Scores [27]

Alternative	A1069	A4	A110	A113	A477
Final score	460.8	282.1	158.8	22.8	14.1
Hits	1321101	815250	610899	96334	56003

Table 7.3. Performance Matrix (DM) of the First Five Alternatives Ranked by AHP [27]

Alternative Label	Network Costs [k€]	Energy Losses [MWh]	Reactive Power Exchange [k€]	Black Start [MW]	DES Cost [k€]	SAIDI $\left[\frac{hr}{yr}\right]$	SAIFI $\left[\frac{occ.}{yr}\right]$	Voltage Regulation Index [pu]	Voltage Dips Index $\left[\frac{Vdips}{year}\right]$
A1069	2676	19415	0	141.6	48965	1.814	0.751	6.022	83.22
A4	2205	11216	974	0	0	2.026	0.837	11.483	100.43
A110	2821	19357	1084	104	23740	1.63	0.735	5.738	83.22
A113	2193	12647	1054	106.3	25020	1.863	0.751	10.934	83.22
A477	2508	13917	976	68.9	9610	1.636	0.79	8.748	83.22

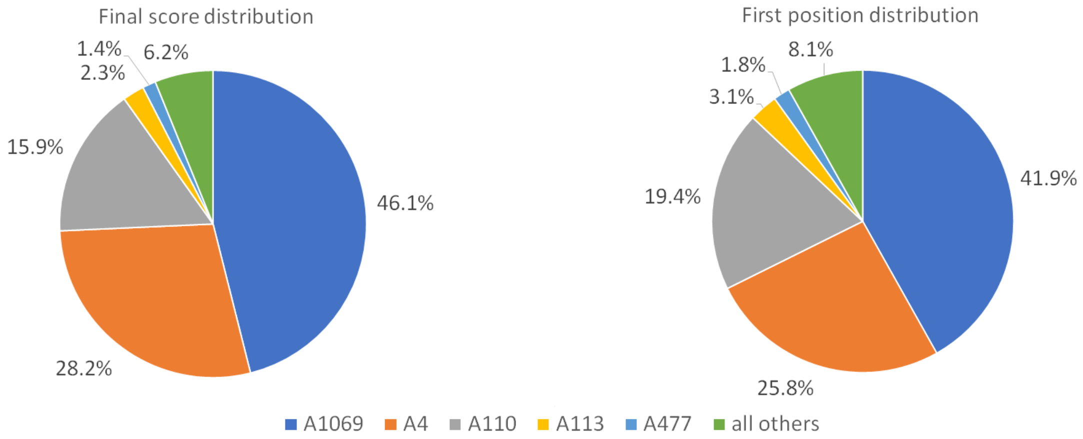

Figure 7.5. Distribution of final scores (on the left) and of "hits" (on the right) obtained by the alternatives [27]

Table 7.4. DES Data of the First Five Alternatives Ranked by AHP [27]

Individual	DES bus		DES power size [kW]		DES nominal duration	
A1069	10	12	3000	2900	10	7
A4	no DES	no DES	---	---	---	---
A110	3	12	2000	2400	9	6
A113	10	16	1600	2900	9	9
A477	3	12	1500	1700	2	9

The overall performance achieved by A1069 is significantly higher than the remaining four top alternatives; hence, the result obtained is considered robust. Among all 1200 analysed alternatives, 857 alternatives obtained a final score greater than zero; while 343 alternatives have not been identified as the best alternative for any of the considered weight scheme. Considering the whole Pareto front, A1069 shows the highest performances on criteria such as voltage dips, reactive power exchange, and black start support. In addition, on SAIDI, SAIFI, and voltage regulation index A1069 exhibits great performances. The performance of A1069 for network investment and energy loss lies between the best and worst alternatives on these criteria. Even though the DES cost related to A1069 is the highest among all top 5 alternatives, it is still less than half of the highest value observed in the Pareto front (115.2 M€). Therefore, A1069 can be considered as the best compromise design option. Along with an average expenditure of DES, it has achieved an overall superiority among all the criteria. The second-best alternative proposed by the evaluation is the baseline scenario (A4). As can be seen in Table 7.3, A4 has the worst performances in five criteria, while it performs exceptionally well on the other four criteria. Due to criteria relevance in some AHP evaluation, the best alternative has been A4 when the weights of these 4 criteria were higher. Namely, the output provided highlights the compensative peculiarity of AHP.

Except for A4 (no DES, the baseline option), all the other alternatives ranked in the top 5 positions encompass siting of DESs in the network zone B2. It confirms that storage is more effective in reducing interruptions and enhancing voltage quality if placed in rural areas with high distributed generation density. Besides these positive aspects, an increased level of losses and network investment is expected in the distribution network. Table 7.3 shows that A1069 involves a share of network investments and energy losses of 21.3% and 73.1%, respectively, greater than the baseline scenario. The alternatives A110, A113, and A447 have an amount of DES CAPEX that is about 50-80% less than A1069. A lower level of DES CAPEX implies devices with less power or energy size. Consequently, the overall benefit achieved with these design options is lower. A1069 can be suitable for DSOs in a scenario where the regulatory framework allows them to focus more on quality of service than on costs (i.e., investments are fully refunded to DSO). On the contrary, an increased level of energy losses and network investment can be undesirable for the decision-maker. Before the MADM assessment, a subset of the Pareto front can be identified based on the decision-makers threshold levels (i.e., a budget cap, maximum and minimum levels on some criteria). For the sake of completeness, alternatives A1069 and A110 are compared with alternative A1, whose final score is zero. The comparison is represented in Figure 7.6, it is made in relative terms to the baseline scenario as in Figure 7.4. A1 involves busses 15 and 21 by installing two DES devices of 2.6 MW ÷ 3 h and 2.7 MW ÷ 2 h, respectively. Although A1069 introduces more network cost, energy loss, and DES cost than A1, the latter has a slightly negative impact in terms of reactive power exchange; no impact in terms of SAIDI, SAIFI, and voltage dips; a lower positive impact on black start support and voltage regulation indexes. Therefore, only on three criteria, A1 has a better performance than the A1069. A110 performs better than A1069 on DES cost, SAIDI, SAIFI, and voltage regulation; it has an equal performance in terms of voltage dips; conversely, on the remaining 4 criteria, A110 is outclassed by A1069.

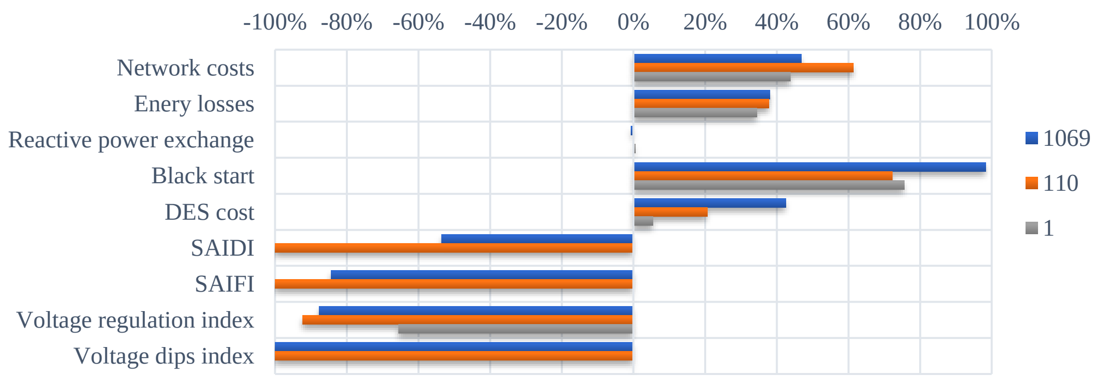

Figure 7.6. Comparison of the performances of A1069, A110, and A1 in relative terms with respect to the baseline scenario

7.1.10 Concluding Remarks

The presented case study concerns the exploitation of the proposed systematic and structured approach for project selection of smart grid development. The deployment of the proposed methodology, which combines multi-objective optimisation planning and MADM techniques, allows for optimal planning of distribution networks helping the decision-maker in finding the design option that best fits with the stakeholders' expectation. By assessing all possible points of view, the most supported planning option is found. The case study concerns the analysis of a Pareto front of flexible distribution system planning options designed by a *posteriori* multi-objective algorithm. Among the optimal set, the best alternative is identified by the proposed automatic MADM evaluation. The *non-network* planning options have been devised concerning siting, sizing, and scheduling of DES devices as flexibility providers.

Even if the MADM technique upon which the proposed approach is based is well available in the literature, the proposed automatized version improves the state of the art of MADM and makes it more suitable to distribution planning in the era of smart grids:

i. it supports the planners in examining large sets of planning options
ii. it enhances the objectivity of the assessment
iii. it is less biased than the CBA.

Eventually, a robust planning option that considers the point of view of several stakeholders can be identified, increasing the effectiveness of multi-objective-attribute optimal planning. As inferable from the discussion of the results, comparing the alternatives is a laborious task, in which complexity increases as the number of the alternatives and the evaluation criteria increases. Therefore, an automatized tool that provides concise information about the best alternative in the set is fundamental for complex decision-making problems as the ones regarding smart grid initiatives.

7.2 Case Study two: application of the MC-CBA approach to the flexible distribution system planning

The case study presented in this section concerns a combined MC-CBA assessment framework for the decision-making problem of smart grid planning alternatives [26]. More specifically, a set of different upgrading plans based on the flexible distribution system approach is analysed for identifying the best planning option. As described in section 6.3, the MC-CBA assessment framework is based on international recommendations and guidelines on project analysis, and it allows for a systematic and simultaneous assessment of different impacts [32], [34], [35]. The aim is to provide a decision-making tool that helps both system operators and regulatory bodies for smart grid projects assessment by complying with the novel distribution system context requirements [26].

As discussed in section 6.1, CBA and MCA are not mutually exclusive tools; therefore, a combined approach for project analysis can be devised to fill the respective gaps while preserving the respective strengths [26], [38]. The proposed MC-CBA assessment framework is characterised by an MCA in which the economic criterion evaluates the result of a CBA focused on monetary impacts. Conversely, other tangible and intangible impacts are appraised employing several evaluation criteria according to MCA principles. The overall assessment of each planning option is obtained by combining the monetary evaluation results with the non-monetary evaluation results [26]. As described in section 6.4, the proposed appraisal methodology computes the overall score of the alternatives based on the fundamentals of the Analytic Hierarchy Process (AHP) [47].

7.2.1 The decision-making problem structure

The decision-making process involves a portion of the distribution grid, which represents the typical rural scenario, as described in section 7.1.2. The planning alternatives under analysis have been devised by a multi-objective planning optimisation, as described in section 7.1.3. The attributes of the planning options are formed by the objective values and the topology information that comes up from the optimisation process. It is assumed that the utility proposes the expansion plans, the externality impacts have been neglected due to the unavailability of data [26]. However, the technical performances achieved by the planning options are evaluated according to the scheme proposed by JRC and described in section 6.2.1.2. Therefore, in this case study, the hierarchical structure is formed by the economic branch and the smart grid paradigm branch. The former is devoted to the evaluation of the monetary impacts, while the latter considers the impacts of the initiatives on the power system in terms of the contribution towards the smart grid realization.

A three-layer hierarchical structure of criteria is considered for the present case study, as depicted in Figure 7.7 [26].

The economic assessment is based on the performance achieved by the alternatives in terms of Net Present Value (NPV). This indicator is evaluated through a CBA concerning the three monetary impacts: the investment cost of traditional network reinforcement solutions, the investment cost in DES devices, and the cost related to the reactive power exchange with the transmission grid.

The smart grid deployment merit is evaluated according to the list of policy criteria (PCs) and KPIs proposed by the JRC [32]–[35]. The proposed list is general purpose for smart grid applications; therefore, the most suitable subset of criteria has to be identified according to the decision-making problem peculiarities [26]. The three PCs chosen for the present case study are network connectivity and access to all categories of network users (PC1), security and quality of supply (PC2), and efficiency and service quality in electricity supply and grid operation (PC3). The related KPIs are operational flexibility provided for dynamic balancing of electricity in the network (KPI_{1A}), the stability of the electricity system (KPI_{2A}), duration (KPI_{2B}) and frequency (KPI_{2C}) of interruptions per customer, voltage quality in terms of voltage variations (KPI_{2D}), and level of losses in distribution networks (KPI_{3A}).

Seven terminal criteria characterise the overall hierarchy. The performances of the alternatives considering these criteria are assessed with quantitative indicators. The formulas for evaluating the numerical value of each indicator are described in this section.

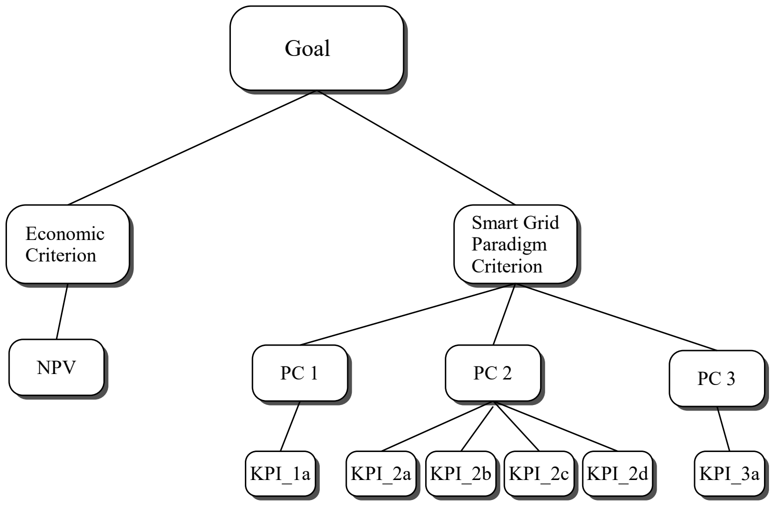

Figure 7.7. Overview of the hierarchy of evaluation criteria (layered case) [26]

NPV

The Net Present Value of each alternative is evaluated as the sum of discounted benefits and costs (7.11).

$$NPV = C_{inv}^{T} + C_{inv}^{DES} + Q_{EXC} \tag{7.11}$$

Where C_{inv}^{T} is the investment cost of traditional network reinforcement solutions; C_{inv}^{DES} is the investment cost of DES devices; Q_{EXC} is the monetary value of the reactive power exchange with the transmission grid. Each term is discounted by considering a fixed discount rate of 4%. The plan which achieves the highest NPV is the best option according to the economic assessment.

KPI_{1A}: Operational flexibility

The KPI_{1A} evaluates the contribution in terms of flexibility given by the alternative to the operation of the grid. This contribution depends on the dispatchable resources available in the network. In the case study, DES devices are the only dispatchable units. Considering the available information on the expansion plans, the KPI_{1A} is evaluated by (7.12) [26].

$$\mathrm{KPI}_{1\mathrm{A}} = \sum_{i=1}^{N_{DES}} \frac{(\hat{P}_{DES,i}^{(out)})_{SG} + \left|(\hat{P}_{DES,i}^{(in)})_{SG}\right|}{2} \tag{7.12}$$

Where N_{DES} is the number of DES devices provided by the alternative; $(\hat{P}_{DES,i}^{(out)})_{SG}$ is the expected maximum power generated by the *i-th* device in the planning horizon; while $(\hat{P}_{DES,i}^{(in)})_{SG}$ is the expected maximum power absorbed from the grid by the *i-th* device in the planning horizon. The alternative which contributes more to operational flexibility is the one which achieves the maximum value of the $\mathrm{KPI}_{1\mathrm{A}}$.

$\mathrm{KPI}_{2\mathrm{A}}$: Power system stability

The $\mathrm{KPI}_{2\mathrm{A}}$ evaluates the contribution of the planning alternatives in relieving the possible sources of system instability. JRC suggests simulating the system behaviour in several extreme scenarios [34], [35]. Since the available information on the alternatives, a different approach is used. Considering that DES devices can contribute to network black-start, a potential ex-post contribution to the system reliability is considered in this case study. The performance indicator for $\mathrm{KPI}_{2\mathrm{A}}$ is computed by (7.13) [26].

$$\mathrm{KPI}_{2\mathrm{A}} = P_{BS} = \sum_{i=1}^{N_{DES}} \sum_{h=1}^{N_h} \min(SoC_{h,i} \cdot \eta_{dis,i}, P_{n,i}) \tag{7.13}$$

Where P_{BS} is the amount of active power available for the black-start service; N_{DES} is the number of DES devices provided by the alternative; N_h is the number of time intervals of the planning period; $SoC_{h,i}$ is the state of charge of the *i-th* device in the *h-th* time interval; $\eta_{dis,i}$ is the discharging efficiency of the *i-th* device; $P_{n,i}$ is the nominal power of the *i-th* device. The planning option that achieves the highest value of $\mathrm{KPI}_{2\mathrm{A}}$ better performs in terms of black-start support.

$\mathrm{KPI}_{2\mathrm{B}}$: Duration of interruption

The $\mathrm{KPI}_{2\mathrm{B}}$ evaluates the contribution of the planning alternatives in reducing the duration of the interruptions for each customer; therefore, the $\mathrm{KPI}_{2\mathrm{B}}$ corresponds to the System Average Interruption Duration Index (SAIDI), it is evaluated as shown in (7.14) [26].

$$KPI_{2B} = SAIDI = \frac{\sum_{i=1}^{n} U_i NC_i}{\sum_{i=1}^{n} NC_i} \tag{7.14}$$

Where U_i is the duration of outages for the customers in the *i-th* bus; NC_i is the number of customers in the *i-th* bus; *n* is the number of busses in the network. The planning option that achieves the lowest value of $\mathrm{KPI}_{2\mathrm{B}}$ better performs in terms of duration of interruptions.

$\mathrm{KPI}_{2\mathrm{C}}$: Frequency of interruption

The $\mathrm{KPI}_{2\mathrm{C}}$ evaluates the contribution of the planning alternatives in reducing the frequency of interruptions for each customer; therefore, the $\mathrm{KPI}_{2\mathrm{C}}$ corresponds to the System Average Interruption Frequency Index (SAIFI), which is evaluated as shown in (7.15) [26].

$$KPI_{2C} = SAIFI = \frac{\sum_{i=1}^{n} \lambda_i NC_i}{\sum_{i=1}^{n} NC_i} \tag{7.15}$$

Where λ_i is the failure rate in the *i-th* bus; NC_i is the number of customers in the *i-th* bus; *n* is the number of busses in the network. The planning option that achieves the lowest value of $\mathrm{KPI}_{2\mathrm{C}}$ better performs in terms of frequency of interruptions.

KPI$_{2D}$: Voltage variations

The KPI$_{2D}$ evaluates the contribution of the planning alternatives in rejecting voltage variations. DES can contribute to voltage regulation through power factor management. In this case study, the KPI$_{2D}$ is evaluated by (7.16) [26].

$$KPI_{2D} = \sum_{i=1}^{n} \sum_{h=1}^{N_h} \left| V_{max.i}^{(h)} - V_{min.i}^{(h)} \right| \tag{7.16}$$

Where n is the number of busses in the network; N_h is the number of time intervals of the planning period; $V_{max.i}^{(h)}$ is the maximum voltage value in the *i-th* bus at the *h-th* interval; $V_{min.i}^{(h)}$ is the minimum voltage value in the *i-th* bus at the *h-th* interval. The planning option that achieves the lowest value of $\mathrm{KPI_{2D}}$ better performs in terms of voltage variations.

KPI$_{3A}$: Energy losses

The KPI$_{3A}$ evaluates the contribution of the planning alternatives in reducing the network energy losses. DES can contribute to reducing network losses by providing the peak shaving service. The KPI$_{3A}$ is evaluated by (7.17) [26].

$$KPI_{3A} = \sum_{j=1}^{N_e} \sum_{k=1}^{N_h} E_{L_{j,k}} \tag{7.17}$$

Where N_e is the number of elements considered for the assessment of energy losses (HV/MV transformers, lines); N_h is the number of time intervals of the planning period; $E_{L_{j,k}}$ is the energy loss of the *j-th* element in the *k-th* time interval. The planning option that achieves the lowest value of $\mathrm{KPI_{3A}}$ better performs in terms of energy losses.

The appraisal approach proposed in this thesis aims to encompass all the impacts determined by the deployment of smart grid-based planning options. To this aim, even if a monetary value can be assigned to the energy losses, the impact of the energy losses has been decoupled from the assessment of the monetary costs and benefits; therefore, an independent indicator has been considered. The monetary value of the energy losses is based on the energy price when the network losses occur. However, the perceived value of the energy losses can be different according to the mix of energy sources used for producing energy and the stakeholders' perspective adopted for the assessment. In addition, discounting the monetary value of the energy losses biases the assessment of the related impact. There is no clear motivation to state that present energy losses are more relevant than the energy losses in the tenth year. Future energy losses will be much more relevant than current energy losses in case of a future increase of the relevance of energy efficiency as a policy objective. As discussed in section 3, the monetary value of an impact is able to capture only part of the corresponding effects and includes underlying hypotheses that bias the overall assessment. Moreover, reducing the energy losses represents not only a monetary goal; it concerns policy objectives related to energy efficiency, improved phase balancing, increased distributed micro-generation, voltage control, and consumption reduction at the transmission level [32]. If network losses are considered a part of the monetary impacts, assessing the effects concerning the mentioned policy objectives becomes of secondary relevance [28]. Finally, the evaluation of the energy losses pertains only to the KPI_{3A} to avoid double counting.

7.2.2 Planning alternatives and Decision Matrix

The case study presented concerns 5 planning alternatives. Each planning option is characterised by both line and substation upgrading and DES siting and sizing. An overview of DES siting and sizing of the alternatives is given in Table 7.5. Since the MC-CBA framework is output-based, for the sake of brevity, only the data required by the assessment is reported. The alternative labelled A_1 is the baseline scenario; hence no DES devices are involved.

Table 7.5. Topological information on DES

Option	DES bus	DES power rate [kW]	DES energy size [kWh]
A_1	No DES	0	0
A_2	7	100	100
A_3	14	200	400
A_4	16	100	100
A_5	14	100	100

Besides, in Table 7.6, the DM of the alternative is shown. The values in Table 7.6 are obtained from data provided as output by the multi-objective planning optimisation process, which devised the alternatives. Therefore, the values are based on simulating the scenario related to each alternative for the whole planning period, as described in Table 7.6. In Table 7.7, the normalised values of the DM are reported. The normalisation is obtained according to the scoring stage described in section 6.4.3.3.

Table 7.6. DM of the decision-making problem

Option	Economic branch	Smart Grid Branch					
	NPV [k€]	*KPI_{1A} [MW]*	*KPI_{2A} [MW]*	*KPI_{2B} [occ/y]*	*KPI_{2C} [h/y]*	*KPI_{2D} [pu]*	*KPI_{3A} [MWh]*
A_1	0	0	0	2.026	0.837	11.48	11216.1
A_2	4.257	66.2	1269.2	2.017	0.751	10.68	10677.7
A_3	3.371	184.2	2903.9	2.017	0.751	10.68	10701.3
A_4	12.905	48.4	984.6	2.017	0.751	10.68	10661.3
A_5	88.587	38.2	574.1	2.017	0.751	10.69	10682.4

Table 7.7.Normalised DM of the decision-making problem

Option	Economic branch	Smart Grid Branch					
	NPV	*KPI_{1A}*	*KPI_{2A}*	*KPI_{2B}*	*KPI_{2C}*	*KPI_{2D}*	*KPI_{3A}*
A_1	0.027	0.027	0.027	0.027	0.027	0.027	0.028
A_2	0.209	0.242	0.242	0.243	0.243	0.243	0.243
A_3	0.209	0.278	0.278	0.243	0.243	0.243	0.207
A_4	0.240	0.242	0.242	0.243	0.243	0.243	0.279
A_5	0.316	0.211	0.211	0.243	0.243	0.243	0.243

7.2.3 Local and global weights of criteria

MCA requires defining a numerical weight for each criterion according to their relevance for the decision-maker and stakeholders. The economic branch has in its lower level a unique criterion; the local weight of the NPV criterion is equal to 1. The smart grid deployment merit branch is divided into three sub-branches. According to JRC recommendation, criteria belonging to the same level of the hierarchy have the same weight; therefore, the PCs are equally relevant: their local weight is 1/3. Furthermore, the local weight of KPI_{1A} and KPI_{3A} is 1, whereas the local weight of each KPI related to PC2 is equal to 0.25. By considering an equal relevance of the two branches, the hierarchical tree has been evaluated according to the hierarchical composition principle; the resulting global weights of the terminal criteria are shown in Table III.

Table 7.8. Global weights of terminal criteria

Terminal criterion	Global weight
NPV	0.5
KPI_{1A}	0.16667
KPI_{2A}	0.04167
KPI_{2B}	0.04167
KPI_{2C}	0.04167
KPI_{2D}	0.04167
KPI_{3A}	0.16667

7.2.4 Results and Discussion

The result obtained utilizing the MC-CBA is shown in Table 7.9. The alternative which achieves the highest overall score is the A_5; therefore, A_5 is the best option according to the MC-CBA assessment made by considering the criteria relevance defined in Table 7.9.

Table 7.9. Overall and partial scores

Option	Overall score	Partial score Economic Branch	Partial score Smart Grid Branch
A_5	0.2749	0.3204	0.2295
A_4	0.2468	0.2387	0.2549
A_3	0.2273	0.2072	0.2475
A_2	0.2242	0.2072	0.2411
A_1	0.0268	0.0265	0.0270

The worst alternative is the baseline scenario (A_1). According to the partial scores on the two branches, the alternative A_5 scores the highest in the economic branch, while the A_4 is the best alternative according to the smart deployment merit evaluation. A_4 is the more effective in satisfying the smart grid criterion; however, it has an economic performance lower than A_5; hence the latter is preferred by the overall evaluation. Since both alternatives provide the same sized DES device, the economic performance difference depends on its management, which yields to a different network investment cost and reactive power exchange. A_3 is similar to A_5, but the DES device installed in bus 14 has a bigger size and lower performance on the economic criterion. Even if A_3 installs a bigger device than A_4, the performances on the smart grid deployment merit branch are lower than A_4; hence, topology and scheduling of storage strongly influence the benefits that a device produces, size is not the only key factor that has to be considered. In Figure 7.8, the result of a sensitive analysis made by varying the relevance assigned to the two branches is depicted. Accordingly to partial scores, the alternatives A_4 and A_5 are the only options identified as the best option in the criteria weight range.

More specifically, the breakpoint is 0.24. If the economic branch has a local weight lower than 0.24 (hence the smart grid deployment merit branch has a local weight higher than 0.76), the best alternative according to the MC-CBA framework is A_4. Contrariwise, the best alternative is A_5.

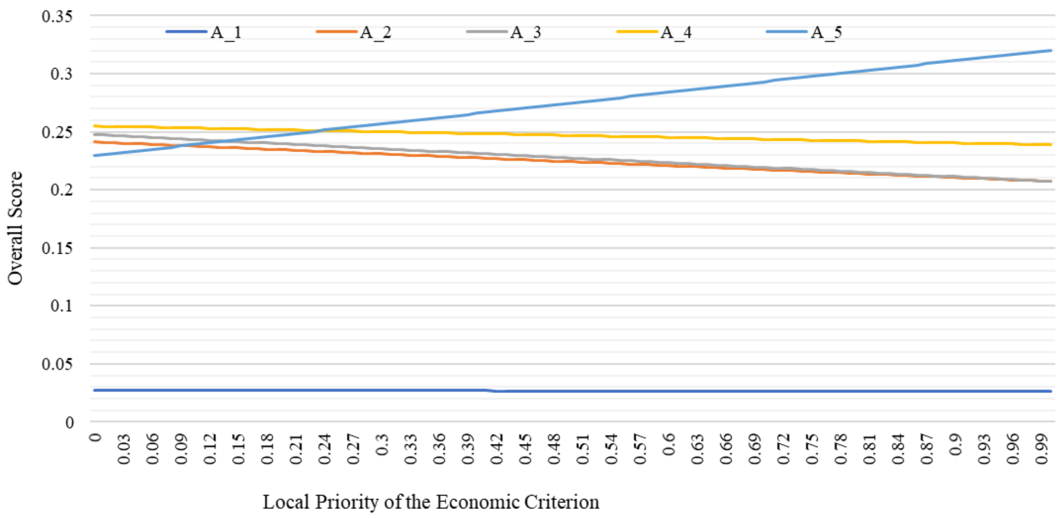

Figure 7.8. Sensitivity analysis on the first level criteria weight

7.2.5 Concluding Remarks

In the presented case study, an MC-CBA framework for smart grid project assessment is presented. The proposed approach is general-purpose since it can be used for assessing any smart grid asset by identifying the relevant evaluation criteria. The proposed MC-CBA framework aims to help decision-makers of companies and government bodies in strategic planning. By identifying the best option and by analysing the sensitivity concerning criteria weights, the decision-makers obtain an overview of the effects produced by each alternative. The effectiveness of complex planning problem is increased since the decision-maker is supported by a systematic framework which simplifies the analysis and rejects personal biases. The usefulness of support decision tools rises together with the decision-making problem dimension. As the number of criteria and alternatives increases, identifying the best option become extremely difficult and burdensome. Moreover, the presented MC-CBA framework does not require converting all impacts in monetary terms; hence it is suitable for accounting social and technical impacts of power system planning without introducing any underlying bias.

7.3 Case study three: application of the MC-CBA approach based on Decision Theory to the flexible distribution planning

The case study presented in this section deals with the application of objective methodologies for determining the criteria weights to a well-known case study. The goal is to study the impact of objective and integrated weighting methodologies reviewed in section 4 to verify the achievable improvements. The ultimate goal of the activity is to identify the most promising technique that can be integrated into the MC-CBA methodology. The updated MC-CBA methodology will be able to identify the best alternative when subjective information on criteria relevance is not available and in the cases of availability of partial subjective information.

The decision-making problem addressed in the case study is focused on identifying the best planning alternative for an MV distribution network. Also in the described case study, the set of planning alternatives has been devised by a multi-objective optimisation which exploits the flexible distribution system planning approach. According to the flexible distribution system planning approach, both traditional network reinforcement and flexible solutions are involved in grid operation. In the case study, the flexible solution is represented by the active management of the Distributed Energy Storage Systems (DESSs). The planning options are proposed by the DSO that owns and operates the DESSs for solving network contingencies. It is not allowed for the DSO to operate the DESSs for energy price arbitrage [176], [177].

The presented case study has been already addressed in section 7.2 by exploiting only subjective information for the evaluation criteria relevance. The decision-making process involves a portion of the distribution grid, which represents the typical rural scenario, as described in section 7.1.2. The planning alternatives under analysis have been devised by a multi-objective planning optimisation described in section 7.1.3. The planning options are described in terms of attributes that are formed by the objective values and the topology information that comes up from the optimisation process.

As recommended by the MC-CBA framework described in section 6.3, the impacts of the alternatives are assessed considering three evaluation areas: economic, smart grid, externalities. The economic evaluation of the alternatives is based on the values of the Cost-Benefit Analysis indicators (CBA). The contribution of each alternative to the transition of the electricity system towards the smart grid paradigm is assessed considering a set of strategic objectives and related indicators, defined by the Joint Research Center (JRC) based on the guidelines of the European Commission [32], [34], [35], as described in section 6.2.1. The structure of the hierarchy of the evaluation criteria and the attributes of the alternatives of the decision-making problem addressed in the case study coincide with the structure described in section 7.2.1. For the sake of consistency, a brief reminder is reported in this section.

As depicted in Figure 7.9, the hierarchical structure is formed by three layers. The economic assessment is based on the performance achieved by the alternatives in terms of Net Present Value (NPV), calculated as in (7.11). The three PCs form the smart grid branch: network connectivity and access to all categories of network users (PC1), security and quality of supply (PC2), and efficiency and service quality in electricity supply and grid operation (PC3). The related KPIs are operational flexibility provided for dynamic balancing of electricity in the network (KPI_{1A} calculated as in (7.12)), the stability of the electricity system (KPI_{2A} calculated as in (7.14)), duration (KPI_{2B} calculated as in (7.15)) and frequency (KPI_{2C} calculated as in (7.16)) of interruptions per customer, voltage quality in terms of voltage variations (KPI_{2D}), and level of losses in distribution networks (KPI_{3A} calculated as in (7.17)). Seven terminal criteria characterise the overall hierarchy. The performances of the alternatives considering these criteria are assessed employing quantitative indicators. The formulas for evaluating the numerical value of each indicator are described in section 7.2.2.

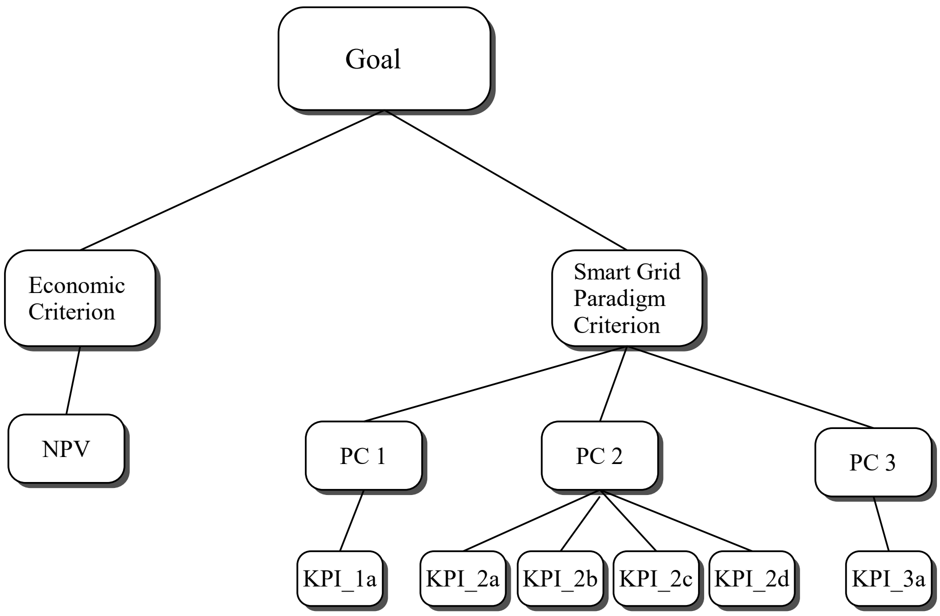

Figure 7.9. Overview of the hierarchy of evaluation criteria (layered case) [26]

The DM that corresponds to the decision-making problem under analysis is represented in Table 7.10. In which the alternative A_1 represents the reference scenario (*Business as Usual* - BaU).

Table 7.10. DM of the decision-making problem

Option	Economic branch *NPV [k€]*	Smart Grid Branch					
		KPI1A [MW]	***KPI2A [MW]***	***KPI2B [occ/y]***	***KPI2C [h/y]***	***KPI2D [pu]***	***KPI3A [MWh]***
A_1	0	0	0	2.026	0.837	11.48	11216.1
A_2	4.257	66.2	1269.2	2.017	0.751	10.68	10677.7
A_3	3.371	184.2	2903.9	2.017	0.751	10.68	10701.3
A_4	12.905	48.4	984.6	2.017	0.751	10.68	10661.3
A_5	88.587	38.2	574.1	2.017	0.751	10.69	10682.4

7.3.1 Appraisal of the project alternatives based on objective weights

Through a comparative analysis, the objective weighting methods are evaluated trought the decision-making problem studied in section 7.2.

7.3.1.1 Analysis according to Shannon's entropy method

The procedure for weighting the evaluation criteria according to Shannon's entropy method is described in section 4.2.2. The DM containing the attributes of the alternatives used as input for the weighting procedure is represented by Table 7.10. The first step of the weighting procedure is the normalisation of the DM, according to (4.19) and (4.20). The criteria NPV, KPI_{1A}, and KPI_{2A} have to be maximised, while the remaining criteria have to be minimised. In Table 7.11, the DM of the decision-making problem normalised in terms of relative frequencies is represented.

Table 7.11. Normalised decision matrix in terms of relative frequencies

Alternative	**NPV**	**KPI_{1A}**	**KPI_{2A}**	**KPI_{2B}**	**KPI_{2C}**	**KPI_{2D}**	**KPI_{3A}**
A_1	0.0000	0.0000	0.0000	0.1993	0.1832	0.1887	0.1923
A_2	0.0390	0.1963	0.2214	0.2002	0.2042	0.2028	0.2020
A_3	0.0309	0.5467	0.5066	0.2002	0.2042	0.2029	0.2015
A_4	0.1183	0.1436	0.1718	0.2002	0.2042	0.2028	0.2023
A_5	0.8118	0.1134	0.1002	0.2002	0.2042	0.2028	0.2019

Starting from the data in Table 7.11 and by exploiting (4.22), (4.23), and (4.24) is possible to calculate the entropy, the divergence, and the weight of each evaluation criteria. The result of the evaluation is in Table 7.12.

Table 7.12. Result of Shannon's entropy weighting process

Criterion	**Entropy**	**Divergence**	**Entropic weight**
NPV	0.4074	0.5926	0.5336
KPI_{1A}	0.7303	0.2697	0.2429
KPI_{2A}	0.7527	0.2473	0.2227
KPI_{2B}	≅1.0000	$\cong 10^{-7}$	$\cong 10^{-7}$
KPI_{2C}	0.9994	0.0006	0.0005
KPI_{2D}	0.9997	0.0003	0.0002
KPI_{3A}	0.9998	0.0001	0.0001

As shown in Table 7.12, the NPV criterion is dominant over the remaining evaluation criteria. Shannon's entropy method has identified that the economic criterion has the highest share of information for this decision-making problem. On the contrary, KPI_{2B} has to be neglected to analyse the decision-making problem of this case study. The relevance assigned to the criteria KPI_{2C}, KPI_{2D}, and KPI_{3A} is insignificant by considering the remaining criteria of the set. By considering the weights obtained utilizing the subjective weighting, the weighting scheme obtained through Shannon's entropy method differs. By linearly combining the normalised local scores of the alternatives (Table 7.11) and the entropy weight (Table 7.12), the overall score for each alternative is obtained (Table 7.13).

Table 7.13. The overall score obtained by the alternatives (Shannon's entropy weights)

Alternative	Overall score	Ranking
A_1	0.0266	5
A_2	0.2224	4
A_3	0.2419	2
A_4	0.2393	3
A_5	0.2698	1

According to the result presented in Table 7.13, the alternative A_5 is suggested as the best alternative by the MC-CBA method, exploiting the entropy weights. The relevance assigned to the NPV criterion strongly influence the outcome of the analysis; A_5 is the alternative that shows the highest normalised local score on this criterion. The second-best alternative identified by the method is A_3, unlike the result obtained in the evaluation based on the subjective weights in which A_4 occupies the second place in the ranking of alternatives.

7.3.1.2 Analysis according to the standard deviation weighting method

The procedure for weighting the evaluation criteria according to the standard deviation method is described in section 4.2.4. The standard deviation of the attributes is calculated by considering the DM normalised in terms of relative frequency presented in Table 7.11; the weights of the evaluation criteria obtained according to (4.27) are shown in Table 7.14.

Table 7.14. Standard deviation weights

Criteria	Standard deviation	Weight
NPV	0.3448	0.4522
KPI_{1A}	0.2067	0.2711
KPI_{2A}	0.1906	0.2499
KPI_{2B}	0.0004	0.0005
KPI_{2C}	0.0094	0.0123
KPI_{2D}	0.0063	0.0083
KPI_{3A}	0.0043	0.0057

The standard deviation method assigns the highest relevance to the NPV criterion; however, it is not dominant over the criteria set. By comparing Table 7.14 and Table 7.12, the same trend in assigning the relevance of the evaluation criteria can be observed; nonetheless, no criterion is excluded from the analysis. However, the weight assigned to KPI_{2B} makes the influence of this criterion on the final evaluation result negligible. The overall relevance of the criteria KPI_{2C}, KPI_{2D}, and KPI_{3A} concerning the overall criteria set is about 2.5%; therefore, these three criteria can be neglected from the analysis. The overall scores are calculated by the linear combination of the normalised local scores (Table 7.11) and the standard deviation (Table 7.14) weights. From the overall result of the MC-CBA assessment presented in Table 7.15, it is highlighted that the overall result of the analysis is highly influenced by the criteria NPV, KPI_{1A}, and KPI_{2A} since the alternatives show a high dispersion of the attribute values.

Table 7.15. The overall score of the alternatives (Standard deviation weights)

Alternative	Overall score	Ranking
A_1	0.0266	5
A_2	0.2251	4
A_3	0.2468	2
A_4	0.2396	3
A_5	0.2618	1

The overall result of the evaluation obtained using the standard deviation weights coincides, in terms of sorting, with the result of the analysis performed considering the entropy weights.

7.3.1.3 Analysis according to the CRITIC weighting method

The procedure for weighting the evaluation criteria according to the CRITIC method is described in section 4.2.5. The CRITIC weights of the evaluation criteria are obtained by evaluating the DM normalised according to (4.11) and (4.12). The criteria NPV, KPI_{1A}, and KPI_{2A} have to be maximised, while the remaining criteria have to be minimised. The normalised DM is represented in Table 7.16.

Table 7.16. Decision Matrix normalised according to the interval min-max

Alternative	NPV	KPI_{1A}	KPI_{2A}	KPI_{2B}	KPI_{2C}	KPI_{2D}	KPI_{3A}
A_1	0	0	0	0	0	0	0
A_2	0.0481	0.3591	0.4371	1	1	0.9988	0.9703
A_3	0.0381	1	1	1	1	1.0000	0.9279
A_4	0.1457	0.2628	0.3391	1	1	0.9975	1
A_5	1	0.2074	0.1977	1	1	0.9950	0.9618

The CRITIC weight for the evaluation criteria are obtained by exploiting (4.28), (4.29), and (4.30). The obtained CRITIC weights are shown in Table 7.17.

Table 7.17. CRITIC weights

Criteria	Weight
NPV	0.3039
KPI_{1A}	0.1614
KPI_{2A}	0.1534
KPI_{2B}	0.0950
KPI_{2C}	0.0950
KPI_{2D}	0.0947
KPI_{3A}	0.0967

As highlighted by Table 7.17, the NPV criterion achieves the highest weight. By considering the entropy and the standard deviation weights, the criteria KPI_{1A} and KPI_{2A} halve their relevance. Criteria KPI_{2B}, KPI_{2C}, KPI_{2D}, KPI_{3A} obtain an overall relevance of about 1% of the whole criteria set relevance. Even though the weights obtained using the CRITIC weighting method are different from the values obtained by the entropy and standard deviation method, the trend of emphasizing the relevance of the NPV, KPI_{1A} and KPI_{2A} is maintained. By linearly combining the local normalised scores of the alternatives (Table 7.11) and the criteria weights (Table 7.17), the overall score related to each alternative is obtained (Table 7.18).

Table 7.18. The overall scores of the alternatives (CRITIC weights)

Alternative	Overall score	Ranking
A_1	0.0268	5
A_2	0.2310	4
A_3	0.2410	3
A_4	0.2446	2
A_5	0.2566	1

Unlike the result obtained through the use of entropy weights and the weights based on the standard deviation of the attributes, the result offered by the CRITIC method coincides, in terms of ordering alternatives, with the result obtained using the subjective weights. This compliance of final results is obtained, although the CRITIC weighting scheme is different from the subjective weighting scheme. Excluding A_1, A_5 is the alternative that behaves worse in 3 of 7 criteria; however, the greater relevance of the NPV criterion combined with the evident prevalence of A_5 in this criterion is decisive for defining the overall result.

7.3.1.4 Analysis according to the Ideal Point weighting method

The procedure for weighting the evaluation criteria according to the Ideal Point method is described in section 4.3.1. The Ideal Points weights of the evaluation criteria are obtained by evaluating the DM normalised using (4.11) and (4.12). The criteria NPV, KPI_{1A}, and KPI_{2A} have to be maximised, while the remaining criteria have to be minimised. The normalised DM is represented in Table 7.16.

The Ideal Point method involves the definition of a virtual alternative composed by considering the maximum values of the attributes of the alternatives on all evaluation criteria. The criteria weights are then determined as a function of the distance between the real alternatives and the virtual (ideal) alternative. For the case study, the Euclidean distance that exists between the real alternatives and the ideal alternative considering each evaluation criterion is reported in Table 7.19.

Table 7.19. Distances among the real alternatives and the ideal point

Alternative	NPV	KPI_{1A}	KPI_{2A}	KPI_{2B}	KPI_{2C}	KPI_{2D}	KPI_{3A}
A_1	1	1	1	1	1	1	1
A_2	0.9062	0.4107	0.3169	0	0	0	0.0009
A_3	0.9253	0	0	0	0	0	0.0052
A_4	0.7299	0.5435	0.4368	0	0	0	0
A_5	0	0.6282	0.6437	0	0	0	0.0015

Considering the distances in Table 7.19, the Ideal Point weights are obtained by solving the model (4.34) and (4.35), the result is presented in Table 7.20.

Table 7.20. Ideal Point weights

Criteria	Weight
NPV	0.0553
KPI_{1A}	0.0763
KPI_{2A}	0.0821
KPI_{2B}	0.1969
KPI_{2C}	0.1969
KPI_{2D}	0.1969
KPI_{3A}	0.1955

The weighting scheme obtained by the Ideal Point method is widely different from the weighting scheme obtained with the methods analysed in sections 7.2 (subjective method), 7.3.1.1 (entropic method), 7.3.1.2 (SD method), and 7.3.1.3 (CRITIC method). According to the Ideal Point method, the NPV criterion is the least relevant criterion of the set; its impact on the final assessment is equal to 5.5% of the total criteria relevance. Similarly, the KPI_{1A} and KPI_{2A} criteria have a significantly lower importance than the remaining criteria of the set. This result is opposite to the result obtained using the objective methods studied in sections 7.3.1.1, 7.3.1.2, and 7.3.1.3. The weight assigned to KPI_{2B}, KPI_{2C}, KPI_{2D}, KPI_{3A} is about 19% of the total criteria relevance. The Ideal Point method exalts the evaluation metrics to which the real alternatives are close to the ideal alternative. In the case study, the four smart grid alternatives have the highest attribute value in KPI_{2B}, KPI_{2C}, KPI_{2D}, KPI_{3A}. The overall scores for the alternatives are obtained by the linear combination of the normalised local scores in Table 7.16 and the Ideal Point weight in Table 7.20, the result obtained is shown in Table 7.21.

Table 7.21. The overall score (Ideal Point weights)

Alternative	Overall score	Ranking
A_1	0.0270	5
A_2	0.2403	4
A_3	0.2404	3
A_4	0.2501	1
A_5	0.2422	2

The Ideal Point weighting method emphasizes the criteria KPI_{2B}, KPI_{2C}, KPI_{2D}, KPI_{3A} over the criteria NPV, KPI_{1A} e KPI_{2A}. In general, the Ideal Point method favours the criteria to which the alternatives have a high normalised attribute value, i.e. closer to the value of the ideal virtual alternative. In the case study, this behaviour is emphasized because four alternatives out of five have values equal to the attribute values of the ideal alternative. As shown in Table 7.21, the value of the overall score obtained from the first four alternatives of the ranking is similar: these alternatives have similar attribute values for the majority of the criteria, these values are in turn close to the values of the ideal alternative. It highlights that the result of the analysis of the alternatives is strongly influenced by the logic behind the procedure of assigning relevance to the criteria. The first four alternatives can be considered equivalents in terms of merit. The differences in the values of the attributes on the four most relevant criteria determine that the alternative A_4 is suggested as the best of the set.

7.3.1.5 Analysis according to the maximising the generalized deviation method

The procedure for weighting the evaluation criteria according to the MGD method follows the procedure described in section 4.3.3. The weights of the evaluation criteria are obtained by evaluating the DM normalised using to (4.11) and (4.12). The criteria NPV, KPI_{1A}, and KPI_{2A} have to be maximised, while the remaining criteria have to be minimised. The normalised DM is represented in Table 7.16. For each criterion, the generalized deviation is calculated by using the Euclidean distance (4.47). The obtained distances are reported in Table 7.21, Table 7.22, Table 7.23, Table 7.24, Table 7.25, Table 7.26, and Table 7.27.

Table 7.22. Distances among alternatives considering NPV criterion

NPV	A_1	A_2	A_3	A_4	A_5
A_1	0	0.0481	0.0381	0.1457	1
A_2	0.0481	0	0.0100	0.0976	0.9519
A_3	0.0381	0.0100	0	0.1076	0.9619
A_4	0.1457	0.0976	0.1076	0	0.8543
A_5	1	0.9519	0.9619	0.8543	0

Table 7.23. Distances among alternatives considering KPI_{1A} criterion

KPI_{1A}	A_1	A_2	A_3	A_4	A_5
A_1	0	0.3591	1	0.2628	0.2074
A_2	0.3591	0	0.6409	0.0964	0.1517
A_3	1	0.6409	0	0.7372	0.7926
A_4	0.2628	0.0964	0.7372	0	0.0554
A_5	0.2074	0.1517	0.7926	0.0554	0

Table 7.24. Distances among alternatives considering KPI_{2A} criterion

KPI_{2A}	A_1	A_2	A_3	A_4	A_5
A_1	0	0.4371	1	0.3391	0.1977
A_2	0.4371	0	0.5629	0.0980	0.2394
A_3	1	0.5629	0	0.6609	0.8023
A_4	0.3391	0.0980	0.6609	0	0.1414
A_5	0.1977	0.2394	0.8023	0.1414	0

Table 7.25. Distances among alternatives considering KPI_{2B} criterion

KPI_{2B}	A_1	A_2	A_3	A_4	A_5
A_1	0	1	1	1	1
A_2	1	0	0	0	0
A_3	1	0	0	0	0
A_4	1	0	0	0	0
A_5	1	0	0	0	0

Table 7.26. Distances among alternatives considering KPI_{2c} criterion

KPI_{2C}	A_1	A_2	A_3	A_4	A_5
A_1	0	1	1	1	1
A_2	1	0	0	0	0
A_3	1	0	0	0	0
A_4	1	0	0	0	0
A_5	1	0	0	0	0

Table 7.27. Distances among alternatives considering KPI_{2D} criterion

KPI_{2D}	A_1	A_2	A_3	A_4	A_5
A_1	0	0.9988	1	0.9975	0.9950
A_2	0.9988	0	0.0012	0.0012	0.0037
A_3	1	0.0012	0	0.0025	0.0050
A_4	0.9975	0.0012	0.0025	0	0.0025
A_5	0.9950	0.0037	0.0050	0.0025	0

Table 7.28. Distances among alternatives considering KPI_{3A} criterion

KPI_{3A}	A_1	A_2	A_3	A_4	A_5
A_1	0	0.9703	0.9279	1	0.9618
A_2	0.9703	0	0.0424	0.0297	0.0085
A_3	0.9279	0.0424	0	0.0721	0.0339
A_4	1	0.0297	0.0721	0	0.0382
A_5	0.9618	0.0085	0.0339	0.0382	0

By considering the obtained distances, the weight of each evaluation criteria is evaluated according to (4.52), results are shown in Table 7.29.

Table 7.29. Criteria weights obtained according to the Maximising generalized deviation method

Criterion	Weight
NPV	0.1467
KPI_{1A}	0.1529
KPI_{2A}	0.1656
KPI_{2B}	0.1321
KPI_{2C}	0.1321
KPI_{2D}	0.1326
KPI_{3A}	0.1378

Table 7.29 shows that the evaluation criteria have a similar relevance. The distribution of the value of the weights among criteria is completely different from that observed for the methodologies analysed in the previous sections. The MGD method has assigned a lower relevance to the criteria related to a low deviation between the attributes of the four smart grid alternatives. However, the deviation between the attributes of the smart grid alternatives and the reference alternative has influenced the method of determining a homogeneous distribution of the weights between the criteria. By the linear combination of the normalised local scores of the alternatives (Table 7.16) and the weights of criteria (Table 7.29), the overall score of the alternatives is obtained (Table 7.30).

Table 7.30. The overall score of the alternatives (Maximising generalized deviation method)

Alternative	Overall score	Ranking
A_1	0.0269	5
A_2	0.2366	4
A_3	0.2453	2
A_4	0.2469	1
A_5	0.2443	3

Table 7.30 highlights that the MGD method produces the same final ranking as the ranking obtained with the Ideal Point method. The four smart grid initiatives obtain a similar value for the overall score; therefore, the MGD seems not able to discriminate among them.

7.3.2 Aggregating subjective and objective weights

In this section, the subjective weights obtained in section 7.2.4 are aggregated with the objective weights obtained in section 7.3.1 by exploiting the aggregation strategies described in section 4.4. The analysis considers an equal relevance of the subjective and objective weights ($\alpha=0.5$). For the sake of simplicity, the strategy described in sections 4.4.1, 4.4.2, and 4.4.3 are renamed respectively, A-Strategy (S. A), B-Strategy (S. B), and C-Strategy (S. C).

Table 7.31 shows the weights obtained by aggregating the subjective and entropy weights.

Table 7.31. Aggregated weighs (subjective and entropy methods)

Criterion	Objective weight	Subjective weight	Aggregated weight (S. A)	Aggregated weight (S. B)	Aggregated weight (S. C)
NPV	0.5336	0.5000	0.8427	0.5168	0.6253
KPI_{1A}	0.2429	0.1667	0.1279	0.2048	0.2436
KPI_{2A}	0.2227	0.0417	0.0293	0.1322	0.1166
KPI_{2B}	$\cong 9E10^{-7}$	0.0417	$\cong 1E10^{-7}$	0.0208	0.0002
KPI_{2C}	0.0005	0.0417	0.0001	0.0211	0.0055
KPI_{2D}	0.0002	0.0417	$\cong 3E10^{-5}$	0.0209	0.0037
KPI_{3A}	0.0001	0.1667	0.0001	0.0834	0.0051

The overall scores obtained by exploiting the aggregated weights in Table 7.31 are displayed in Table 7.32.

Table 7.32. Overall scores (subjective and entropy methods)

	A_1	A_2	A_3	A_4	A_5
Overall score (subj.)	0.0268	0.2242	0.2273	0.2468	0.2749
Ranking (subj.)	5	4	3	2	1
Overall score (obj.)	0.0266	0.2224	0.2419	0.2393	0.2698
Ranking (obj.)	5	4	2	3	1
Overall score (S. A)	0.0265	0.2123	0.2189	0.2389	0.3033
Ranking (S. A)	5	4	3	2	1
Overall score (S. B)	0.0267	0.2233	0.2346	0.2430	0.2724
Ranking (S. B)	5	4	3	2	1
Overall score (S. C)	0.0266	0.2195	0.2344	0.2394	0.2802

Table 7.33 shows the weights obtained by aggregating the subjective and standard deviation weights.

Table 7.33. Aggregated weighs (subjective and standard deviation methods)

Criterion	**Objective weight**	**Subjective weight**	**Aggregated weight (S. A)**	**Aggregated weight (S. B)**	**Aggregated weight (S. C)**
NPV	0.4522	0.5000	0.7975	0.4761	0.5486
KPI_{1A}	0.2711	0.1667	0.1593	0.2189	0.2452
KPI_{2A}	0.2499	0.0417	0.0367	0.1458	0.1177
KPI_{2B}	0.0005	0.0417	0.0001	0.0211	0.0054
KPI_{2C}	0.0123	0.0417	0.0018	0.0270	0.0261
KPI_{2D}	0.0083	0.0417	0.0012	0.0250	0.0214
KPI_{3A}	0.0057	0.1667	0.0033	0.0862	0.0355

The overall scores obtained by exploiting the aggregated weights in Table 7.33 are displayed in Table 7.34.

Table 7.34. Overall scores (subjective and standard deviation methods)

	A_1	**A_2**	**A_3**	**A_4**	**A_5**
Overall score (subj.)	0.0266	0.2138	0.2219	0.2391	0.2986
Ranking (subj.)	5	4	3	2	1
Overall score (obj.)	0.0267	0.2247	0.2371	0.2432	0.2684
Ranking (obj.)	5	4	3	2	1
Overall score (S. A)	0.0266	0.2222	0.2362	0.2409	0.2741
Ranking (S. A)	5	4	3	2	1
Overall score (S. B)	0.0266	0.2138	0.2219	0.2391	0.2986
Ranking (S. B)	5	4	3	2	1
Overall score (S. C)	0.0267	0.2247	0.2371	0.2432	0.2684

Table 7.35 shows the weights obtained by aggregating the subjective and CRITIC weights.

Table 7.35. Aggregated weighs (subjective and CRITIC methods)

Criterion	Objective weight	Subjective weight	Aggregated weight (S. A)	Aggregated weight (S. B)	Aggregated weight (S. C)
NPV	0.3039	0.5000	0.7126	0.4019	0.4106
KPI_{1A}	0.1614	0.1667	0.1262	0.1640	0.1728
KPI_{2A}	0.1534	0.0417	0.0300	0.0975	0.0842
KPI_{2B}	0.0950	0.0417	0.0186	0.0683	0.0663
KPI_{2C}	0.0950	0.0417	0.0186	0.0683	0.0663
KPI_{2D}	0.0947	0.0417	0.0185	0.0682	0.0662
KPI_{3A}	0.0967	0.1667	0.0756	0.1317	0.1337

The overall scores obtained by exploiting the aggregated weights in Table 7.35 are displayed in Table 7.36.

Table 7.36. Overall scores (subjective and CRITIC methods)

	A_1	A_2	A_3	A_4	A_5
Overall score (subj.)	0.0266	0.2138	0.2219	0.2391	0.2986
Ranking (subj.)	5	4	3	2	1
Overall score (obj.)	0.0268	0.2310	0.2410	0.2446	0.2566
Ranking (obj.)	5	4	3	2	1
Overall score (S. A)	0.0266	0.2169	0.2209	0.2425	0.2932
Ranking (S. A)	5	4	3	2	1
Overall score (S. B)	0.0268	0.2276	0.2342	0.2457	0.2658
Ranking (S. B)	5	4	3	2	1
Overall score (S. C)	0.0268	0.2273	0.2336	0.2457	0.2666

Table 7.37 shows the weights obtained by aggregating the subjective and ideal point weights.

Table 7.37. Aggregated weighs (subjective and ideal point methods)

Criterion	Objective weight	Subjective weight	Aggregated weight (S. A)	Aggregated weight (S. B)	Aggregated weight (S. C)
NPV	0.0553	0.5000	0.2738	0.2776	0.2105
KPI_{1A}	0.0763	0.1667	0.1259	0.1215	0.1427
KPI_{2A}	0.0821	0.0417	0.0339	0.0619	0.0741
KPI_{2B}	0.1969	0.0417	0.0813	0.1193	0.1147
KPI_{2C}	0.1969	0.0417	0.0813	0.1193	0.1147
KPI_{2D}	0.1969	0.0417	0.0813	0.1193	0.1147
KPI_{3A}	0.1955	0.1667	0.3226	0.1811	0.2285

The overall scores obtained by exploiting the aggregated weights in Table 7.37 are displayed in Table 7.38.

Table 7.38. Overall scores (subjective and ideal point methods)

	A_1	**A_2**	**A_3**	**A_4**	**A_5**
Overall score (subj.)	0.0266	0.2138	0.2219	0.2391	0.2986
Ranking (subj.)	5	4	3	2	1
Overall score (obj.)	0.0270	0.2403	0.2404	0.2501	0.2422
Ranking (obj.)	5	4	3	1	2
Overall score (S. A)	0.0269	0.2322	0.2281	0.2541	0.2587
Ranking (S. A)	5	4	2	3	1
Overall score (S. B)	0.0269	0.2322	0.2339	0.2484	0.2586
Ranking (S. B)	5	4	3	2	1
Overall score (S. C)	0.0269	0.2344	0.2359	0.2505	0.2522

Table 7.39 shows the weights obtained by aggregating the subjective and MGD weights.

Table 7.39. Aggregated weighs (subjective and maximising generalized deviation methods)

Criterion	**Objective weight**	**Subjective weight**	**Aggregated weight (S. A)**	**Aggregated weight (S. B)**	**Aggregated weight (S. C)**
NPV	0.1467	0.5000	0.5051	0.3234	0.3051
KPI_{1A}	0.1529	0.1667	0.1755	0.1598	0.1798
KPI_{2A}	0.1656	0.0417	0.0475	0.1037	0.0936
KPI_{2B}	0.1321	0.0417	0.0379	0.0869	0.0836
KPI_{2C}	0.1321	0.0417	0.0379	0.0869	0.0836
KPI_{2D}	0.1326	0.0417	0.0380	0.0871	0.0837
KPI_{3A}	0.1378	0.1667	0.1581	0.1522	0.1707

The overall scores obtained by exploiting the aggregated weights in Table 7.39 are displayed in Table 7.40.

Table 7.40. Overall scores (subjective and maximising generalized deviation methods)

	A_1	**A_2**	**A_3**	**A_4**	**A_5**
Overall score (subj.)	0.0266	0.2138	0.2219	0.2391	0.2986
Ranking (subj.)	5	4	3	2	1
Overall score (obj.)	0.0269	0.2366	0.2453	0.2469	0.2443
Ranking (obj.)	5	4	2	1	3
Overall score (S. A)	0.0267	0.2240	0.2280	0.2464	0.2749
Ranking (S. A)	5	4	3	2	1
Overall score (S. B)	0.0268	0.2304	0.2363	0.2468	0.2596
Ranking (S. B)	5	4	3	2	1
Overall score (S. C)	0.0268	0.2310	0.2367	0.2476	0.2579

The results obtained in the five assessments presented in this section show that the value assigned to criteria weights varies according to the aggregation strategy adopted. As expected, the aggregation strategies define a compromise between the weights obtained by subjective methods and the values obtained by objective methods. Consequently, the overall scores of alternatives vary according to the aggregate weight values. In some cases, the result obtained by considering the aggregated weights is different compared to the result of the evaluation made with both subjective and objective weights. Therefore, it is the analyst in charge of comparing the results of the three scenarios and determining if compliance with stakeholder expectations exists. The aggregation of subjective and objective weights can be useful to smooth out the subjective assessment result with objective information on the alternatives. However, none of the objective methods has a recognized absolute validity; the indication given by each depends on the hypothesis on which the method is based. In this context, the decisional problem for the analyst shifts from choosing the best alternative to establishing the method to rely on. The comparative analysis of the results of the various methods has the advantage of increasing the knowledge on the performances of the alternatives; however, this advantage is lost when conflicting final indications are obtained. In this scenario, the decision problem is not simplified; the analysis of the stability of the solution is relevant to support the analyst.

7.3.3 Analysis of the solution stability

The result of the MCA evaluation is often represented by a ranking drawn up based on the overall score obtained by each alternative. This overall score is a function of the value of the attributes of the alternatives and the weights of the evaluation criteria. To verify the robustness of the final result obtained, it is of interest to evaluate the stability of the solution or to verify within which range the criteria weights may vary without having changes in the ranking order. In the case study, the robustness of the result concerning the stability of the best alternative position is studied. In general, in planning activities, it is of interest to identify the best alternative of the set to evaluate its implementation; therefore, it is crucial to assess the degree of robustness of the best alternative with respect to the relevance of the evaluation criteria. The variation in the ranking of the other alternatives is of interest only when it becomes necessary to deepen the study of the decision-making problem. In this section, the stability analysis of the best solution is performed according to the methodology described in section 4.5. The value of the parameter η^* has been calculated for each case; it represents the proportionality coefficient according to which the criteria weights can vary without determining final ranking changes [128]. According to the value of η^*, the range of the criteria weights within which the final solution is stable can be calculated. The parameter η^* represent the degree of robustness of the solution, as the value of the parameter η^* grows, the robustness of the solution increases.

7.3.3.1 Stability of the subjective weight evaluation

The analysis of the stability of the result obtained considering subjective weights has led to a parameter value of η^* = 0.5265, the interval of weights is shown in Table 7.41.

Table 7.41. Stability interval for subjective weights

Criteria	Lower value	Central value	Upper value
NPV	0.2367	0.5000	0.7633
KPI_{1A}	0.0789	0.1667	0.2544
KPI_{2A}	0.0197	0.0417	0.0636
KPI_{2B}	0.0197	0.0417	0.0636
KPI_{2C}	0.0197	0.0417	0.0636
KPI_{2D}	0.0197	0.0417	0.0636
KPI_{3A}	0.0789	0.1667	0.2544

7.3.3.2 Stability of the objective weight evaluation

The analysis of the stability of the result obtained considering entropy weights has led to a parameter value of η^{*} = 0.3006, the interval of weights is shown in Table 7.42.

Table 7.42. Stability interval for entropy weights

Criteria	Lower value	Central value	Upper value
NPV	0.3934	0.5336	0.6738
KPI_{1A}	0.1699	0.2429	0.3159
KPI_{2A}	0.1558	0.2227	0.2896
KPI_{2B}	6.19E-07	8.86E-07	1.15E-06
KPI_{2C}	3.52E-04	5.03E-04	6.55E-04
KPI_{2D}	1.59E-04	2.27E-04	2.95E-04
KPI_{3A}	7.37E-05	1.05E-04	1.37E-04

The analysis of the stability of the result obtained considering standard deviation weights has led to a parameter value of η^{*} = 0.1713, the interval of weights is shown in Table 7.43.

Table 7.43. Stability interval for standard deviation weights

Criteria	Lower value	Central value	Upper value
NPV	0.3748	0.4522	0.5297
KPI1A	0.2247	0.2711	0.3175
KPI2A	0.2071	0.2499	0.2927
KPI2B	0.0004	0.0005	0.0006
KPI2C	0.0102	0.0123	0.0144
KPI2D	0.0069	0.0083	0.0097
KPI3A	0.0047	0.0057	0.0066

The analysis of the stability of the result obtained considering CRITIC weights has led to a parameter value of η^{*} = 0.2628, the interval of weights is shown in Table 7.44.

Table 7.44. Stability interval for CRITIC weights

Criteria	Lower value	Central value	Upper value
NPV	0.2240	0.3039	0.3837
KPI_{1A}	0.1190	0.1614	0.2038
KPI_{2A}	0.1131	0.1534	0.1937
KPI_{2B}	0.0700	0.0950	0.1199
KPI_{2C}	0.0700	0.0950	0.1199
KPI_{2D}	0.0698	0.0947	0.1195
KPI_{3A}	0.2240	0.3039	0.3837

The analysis of the stability of the result obtained considering ideal point weights has led to a parameter value of η^{*} = 0.4213, the interval of weights is shown in Table 7.45.

Table 7.45. Stability interval for ideal point weights

Criteria	Lower value	Central value	Upper value
NPV	0.0320	0.0553	0.0786
KPI_{1A}	0.0441	0.0763	0.1084
KPI_{2A}	0.0475	0.0821	0.1168
KPI_{2B}	0.1140	0.1969	0.2799
KPI_{2C}	0.1140	0.1969	0.2799
KPI_{2D}	0.1140	0.1969	0.2799
KPI_{3A}	0.1131	0.1955	0.2778

The analysis of the stability of the result obtained considering MGD weights has led to a parameter value of $\eta^* = 0.4213$, the interval of weights is shown in Table 7.46.

Table 7.46. Stability interval for MGD weights

Criteria	Lower value	Central value	Upper value
NPV	0.1387	0.1467	0.1547
KPI_{1A}	0.1446	0.1529	0.1613
KPI_{2A}	0.1566	0.1656	0.1747
KPI_{2B}	0.1249	0.1321	0.1393
KPI_{2C}	0.1249	0.1321	0.1393
KPI_{2D}	0.1254	0.1326	0.1399
KPI_{3A}	0.1303	0.1378	0.1453

7.3.3.3 Stability of the aggregated weight evaluation

In this section, the results of the stability analysis of the 15 cases in which criteria weights are obtained through an aggregation strategy are presented.

In Table 7.47, the stability interval for the weights obtained by aggregating subjective and entropy weights is shown.

Table 7.47. Stability interval for aggregated subjective-entropy weights

Criterion	A-**strategy**			B-**strategy**			C-**strategy**		
	Lower value	**Central value**	**Upper value**	**Lower value**	**Central value**	**Upper value**	**Lower value**	**Central value**	**Upper value**
NPV	0.7178	0.8427	0.9676	0.3016	0.5168	0.7320	0.4466	0.6253	0.8040
KPI_{1A}	0.0264	0.1279	0.2294	0.1136	0.2048	0.2960	0.1274	0.2436	0.3597
KPI_{2A}	0.0060	0.0293	0.0526	0.0733	0.1322	0.1911	0.0610	0.1166	0.1722
KPI_{2B}	2.4E-08	1.2E-07	2.1E-07	1.2E-02	2.1E-02	3.0E-02	1.2E-04	2.3E-04	3.4E-04
KPI_{2C}	1.4E-05	6.6E-05	1.2E-04	1.2E-02	2.1E-02	3.1E-02	2.9E-03	5.5E-03	8.2E-03
KPI_{2D}	6.2E-06	2.9E-05	5.4E-05	1.2E-02	2.1E-02	3.0E-02	1.9E-03	3.7E-03	5.5E-03
KPI_{3A}	1.2E-05	5.6E-05	9.9E-05	4.6E-02	8.4E-02	1.2E-01	2.7E-03	5.1 E-03	7.5E-03
$\boldsymbol{\eta^*}$	0.7938			0.4454			0.4769		

In Table 7.48, the stability interval for the weights obtained by aggregating subjective and standard deviation weights is shown.

Table 7.48. Stability interval for aggregated subjective-standard deviation weights

Criterion	A-strategy			B-strategy			C-strategy		
	Lower value	Central value	Upper value	Lower value	Central value	Upper value	Lower value	Central value	Upper value
NPV	0.6482	0.7975	0.9468	0.2947	0.4761	0.6575	0.3553	0.5486	0.7420
KPI_{1A}	0.0419	0.1593	0.2768	0.1355	0.2189	0.3023	0.1402	0.2452	0.3503
KPI_{2A}	0.0097	0.0367	0.0638	0.0902	0.1458	0.2013	0.0673	0.1177	0.1682
KPI_{2B}	0.0000	0.0001	0.0001	0.0131	0.0211	0.0291	0.0031	0.0054	0.0077
KPI_{2C}	0.0005	0.0018	0.0031	0.0167	0.0270	0.0373	0.0149	0.0261	0.0373
KPI_{2D}	0.0003	0.0012	0.0021	0.0155	0.0250	0.0345	0.0123	0.0214	0.0306
KPI_{3A}	0.0009	0.0033	0.0058	0.0533	0.0862	0.1190	0.0203	0.0355	0.0506
η^*	0.7371			0.3810			0.4284		

In Table 7.49, the stability interval for the weights obtained by aggregating subjective and CRITIC weights is shown. In Table 7.50, the stability interval for the weights obtained by aggregating subjective and ideal point weights is shown. In Table 7.51, the stability interval for the weights obtained by aggregating subjective and MGD weights is shown.

Table 7.49. Stability interval for aggregated subjective-CRITIC weights

Criterion	A-strategy			B-strategy			C-strategy		
	Lower value	Central value	Upper value	Lower value	Central value	Upper value	Lower value	Central value	Upper value
NPV	0.4918	0.7126	0.9334	0.2244	0.4019	0.5795	0.2251	0.4106	0.5961
KPI_{1A}	0.0292	0.1262	0.2231	0.0916	0.1640	0.2365	0.0947	0.1728	0.2508
KPI_{2A}	0.0069	0.0300	0.0530	0.0544	0.0975	0.1406	0.0462	0.0842	0.1223
KPI_{2B}	0.0043	0.0186	0.0328	0.0381	0.0683	0.0985	0.0363	0.0663	0.0962
KPI_{2C}	0.0043	0.0186	0.0328	0.0381	0.0683	0.0985	0.0363	0.0663	0.0962
KPI_{2D}	0.0043	0.0185	0.0327	0.0380	0.0682	0.0983	0.0363	0.0662	0.0960
KPI_{3A}	0.0175	0.0756	0.1337	0.0735	0.1317	0.1899	0.0733	0.1337	0.1941
η^*	0.7684			0.4418			0.4517		

Table 7.50. Stability interval for aggregated subjective-ideal point weights

Criterion	A-strategy			B-strategy			C-strategy		
	Lower value	Central value	Upper value	Lower value	Central value	Upper value	Lower value	Central value	Upper value
NPV	0.2422	0.2738	0.3054	0.1980	0.2776	0.3573	0.1993	0.2105	0.2218
KPI_{1A}	0.1113	0.1259	0.1404	0.0866	0.1215	0.1563	0.1351	0.1427	0.1504
KPI_{2A}	0.0300	0.0339	0.0378	0.0441	0.0619	0.0797	0.0701	0.0741	0.0780
KPI_{2B}	0.0719	0.0813	0.0907	0.0851	0.1193	0.1535	0.1086	0.1147	0.1208
KPI_{2C}	0.0719	0.0813	0.0907	0.0851	0.1193	0.1535	0.1086	0.1147	0.1208
KPI_{2D}	0.0719	0.0813	0.0906	0.0851	0.1193	0.1535	0.1086	0.1147	0.1208
KPI_{3A}	0.2854	0.3226	0.3599	0.1291	0.1811	0.2330	0.2163	0.2285	0.2408
η^*	0.1155			0.2870			0.0535		

Table 7.51. Stability interval for aggregated subjective-MGD weights

Criterion	A-strategy			B-strategy			C-strategy		
	Lower value	**Central value**	**Upper value**	**Lower value**	**Central value**	**Upper value**	**Lower value**	**Central value**	**Upper value**
NPV	0.2435	0.5051	0.7667	0.2199	0.3234	0.4268	0.2259	0.3051	0.3843
KPI_{1A}	0.0827	0.1755	0.2682	0.1087	0.1598	0.2109	0.1331	0.1798	0.2265
KPI_{2A}	0.0224	0.0475	0.0726	0.0705	0.1037	0.1368	0.0693	0.0936	0.1179
KPI_{2B}	0.0179	0.0379	0.0579	0.0591	0.0869	0.1147	0.0619	0.0836	0.1053
KPI_{2C}	0.0179	0.0379	0.0579	0.0591	0.0869	0.1147	0.0619	0.0836	0.1053
KPI_{2D}	0.0179	0.0380	0.0581	0.0593	0.0871	0.1150	0.0620	0.0837	0.1055
KPI_{3A}	0.0745	0.1581	0.2417	0.1035	0.1522	0.2009	0.1264	0.1707	0.2150
$\boldsymbol{\eta}^*$	0.5286			0.3199			0.2596		

From the results obtained from the stability analysis of the solution obtained with subjective and objective methods, the solution to the decision-making problem that achieves the greatest degree of stability is obtained in subjective weights. The criteria weights may vary for an interval of approximately 52% of their central value. This result is influenced by the dominance of the NPV criterion and by the fact that the best alternative (A_5) has the highest value of this attribute. The low robustness obtained by the Generalized Deviation Maximisation method evaluation is because the first and second alternatives of the ranking achieve a similar overall score. Therefore, the two alternatives can be considered first ranked.

The use of an aggregation strategy defines a new pattern of weights; the related robustness of the solution can be assessed independently from the robustness of the component weights. In the case study, the use of aggregation strategies for the weights determined by the entropy method, the standard deviation, CRITIC and the Maximisation of the Generalized Deviation determines a general increase in the degree of robustness of the solution. Conversely, the weights obtained by aggregating the subjective weights and the ideal point weights determine a solution for the decision-making problem characterised by low robustness.

The robustness measures the extent of the range for criteria weights values can change while the best alternative of the ranking remains unchanged. Each weight scheme represents a stakeholder point of view, the greater the extension of the stability range, the greater is the acceptability related to the identified best alternative. However, this approach does not ensure that a robust alternative is identified for all decision-making problems.

Once stability analysis is accomplished, the decision-maker assesses the degree of robustness of the solution found by the method and verifies if the stakeholder point of view is represented within the stability interval. In cases where more than one methodology has been used, the decision-maker can compare the results and opt for the solution with greater stability. The information regarding the robustness of the solution supports the decision-maker when using several methodologies for objective weighting gives different indications.

7.3.4 MinMaxRegret assessment

The assessment based on the MinMaxRegret (MMR) optimisation method is performed according to the procedure described in section 5.4. The DM is normalised using to (4.11) and (4.12). The criteria NPV, KPI_{1A}, and KPI_{2A} have to be maximised, while the remaining criteria have to be minimised. The normalised DM is represented in Table 7.52.

Table 7.52. Normalised DM

Alternative	NPV	KPI_{1A}	KPI_{2A}	KPI_{2B}	KPI_{2C}	KPI_{2D}	KPI_{3A}
A_1	0	0	0	0	0	0	0
A_2	0.0481	0.3591	0.4371	1	1	0.9988	0.9703
A_3	0.0381	1	1	1	1	1	0.9279
A_4	0.1457	0.2628	0.3391	1	1	0.9975	1
A_5	1	0.2074	0.1977	1	1	0.9950	0.9618

The optimisation model is characterised by the constraints described in (5.31) and by the non-dominance constraint (5.32). Furthermore, a constraint for avoiding that a criterion is excluded from the analysis is considered; therefore, each entry of the weight vector W_k can assume values within the interval (7.18), where *m* is the number of the evaluation criteria.

$$w_{k,j} \in [0.01m^{-1}, 0.5) \tag{7.18}$$

The optimisation model is evaluated by considering three different values for the parameter ε:

ε=0 - all weight schemes have the same probability;

ε=0.5;

ε=1 – extreme weight schemes are excluded from the analysis.

The starting point for searching the maximum regret value for each of the alternatives of the set is obtained by solving the model using a brute force approach using a step of Δw=0.05. Then, the problem of maximising the regret is solved analytically for each alternative of the set. This problem has been converted into a minimising problem by changing the sign of the objective function. The minimisation problem has been solved within the Matlab environment using the Interior Point method, which allows solving constrained non-linear optimisation problems. The result of each of the 5 optimisation problems is the maximum regret determined by the alternative in its worst-case scenario. The solution to the overall decision-making problem is identified by selecting the best alternative of the set that leads to the minimum-maximum regret value.

As shown in Table 7.53, the MMR method suggests alternative A_4 as the solution to the decision-making problem. As one can see in Table 7.52, the alternative A_4 has the best performances on 3 of 7 criteria; in the worst-case scenario for A_4, the best alternative is A_5. The worst-case scenario for A_4 is defined by a weighting scheme in which the criteria NPV, KPI_{2A}, and KPI_{3A} have a higher relevance (Table 7.54). In this scenario, the alternative A_5 is emphasized since the economic performance of A_4 is lower. However, A_4 can be considered as the compromising alternative when all possible scenarios are considered. The alternative A_3 has the highest value on 5 out of 7 attributes, while excluding the reference alternative (A_1), it shows the lowest attribute value on the remaining two attributes. This characteristic allows A_3 to achieve a low value of maximum regret in a large number of scenarios. Table 7.55 resumes the ranking obtained in the worst scenario of the alternative A_4.

Table 7.53. The best alternative suggested by the MMR method

ε	**Alternative**	**max(R)**
0	A_4	0.4260
0.5	A_4	0.3566
1	A_4	0.2928

Table 7.54. Weight schemes related to the worst-case scenarios

ε	**NPV**	**KPI_{1A}**	**KPI_{2A}**	**KPI_{2B}**	**KPI_{2C}**	**KPI_{2D}**	**KPI_{3A}**
0	0.4990	0.0014	0.0014	0.2716	0.2237	0.0014	0.0014
0.5	0.4990	0.0275	0.0014	0.1384	0.1384	0.1334	0.0619
1	0.4990	0.0697	0.0014	0.1159	0.1159	0.1139	0.0841

Table 7.55. Rankings obtained in the worst-case scenarios

A	**Overall score ε=0**	**Rank**	**Overall score ε=0.5**	**Rank**	**Overall score ε=1**	**Rank**
A_1	0	5	0	5	0	5
A_2	0.5232	3	0.5046	4	0.4769	4
A_3	0.5199	4	0.5155	3	0.5139	3
A_4	0.5717	2	0.5522	2	0.5211	2
A_5	0.9977	1	0.9741	1	0.9398	1

In Table 7.56, the maximum regret caused by each alternative in the related worst scenario is reported. The maximum regret is expressed both in absolute terms and relative terms concerning the best alternative. The result proposed by the MMR method can be considered robust since the second-best alternative produces a regret higher than 10% of the maximum regret related to the best alternative (A_4). Excluding the alternative A_1, the A_5 shows the greater value of the maximum regret for all the analysed **ε** values. When the value of **ε** increases (i.e. the probability related to the extreme scenario decreases), the maximum regret related to the choice of the alternative A_5 is lower.

Table 7.56. Maximum regret of alternatives on the related worst scenario

A	**MaxRegret ε=0**	**$\Delta_{\%}$MaxRegret ε=0**	**MaxRegret ε=0.5**	**$\Delta_{\%}$MaxRegret ε=0.5**	**MaxRegret ε=1**	**$\Delta_{\%}$MaxRegret ε=1**
A_1	0.9977	134.2 %	0.9065	154.2 %	0.8234	181.2 %
A_2	0.4744	11.4 %	0.3994	12.0 %	0.3259	11.3 %
A_3	0.4945	16.1 %	0.4072	14.2 %	0.3319	13.3 %
A_4	0.4260	0 %	0.3566	0 %	0.2928	0 %
A_5	0.7904	85.5 %	0.5956	67.0 %	0.4279	46.1 %

As can be observed in Table 7.53, for the scenarios in which all the criteria have a similar relevance, the maximum regret caused by A_4 increases since the criteria in which A_4 has low attribute values are emphasized.

Concluding remarks

Planning activities are complex decisional problems in which different aspects have to be considered simultaneously through mutually conflicting evaluation criteria. To effectively address planning activities, it is essential to use systematic methodologies of decision-making support. Among the decision support methodologies proposed in the literature, the MCA / MADM approaches have been designed to help the decision-maker to identify the best alternative within a set of alternatives. The MC-CBA framework for the assessment of smart grid initiatives represents a general-purpose support tool for the decision-makers in the context of smart grids. The smart grid initiatives can be assessed by considering simultaneously the economic impacts, the contribution towards the smart grid realization, and the externalities produced.

The validation and use of the proposed MC-CBA approach for smart grids highlighted the drawbacks of using criteria weights defined only on a subjective basis. The main objective and integrated weighting methodologies have been studied in this report to improve the MC-CBA approach and reduce the subjectivity of the obtained outcome.

Objective weighting methods determine criteria weights only by considering the information on the attributes of the alternatives. These methodologies suppress the subjectivity of the weighting stage. Integrated weighting methods are based on approaches that allow to include incomplete information about criteria relevance. If subjective information about criteria relevance is missing, integrated methods are brought back to an objective approach. Moreover, objective and subjective weights can be combined for obtaining a unique weight scheme by exploiting the aggregation strategies.

The result obtained through the MC-CBA assessment is represented by a ranking defined according to each alternative's overall score. The global stability analysis can evaluate the robustness of the solution suggested by the method. This method allows to calculate the degree of robustness of the obtained solution and identify the interval in which the criteria weights can vary without lead to a change in the final ranking.

The weighting methods described in this paper are assessed through a comparative analysis. The case study highlighted the strengths and drawbacks of the methodologies by highlighting each approach's inherent trend. The obtained result shows that objective methods may lead to a weighting scheme which does not represent all the stakeholders’ point of view. Aggregating strategies can be exploited to define a compromise between the objective and subjective weights.

In the analysis of decision-making problems, objective weighting methods show many advantages: the cancellation of the subjectivity, reduced workload for the analysis (especially as the number of criteria increases); increased discrimination among the alternatives. The methods analysed allow to cancel out the subjectivity in the result proposed for the decision-making problem and indicate its robustness. Through such methodologies, the decision-making process's transparency grows; as a second step of the analysis, the decision-maker can verify the satisfaction brought by the solution to the stakeholders and then include subjective information.

However, the study of objective weighting available in literature has highlighted the great variety of techniques based on different approaches and hypotheses. As demonstrated by the described case study, different methodologies applied to the same decision-making problem may lead to conflicting results. Since none of the objective methodologies is of general validity, the choice of using an approach over another is arbitrary and is left to the analyst. Therefore, the use of objective techniques can prove to be not decisive in solving decision-making problems.

In the multi-criteria analysis, the evaluation criteria weights are related to their influence on achieving the strategic objective of the overall decision-making problem and the capability of discriminating the alternatives. The objective methods for criteria weighting represent useful tools for evaluating the relevance of each criterion for the selection of alternative options. Consequently, objective methods can simplify complex decision problems by contextualizing the set of evaluation criteria concerning the set of alternatives at hand. Therefore, objective methods can support the decision-maker in excluding non-relevant criteria for the analysis of the set of alternatives. On the contrary, the task of determining the relevance of each criterion can be faced by approaches able to consider the expectations of stakeholders.

Integrated methodologies are based on optimisation algorithms to determine the criteria weights. Subjectivity is introduced in the analysis by the constraints on the value of the weights. Also in this case, the choice of the objective function to be optimised, which is the core of the integrated methodology, is left to the analyst. The objective functions of the integrated techniques magnify an aspect of the set of alternatives to synthesize a single weight scheme and identify the best alternative. Preference information represents a constraint for the optimisation process; hence these methodologies do not ensure a robust or shared result.

The use of an optimisation methodology based on Decision Theory allows to consider the stakeholder satisfaction in conjunction with the appraisal process. The optimisation methodology proposed in section 5.4 uses an objective function defined on the principle of minimising the maximum regret (Regret Theory). According to the proposed model, the best alternative of the set is the option that produces less dissatisfaction to the most critical stakeholder. This approach does not define a particular weight scheme but identifies the most shared alternative. The robustness of the decision is evaluated within the decision-making problem analysis; all possible points of view are considered. The robustness of the solution can be understood by observing the difference between the alternatives in terms of the maximum regret produced in their worst-case scenario. The proposed approach identifies the best alternative of the set, eliminating the need to determine weights. This aspect allows avoiding the cognitive burden and the conditionings related to the determination of weights by subjective methods. Partial information on the relevance of the criteria can be included to limit the weight-space region considered for the evaluation of alternatives.

The method of the minimisation of the maximum regret proposed in section 5.4 and tested in this case study provides support to the decision-maker in the task of identifying the alternative of the set that achieves the highest degree of consensus among the stakeholders of the decision-making problem.

7.4 Case study four: comparison of different distribution planning approach using the MC-CBA approach based on Decision Theory

7.4.1 Introduction

The case study described in this section concerns the comparison of different approaches to distribution system planning. As described in section 1.3, the growing diffusion of distributed generation and the increase of energy-intensive loads in the transportation and heating sectors highlight the strategic importance of distribution networks, which management is becoming increasingly complex due to the problems of flow reversal, line congestion and voltage regulation.

In this scenario, to ensure high service quality and reliability, significant investments are required for upgrading the distribution system. These investments could be reduced using the flexibility offered by grid resources (generators, active users, storage systems and electric vehicles). Assessing the viability of using distributed resources to operate distribution networks is a complicated exercise, requiring a comparison of long-term costs and benefits.

Cost-Benefit Analysis represents the most acknowledged methodology for this type of assessment; however, as illustrated in section 3.1.4, this tool has relevant shortcomings when employed in the appraisal of investments characterised by a large share of societal impacts.

The exploitation of the flexibility potential from third-part resources means involving stakeholders that traditionally have played a passive role in the distribution system planning and operation. Therefore, the impacts related to the exploitation of flexibility services are not completely acknowledged. Not for all impacts, the corresponding equivalent monetary value could be reliable or even obtainable due to the lack of information or the intangible nature. In this context, resorting to assessment tools as the MCA is crucial to assess most of the effects caused by a smart grid initiative that involves the exploitation of flexibility from third-parties. An MC-CBA appraisal allows assessing monetary and no-monetary impact in a systematic framework to support decision-makers in the planning stage.

The case study described in this section concerns the MC-CBA methodology presented in sections 6.3 and 6.4. The CBA enclosed in the MCA framework is undertaken considering the Italian Regulator's guidelines [177]. Accordingly, the assessment has been characterised by five steps: definition of future scenarios, identification of the network expansion plan, evaluation of investment and operating costs, benefits assessment, the composition of costs and benefits according to the MC-CBA methodology.

The financial CBA of the planning options is extended according to the MC-CBA approach proposed in section 6.3. The application of the MC-CBA approach to this case study is described in section 7.4.6. The options are evaluated according to their impacts in three areas: economic, smart grid transformation, and externalities. Criteria related to enhanced network capacity, connectivity, supply, and service security and quality are considered for the appraisal. Several decision-making techniques are exploited to address the decision-making problem and develop an indication of the most valuable planning option. The exploited multi-criteria techniques rely on the subjective, objective, and Decision Theory-based approaches. As described in 7.4.6.3, three different subjective weight schemes, Shannon's Entropy, Standard Deviation, Ideal Point, and the multi-criteria method based on the Regret Theory are the techniques used for analysing the decision-making problem of this case study which goal is to identify the most valuable planning option comparing in this way different approaches to power distribution system planning. The aim of this case study is to undertake a comparative analysis of different distribution system planning approaches. The planning approaches which have been identified for the distribution system are six. The planning options studied in the present case study are the realisation of those six approaches. The first planning approach considered is *Fit and Forget.* This approach represents the traditional planning practice for the distribution system. The network is designed and operated to comply with the worst-case scenario of a given demand forecast, especially in terms of load and voltage drops, considering safety-related limits, without any probabilistic assessment. In this option, contingencies are resolved exclusively by reinforcing the network (e.g. resizing of existing conductors and construction of new connections), active management of the network and the flexibility from the assets are not used, and the acceptable level of risk for constraints violation (as defined in section 2.5) is zero.

The second planning approach considered in this case study is traditional network reinforcement with the inclusion of the probabilistic evaluation of constraints violation. In this approach, contingencies are resolved exclusively by reinforcing the network (e.g. resizing of existing conductors and construction of new connections), active management of the network and the flexibility of the assets are not used. Unlike *fit and forget,* is accepted a certain probability of constraint violation risk violation (risk defined as in section 2.5).

The third planning approach considered concerns the probabilistic planning and active management of distributor-owned storage devices. A certain probability of constraint violation risk is accepted. Moreover, this planning approach encompasses the flexibility provided by storage systems owned by the DSO. The storage systems are capable of providing both active and reactive power. As indicated in the Winter Package 2016-2017 [176], DSOs are prohibited from owning and operating storage systems, allowing exceptions. In this context, in anticipation of the Winter Package, ARERA allows a DSO to own and operate storage systems on its networks provided that it has already implemented at least the lowest levels of digitalisation of its networks (i.e. guaranteeing at least network observability), that it is proven to be useful for network management, and that the related CBA is positive [177]. Recent studies have highlighted the general context characteristics which allow complying with the Italian and European regulation on the ownership of storage systems by the DSOs [179], [182], [183].

The fourth planning approach concerns the probabilistic planning and active management of the flexibility offered by distributed generators and loads. A certain probability of constraint violation risk is accepted. Moreover, the control of both active and reactive power is considered. In this planning approach, if the constraints on the voltages or conductor capacities are exceeded, it is possible to reduce the active power production of generators (until the generators are completely disconnected) and contextual dispatching of the reactive power. To guarantee full reactive power control capacity even during the hours when there is no active power production, it is necessary that the generators' inverter interface is equipped with a small battery for supplying the DC side. Generally, the control of the active power of generators is not allowed in ordinary grid operation, whereas control of reactive power is always allowed. Moreover, it is possible to control the loads that offer their availability for being disconnected.

7.4.2 The planning options under analysis

The planning alternatives that have been considered in the present case study are four. Each of them is devised according to a different planning approach that considers a horizon of 10 years, as described in Table 7.57. For the sake of clarity, the main features of the planning options considered in this case study are summarised in Table 7.58.

Table 7.57. Planning approaches used for devising the planning options

Planning option		**Description of the planning approach**
A1	Traditional planning with a *Fit and Forget* approach	The network is designed and operated to comply with the worst-case scenario of a given demand and generation forecast (deterministic approach), no risk of network constraints violation is accepted Contingencies are resolved exclusively by reinforcing the network (e.g. resizing existing conductors and constructing new connections). Active management of the network and the flexibility of the connected assets are not used. This planning approach is the reference against which the performances of the other planning approaches are assessed.
A2	Traditional planning with the probabilistic approach	The network is designed and operated to comply with future scenarios of a given demand and generator forecast considering a probabilistic approach. A certain probability of constraint violation risk is accepted. Contingencies are resolved exclusively by reinforcing the network (e.g. resizing existing conductors and constructing new connections). Active management of the network and the flexibility of the connected assets are not used.
A3	Probabilistic planning and active management of network and distributor-owned storage devices	The network is designed and operated to comply with a given demand and generator forecast future scenarios considering a probabilistic approach. A certain probability of constraint violation risk is accepted. Contingencies are resolved by reinforcing the network (e.g. resizing of existing conductors and construction of new connections) and exploiting the flexibility provided by the active management of the network and the DSO's storage devices. The storage systems are capable of providing both active and reactive power.
A4	Planning with a probabilistic approach and active management of the networks, distributed generators, and controllable loads	The network is designed and operated to comply with a given demand and generator forecast future scenarios considering a probabilistic approach. A certain probability of constraint violation risk is accepted. Contingencies are resolved by reinforcing the network (e.g. resizing existing conductors and construction of new connections) and exploiting the flexibility provided by the active management of the network, distributed generators, and controllable loads. The distributed generators are capable of providing both active and reactive power.

Table 7.58. Summary of the characteristics of the planning approaches considered

Planning option	Strategy for the management of uncertainties	Risk of network constraint violation accepted	Planning actions				
			Network reinforcement	Network active management	Flexible storage systems	Flexible distributed generators	Flexible demand
A1	Deterministic	No	Yes	No	No	No	No
A2	Probabilistic	Yes	Yes	No	No	No	No
A3	Probabilistic	Yes	Yes	Yes	Yes	No	No
A4	Probabilistic	Yes	Yes	Yes	No	Yes	Yes

7.4.3 The network under analysis

The distribution network considered in the present case study is a rural Medium Voltage (MV) grid-connected to the transmission system through an HV/MV transformer of 25 MVA. The network model is part of the project ATLANTIDE repository [184], [185]. As represented in Figure 7.10, the rural MV grid is formed by seven feeders and includes 102 busses (16 MV loads and 175 LV grids connected through an MV/LV transformer).

The network is characterised by medium-length overhead power lines with modest cross-sections, especially in the periphery. There are two levels of secondary substations: trunk and lateral. For the former, there is always the possibility of counter-feeding; while for the latter, the grid topology is purely radial, although there may still be counter-feeder connections. Non-dispatchable photovoltaics power plants represent the existing rural generation.

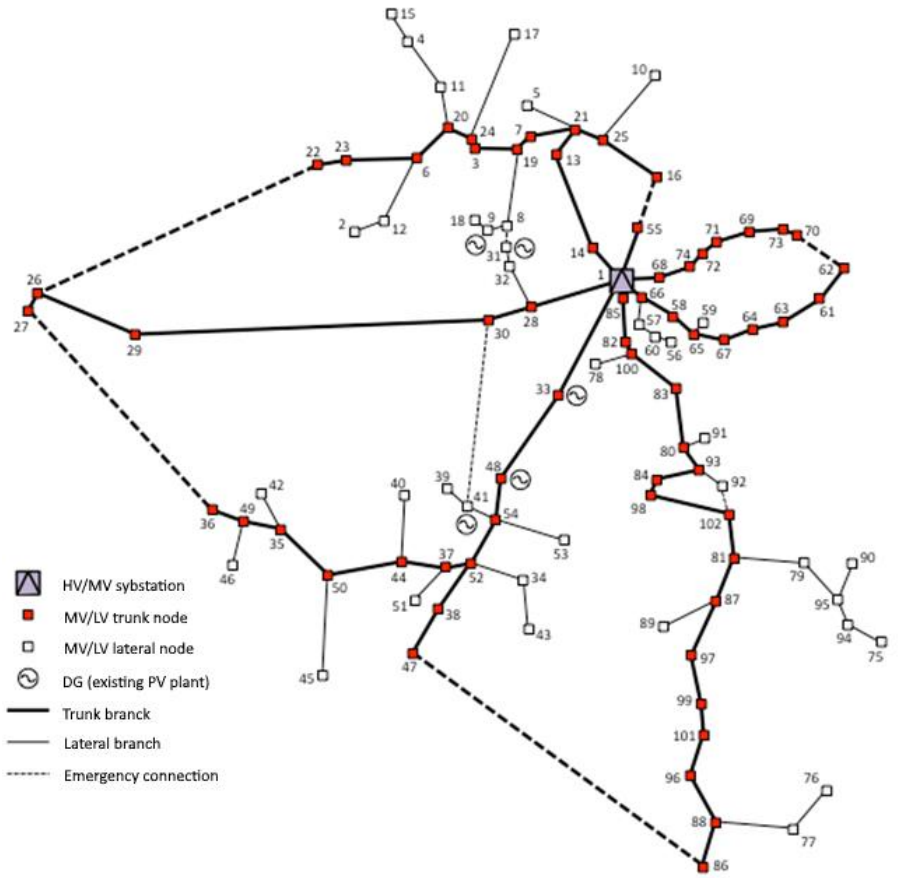

Figure 7.10. The rural distribution network of the case study in year 0 of the planning activity [185]

Different representative daily load profiles are used for modelling the consumption patterns of the different categories of customers. Since the network represents a rural scenario, residential and agricultural users are considered and three different types of MV consumers. Except for the nodes to which are connected MV customers, the MV nodes of the networks have been characterised by the prevalent category of customers connected to the low voltage network. Therefore, two different load profiles are considered a baseline for the LV customers (agricultural and residential) and three profiles for the MV nodes that supply MV customers. Figure 7.11 shows the normalised representative profiles used as a baseline for the planning activity. The generation connected to the distribution network is based on photovoltaic power plants which representative generation profile is depicted in Figure 7.12. Details on the allocation of the different node types, photovoltaic generators connected to the MV network, and storage devices is described in [88], [186].

The LV networks connected to the MV networks trough MV/LV transformer are also modelled and part of the planning activity. To this aim, reference LV networks are considered for modelling the typical rural scenario. Therefore, 60% of the LV network considered in this study are low-density networks, and the remaining share is formed by medium density networks [186]. The low-density LV networks are characterised by MV/LV transformer which size is less or equals to 100 kVA and topology with two feeders with a total extension of 1.5 km in overhead lines (section 35 mm^2) [186]. The resources connected to these feeders are 11 typical loads and four photovoltaic generators located at the end of one of the feeders [186]. The medium density LV networks are characterised by an MV/LV transformer, which size is greater than 100 kVA but equal to or less than 400 kVA [186]. These networks are characterised by four feeders that connect 209 loads and 101 photovoltaic generators (307 kW), for a total of 4 km of overhead lines and 2 km of underground cables [186].

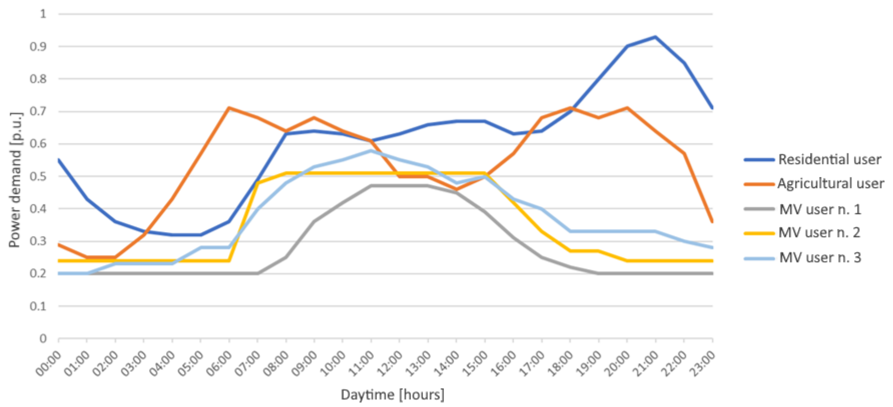

Figure 7.11. Daily load profiles used in the rural network [186]

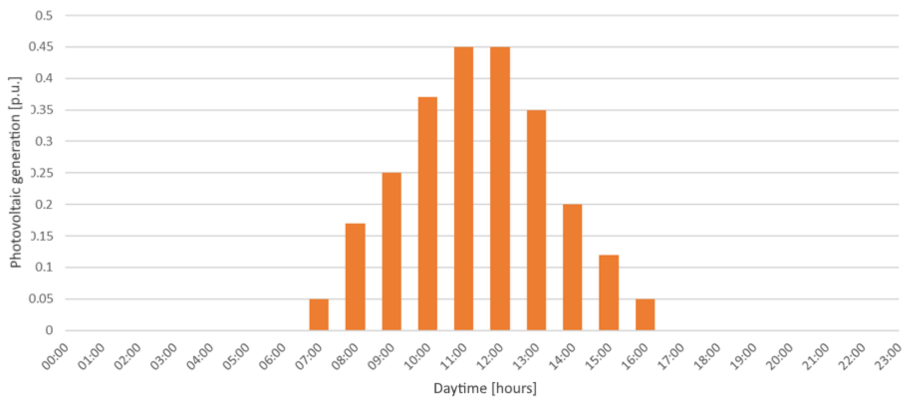

Figure 7.12. Daily photovoltaic profiles in the rural network [186]

7.4.4 How the planning options have been devised

This case study aims to compare the outcome of different planning approaches according to an output-based appraisal. Therefore, the procedures followed for developing the planning options are out of the scope of this dissertation. However, for the sake of clarity, a general overview of the procedure adopted is provided. Detailed information on the activities undertaken and the procedures used for devising the planning options are available in [186].

The general approach followed for developing the planning options is characterised by four steps, definition of the expected future scenarios, the definition of the network upgrade plan, assessment of CAPEX and OPEX, assessment of monetary benefits [186]. The expected future scenarios are based on the forecasts provided by the Italian National Energy and Climate Plan (NECP) described in [88], [187] and the data processed by the Italian Energy Service System Operator (GSE) regarding solar PV installed from 2011 to 2017 [188], [189]. A general description of the expected future scenarios considering in the planning activity is provided in section 7.4.4.1. The network upgrade plans compared in this case study are obtained by means of different planning approaches, traditional *Fit and Forget*, probabilistic *Fit and Forget*, and probabilistic network reinforcement with active management of flexible resources, as described in section 7.4.2. The planning alternatives characterised with a probabilistic approach assume acceptable the risk of a maximum violation duration of 20 hours/year. The acceptable risk of network constraints violation in terms of voltage magnitude and line overcurrent, as defined in section 2.5, is resumed in Table 7.59.

Table 7.59. Technical constraints adopted in planning studies

Operating conditions	Network constraint	Acceptable range (MV network)	Acceptable range (MV+LV networks)
Normal	Bus voltage variation	± 5 %	± 10 %
	Line overcurrent	0	0
Emergency	Bus voltage variation	± 10 %	± 15 %
	Line overcurrent	+ 10 %	+ 10 %

7.4.4.1 The expected future scenario for the grid considering the 2020 – 2030 planning horizon

The growth scenarios were formulated on the basis of forecasts provided by the Italian National Energy and Climate Plan (NECP) described in [88], [187].

Regarding demand, the Italian NECP scenario assumes that a higher load efficiency partially compensates for the electrification trend. As a result, the growth in electricity consumption (shown in Table 7.60) is considered modest in the first part of the study period (about 1% between 2020 and 2025) and then increases in the second part (3.3% between 2025 and 2030). Under these assumptions, the installed capacity of loads in the rural network increases from 16.3 MW to 16.85 MW.

Table 7.60. Actual and estimated Italian national electricity consumption [190]

Year	2010	2017	2020	2025	2030
Electricity consumption [TWh]	330	331.8	329.7	333.1	340.6

On the contrary, it is expected a considerable growth of the installed capacity of distributed generation. In the Italian NECP, the generation from renewable sources is assumed to grow by 30%. In particular, the share of photovoltaics is expected to double, as shown in Table 7.61. The Italian NECP does not provide a breakdown of this growth according to voltage levels and geographical context. Therefore, it is assumed that 50% of PV generation will be connected directly to MV, 10% to HV and

40% to LV based on the data processed by the Italian Energy Service System Operator (GSE) regarding solar PV installed from 2011 to 2017 [188], [189]. According to this hypothesis, PV generation in the rural grid will increase from 35 MW in 2020 to around 83 MW in 2030. In year zero of the planning period, a little less than half of the new generation is connected to the grid as small LV plants and seen aggregated from the nodes of the MV network. The remaining share of PV is connected directly to MV as large installations. By 2020, power plants are assumed to be installed mainly at LV nodes classified as agricultural, while at MV level, at nodes classified as MV private users. Between 2025 and 2030, the diffusion of PV plants is doubled in nodes classified as residential; moreover, large-scale plants have been installed at the MV level.

Table 7.61. Italian NECP power growth targets from renewable sources to 2030 [187]

Energy source installed capacity [GW]	**Year**			
	2016	**2017**	**2025**	**2030**
Hydro	18.641	18.863	19.14	19.2
Geothermal	815	813	919	950
Wind	9.41	9.766	15.39	17.5
Bioenergy	4.124	4.135	3.57	3.764
Solar	19.269	19.682	26.59	50
Total	52.258	53.259	66.159	93.194

Table 7.62 shows the installed capacity of generators and loads and the related expected annual energy consumption and production of the rural network in the last year of the planning horizon.

Table 7.62. Load and generation data for the rural MV network [186]

	Installed power capacity [MW]	**Expected annual energy consumption and production [GWh]**
Agricultural users (Load)	9,00	42,5
Residential users (Load)	5,22	27,6
MV users (Load)	2,57	8,4
Photovoltaic (Generation)	82,57	74,1

7.4.4.2 Coordinated multi-stage MV and LV planning

Due to the introduction of the flexibility concept, the planning activities of the medium voltage networks and low voltage networks have to be explicitly linked. Since the considerable share of distributed generators and flexibility providers is expected to be connected to the low voltage networks, the traditional medium-voltage network planning procedure has to be updated to consider the impact of generators and the contribution provided by the flexibility resources in the low voltage networks. To this aim, in this case study, the planning options concerning the use of flexibility consider the aggregation of LV users produced from time series that consider local forecasts for generation, consumption, and connection of electric vehicles [186]. At the low voltage level, given the network topology, a dedicated probabilistic tool compares reinforcement actions with local flexibility exploitation [186]. Once the planning of the LV distribution networks connected to the MV network is developed, each MV/LV node is characterised by a net-load profile resulting from the active management of the LV system. This profile is then considered for the development of the MV network.

Therefore, all the options are developed according to a multi-stage planning approach that considers both the low voltage and the medium voltage network. The low and medium voltage networks are studied independently on separated stages, but the medium voltage network planning stage considers the low-voltage network planning outcome [186]. The LV network is studied first, load and generation profiles and possible network contingencies are identified. If contingencies are present, they are solved through active management of flexible resources or modification of the network assets if necessary [186]. Subsequently, once the load and generation profiles are identified, this information is used for MV planning studies [186].

The studies of the LV networks produce as the outcome the investment costs related to the violation of technical constraints (component ageing investments are not included), net-load profile at the MV/LV interface, availability of residual flexibility from the LV resources to be used for the management of the MV network, the costs related to the flexibility exploited from the LV resources for the LV network management [186]. The MV network planning studies consider the LV networks as an aggregate of demand and generation characterised by the mean value and standard deviation [186]. The MV network planning studies produce as outcome the total investment costs (equal to the sum of investments on the various LV networks and those on the MV network); the costs related to the flexibility exploited from the MV and LV resources for the MV network management plus the cost for flexibility related to the LV network management, the residual risk, in terms of the number of hours per year in which the network constraints are violated [186].

7.4.4.3 Management of the flexibility potential

The planning options which concern the exploitation of the flexibility from storage, generators and loads do not consider the possible interaction between the TSO and the DSO [186]. The distribution system under analysis is managed independently from the transmission system to which it is connected. In this context, it has been assumed that the DSO has the right to use with priority and in an exclusive way, the flexibility of the distributed resources connected to its own networks. The TSO can exploit the residual flexibility if this does not impact the operativity of the distribution networks managed by the DSO. This assumption allows for assessing the maximum possible impact of flexibility in developing the distribution system [186]. In the cases in which the rights of the TSO on the distribution flexibility are not secondary, there will be compromises that will reduce the flexibility margin available to the DSO and, consequently, increase the need for infrastructure investments.

The power output provided by the distributed generation is considered such that the generators always deliver the full power available from solar irradiation. Therefore, the only control performed on the active power generated is the production curtailment; this measure effectively solves overvoltages (when the solar irradiation is available). However, since each photovoltaic system is connected to the grid through an interface inverter, it is possible to exploit a control that imposes the reactive power provision to compensate the voltage variations (voltage drops and overvoltages) that may occur. In fact, it is assumed that the generators’ inverter interface is equipped with a small battery for supplying the DC side to guarantee the full reactive power control capacity even during the hours when there is no active power production.

Considering the flexibility provided by the controllable loads, the consumers' behaviour is modelled according to a multiagent control system [78], [186], [191]. Each user is characterised by a net-load profile over which the willingness to provide flexibility to the system is evaluated. This willingness to provide flexibility is composed of the maximum percentage of power cut offered. Moreover, the payback effect is considered, i.e. the possibility that the user recovers such flexibility in the following hours [186]. For the planning options considered in this case study, the assumed maximum depth of load participation is 30% [186]. The considered payback effect is such that 50% of the demand is recovered in the two hours next to the flexibility provision [186].

7.4.4.4 The mechanism for acquiring and remunerating flexibility from third-party providers

The planning options, which include the exploitation of the flexibility services from third parties, exploit a mechanism based on bilateral contracts [186]. This mechanism has been set up considering the participation of all generators. An N-1 analysis has been included to consider reliability concerns about the availability of the resources [186]. If the flexibility provider is considered unavailable, the load or generator does not respond to management signals and continues to generate or absorb according to the defined daily profile without providing flexibility. However, not all resources are required for the operation of the distribution network. The useful resources are identified by assuming that all the resources in the network are potential providers. Based on the simulation process result, all the resources not employed (or used under a prefixed threshold) are considered not necessary to resolve the specific contingency. Finally, only the resources actually used are contracted and involved in calculating the overall cost of the planning solution.

The participation of the third-party assets in providing flexibility considers two different remuneration schemes for generators and loads [186]. In any case, flexibility providers in the MV voltages are seen as a unique entity, while the flexibility providers connected to the LV network are considered remunerated as aggregated [186]. The remuneration of the generation curtailment has been assumed according to market prices [186]. Therefore, activation for the active power flexibility is paid, and all generators are obliged to participate in the flexibility provision mechanism. However, the availability of power capacity is not remunerated. The flexibility service provided through reactive power is not remunerated since it is considered a mandatory condition to grid connection [186]. The flexibility provided by loads is composed of the quota for power available to regulation (flexible capacity) equal to 100 €/MW year, and the quota for the energy actually used equals 20 €/MWh (flexible volume) [186]. These prices assumed for load flexibility are in line with the rates provided for interruptible loads [186].

7.4.5 The outcome of the design of the planning options

Given the characteristics of the grid, it is expected that the high presence of photovoltaic generators and the modest density of the electrical load will lead to overvoltage events during the daytime, in correspondence with the peak of production from photovoltaics. Conversely, in the evening, during the peak of demand, there may be frequent events of excessive voltage drop due to long distances. In fact, the length of the feeder of the representative rural network is on average about 18 km, with a maximum value of 23 km; therefore, in an emergency configuration, nodes can be more than 40 km away from the primary substation. Moreover, high overcurrents characterise the network due to the high level of generation installed.

According to the traditional planning approach, new lines would be needed to connect some nodes directly to the primary substation, allowing a better distribution of power flows in the grid and limiting currents, especially in the areas of the grid characterised by strong generation. However, these problems can be addressed by exploiting the network and asset flexibility, i.e. implementing an active and coordinated control of the resources in the network (in this case: generation, loads, and storage systems).

From a technical point of view, storage systems and generation control are also similar [186]. Although the flexibility provided by the active management of storage systems is comparable to generation control, the storage systems are at the distributor's full and exclusive disposal. On the contrary, generation control and storage systems are different from the financial point of view. The use of the flexibility from DSO-owned storage devices requires considering the installation cost, which would become a planning intervention similar to building a new line. This aspect makes the use of storage flexibility different with respect to the use of the generators' flexibility since no capacity remuneration is paid for availability. Furthermore, the use of the flexibility from generators is remunerated according to volumetric payments related to the energy production curtailment. The operational costs of storage systems are considered negligible with respect to the compensation for the producers forced to limit their energy production. However, the storage devices can simultaneously provide several services to the network [27], [182], it represents economic advantage since the additional potential revenues and the consequent reduction in overall network management costs [26], [27], [192], [193].

The planning option A1 built by considering a deterministic *fit and forget* approach represents the reference case for the decision-making problem. The traditional *Fit and Forget* approach determines the highest investment costs due to overly cautious evaluations. These costs are mainly due to the reinforcement of the existing overhead lateral feeders associated with the longest trunk feeder, moving from the existing 20 mm^2, 35 mm^2 and 50 mm^2 sections to the new standardised 70 mm^2 section. In addition to these costs, there are also those related to the construction of new connections (for a total length of about 80 km, some of which directly to the primary substation), which are necessary both to distribute better the power flows and to feed the power generated by large photovoltaic plants directly into the primary substation.

The probabilistic approach used for devising the alternative A2, due to the accepted risk of constraints violation, allows reducing by 31% of the new connections needed (compared to the reference case A1), and the related investments by 70%. In particular, the construction of the new lines with large section is avoided, while the sections resizing is reduced. Despite this substantial reduction in investment, there is a relatively low residual risk, equivalent to the possibility of overvoltage events occurring for a maximum of 4.5 hours/year in the second planning sub-period (2025 to 2030), i.e. the one characterised by the highest generation growth. However, the risk accepted does not jeopardise the performance of the electricity system since the most extreme operating conditions have a low probability of occurrence so that they could be neglected.

The third planning option (A3) is characterised by twelve storage systems (500 kW, 4000 kWh size) positioned in the trunk nodes. The active management of these storage devices allows reducing the contingencies (mainly overvoltages) by absorbing the energy produced by the local photovoltaic generation in the central hours of the day and injecting reactive power. As mentioned in the description of the first case study in section 7.1, the appraisal procedure proposed in this thesis is output-based. Therefore, it is agnostic in terms of the specific assets and control strategies that the planning option deploys. For accomplishing the appraisal procedure are of interest only the corresponding key performance indicator values. Considering this aspect, it is out of the scope of this thesis to describe and discuss the control strategy used for the storage system, which details are available in [88], [89], [185], [186]. However, for the sake of clarity, it is worth highlighting that the planning option A3 shows, with respect to the options A1 and A2, and increased network losses due to the current that flows on branches which section has not been oversized with respect to the A1 and A2 alternatives. Moreover, the siting and sizing of the storage devices have not been addressed using an optimization approach that encompassed network losses reduction. Considering these two aspects, it is possible to observe that the final value of network losses can be not reduced by the presence of storage devices [179].

In the fourth planning option (A4), the provision of flexibility by loads and generators, the control of the active and reactive power of the generators allows eliminating part of the contingencies (overvoltages and overcurrents) that occur at times of maximum irradiation and in particular emergency configurations of the grid. In particular, flexibility is necessary during the second period of the study (when the generation level growth becomes particularly critical for the system) and only in limited and infrequent operational situations (particular grid emergency configurations due to maintenance of some power lines during the central hours of the day).

The flexibility provided by generators is expected to solve the 91% of critical events resorting exclusively reactive control (involving about 2 Mvarh/year), limiting the cut in generated power to 10% of generators characterised by high nominal power (greater than 1 MW), equal to almost 60% of total installed power. The maximum production cut observed is 20%, associated with a residual risk of 6.1 hours/year; the energy moved is about 2 GWh/year. Therefore, this approach allows, by exploiting active management of flexible generators, a further limitation in the construction of new lines. In comparison to the reference scenario, reinforcements of existing lines adopt smaller sections (35 mm^2 and 50 mm^2). The consequent reduction in investments is about 75% compared to the reference case).

The operating cost of the active management of the flexible generation is mainly related to the compensation to be paid to plant owners for the loss of production. The remuneration of the generation curtailment has been assumed according to market prices. Therefore, activation for the active power flexibility is paid, and all generators are obliged to participate in the flexibility provision mechanism. However, the availability of power capacity is not remunerated. The flexibility service provided through reactive power is not remunerated since it is considered a mandatory condition to grid connection. In any case, the probabilistic assessment, considering the probability of occurrence of the interventions, made the volumetric charges for reactive power service provision negligible compared to the benefit obtained in terms of reduced investment.

The use of demand-side flexibility is particularly useful as, in particular, emergency configurations resulting from repair/maintenance on lines where high loads are connected at the end of the feeder. In these scenarios, excessive voltage drops occur, particularly in the evening hours, which cannot be resolved by the intervention of available distributed generation. However, in the present case study, the benefits that can be achieved by demand control are limited. In the rural area examined the most relevant problems are caused by from the high share of generation. However, load control has been particularly effective in improving the voltage profile. Despite the improvement achieved, the required quota of participating loads is limited; only the 15% of load nodes are required to participate with a very low frequency of occurrence of the event, as it is due to emergency situations. Demand participation is limited to a few hours during the year with an observed maximum load reduction of 24% for 1.2 hours/year. Overall, the volumetric flexibility contribution from loads in terms of energy is around 2.5 GWh/year.

The outcome of the simulations for the various planning options presented in Table 7.57, Table 7.58 and described in section 7.4.2 is summarised in Table 7.63. For each planning option, Table 7.63 shows the investment costs, the costs related to the flexibility (CAPEX storage or remuneration for third party providers), the share of grid losses, the residual risk of network constraints violation, the percentage of the loads and generators involved in flexibility (in number and power capacity), the average duration and depth of the flexibility provision by loads, the maximum observed depth and the related duration of the flexibility provided by a load. Furthermore, considering the planning horizon, the average value of the power factor observed at the HV/MV interface and the average voltage magnitude observed.

Table 7.63. Overview of the main characteristics of the different planning options

Performance information	Only traditional network reinforcement	Traditional network reinforcement and flexibility		
	Deterministic	Probabilistic with the accepted risk of constrains violation		
	A1 (Reference)	A2	A3	A4
CAPEX Total[k€]	32386.0	9715.8	28499.7	3238.6
Cost of flexibility [k€]	0	0	20403.2	1943.1
Grid losses [MWh]	2.88	3.89	4.00	4.32
Residual risk [h/year]	0	4.5	12.8	19.1
Average power factor at the HV/MV interface	0.844	0.875	0.875	0.881
Average voltage magnitude	0.9972	0.9995	0.9995	0.9983
Number of loads involved in flexibility	0	0	0	15
Power capacity of flexible loads	0	0	0	30
Average duration of flexibility provision from loads [h/year]	0	0	0	1
Average depth of flexibility provision from loads [%]	0	0	0	9
Maximum duration of flexibility provision from loads [h/year]	0	0	0	1.2
Maximum depth of flexibility provision from loads [%]	0	0	0	24
Number of generators involved in flexibility	0	0	0	10
Power capacity of flexible generation	0	0	0	58
Maximum depth of flexibility provision from generators [%]	0	0	0	20
Overall energy curtailed from distributed generators [GWh]	0	0	0	2

The present case study aims to compare the effectiveness of different planning approaches applied to the same context. The use of the flexibility potential offered by the active management of the network and the assets connected to the distribution grid has proven to reduce investment costs for grid expansion and the cost of grid operation grid.

The financial performances of the planning options are evaluated through a simplified CBA. The costs included in the CBA of the different options are related only to the solution of contingencies (i.e. solution of problems related to the violation of network constraints). For the sake of simplicity, all the costs due to network asset maintenance and replacement caused by ageing are excluded. However, it is acknowledged that the different options may cause a different degradation on the network equipment due to the different operating routine. In Table 7.64, the outcome of the financial CBA of the planning options considered in the present case study is reported. Costs and benefits are discounted considering the planning horizon of 10 years and a discounting rate of 4%. The service life considered for the assets is 40 years.

Table 7.64. Expected capital and operating costs of the planning options

CAPEX, OPEX e Benefits [k€]	Only traditional network reinforcement		Traditional network reinforcement and flexibility	
	Deterministic	Probabilistic with the accepted risk of constrains violation		
	A1 (reference)	A2	A3	A4
CAPEX MV reinforcements	32062.1	9579.8	7930.5	3169.0
CAPEX LV reinforcements	323.9	136.0	166.0	69.6
CAPEX Storage systems	0	0	20403.2	0
CAPEX Total	32386.0	9715.8	28499.7	3238.6
OPEX flexibility in MV	0	0	0	980.1
OPEX flexibility in LV	0	0	0	963.0
CAPEX + OPEX	32386.0	9715.8	28499.7	5181.7
Cost of Losses	1151.10	1556.10	1598.80	1725.90
Benefit B1 (Reduction of network CAPEX)	0	22482.3	24131.6	28893.1
Benefit B2 (Grid losses variation)	0	-405.0	-447.6	-574.8
Total Benefits	0	22077.3	23684.0	28318.3
Net Present Value	-33537.1	11803.30	-5361.30	22814.60
Benefit-Cost Ratio	0	2.05	0.82	4.30

The analysis of the monetary impacts presented in Table 7.64 represents a financial CBA in compliance with the Italian Regulator's guidelines [186], [194]; it considers only some benefits and costs from the DSO point of view. However, to enlarge the analysis to a societal perspective, it would be necessary to considerer the main costs and benefits for all stakeholders involved. To illustrate, the reported CBA does not include the cost of equipping customers, who may have to incur a cost to become flexible, with a consequent impact on the expected remuneration (which must include the infrastructure costs necessary to implement flexibility) [186].

7.4.6 Extension of the financial CBA, the MC-CBA appraisal

7.4.6.1 Introduction

The appraisal of the planning initiatives presented in section 7.4.2 (which the outcome is described in section 7.4.5) according to the and 6.4 require to identify the set of relevant evaluation criteria. As discussed in section 6, the proposed MC-CBA approach enlarges the appraisal of the financial CBA for including tangible and intangible impacts relevant from the societal perspective. The evaluation criteria have to be useful for decomposing the overall decision-making problem, discriminating the alternatives, and ensuring a satisfactory level of confidence.

According to the MC-CBA approach proposed in section 6.3, the decomposition of the decision-making problem of identifying the most valuable smart grid planning initiative considers the EU climate goals and the path established for the transformation of the energy and the electricity sectors. The decision-making decomposition is made according to the recommendation provided by the JRC guidelines [32]–[35], as described in section 6.2. These criteria are in line with the EU regulation [39], whose mentioned aspects cannot be covered by a full monetary CBA [35].

Among all possible evaluation criteria, the evaluation criteria that have to be actually used for appraising the planning options have to discriminate the alternatives. To this aim, are not of interest the criteria to which all the alternatives have the same performance. Since if all the alternatives of the set have the same value for a given attribute, then the related criterion can be removed from the analysis as it does not influence the final result of the appraisal.

Moreover, to provide robustness and soundness to the appraisal outcome, all the attributes that the evaluation criteria consider must be assessed with a satisfactory level of confidence. In fact, if some of the attributes on which the appraisal relies are assessed with insufficient confidence (due to the high level of uncertainty on data, the lack of information, or a poor formalisation of the criteria), the overall outcome of the MCA could be unreliable.

Moreover, to avoid a biased outcome, double counting of impacts has to be avoided in the MCA. Therefore, the set of evaluation criteria has to be double-checked by considering the whole to identify repetitions and eliminate the exceeding criteria. This double-check aims to obtain a set of evaluation criteria that have a one-to-one correspondence with the impacts caused by the set of planning options.

The set of relevant criteria defined for decomposing the decision-making problem is based on the MC-CBA approach proposed in section 6.3. As described in section 7.4.6.2, the options are evaluated according to their impacts in three areas: economic, smart grid transformation, and externalities. The application of the possible criteria are discussed, the reliability of the assessment and the metrics for evaluating the impacts are defined. The set of relevant evaluation criteria leads to the definition of the hierarchical structure that models the decision-making problem and the decision matrix, which contains the attributes of the options to be evaluated. The decision-matrix represents the initial point for the assessment with the multi-criteria techniques. The exploited multi-criteria techniques rely on the subjective, objective, and Decision Theory-based approaches. As described in 7.4.6.3, three different subjective weight schemes are used for the evaluation made according to the AHP-based technique presented in section 6.4. The Shannon’s Entropy, Standard Deviation, and Ideal Point are the objective techniques exploited for this case study for analysing the decision matrix. Identifying the most valuable planning option in the set of the present case study is also performed using the multi-criteria method based on the MiniMax Regret decision rule presented in section 5.4. The results obtained by exploiting the mentioned methodologies are described in section 7.4.6.3.

7.4.6.2 Definition of the set of evaluation criteria

In this section, the process of defining the set of the evaluation criteria for appraising the impacts generated by the distribution planning options presented in section 7.4.5 is described. According to the JRC guidelines, the evaluation criteria are selected and defined [32]–[35]. The criteria selection and definition are guided by the principles of discrimination, confidence, uniqueness, as described in section 7.4.6.1.

Cost-benefit analysis requires all impacts expressed in monetary terms to calculate economic or financial feasibility indicators. However, not all impacts generated by an infrastructure development option are quantifiable and can adequately be expressed in monetary terms; therefore, impact analysis based on KPIs is a complementary approach that can increase the transparency and level of detail of the overall assessment [32]–[35].

The evaluation of impacts that cannot be expressed in monetary terms due to their nature or the characteristics of the information available on the options under analysis can be done in quantitative or qualitative terms using Key Performance Indicators (KPIs). A qualitative scale useful to estimate the confidence level associated with the evaluation of each KPI is proposed in [35]. Accordingly, in this document, a scale characterised by three points identified according to the colours green, yellow and red is used, as presented in Table 7.65.

Table 7.65. Colour scale for the confidence level of the evaluation of the KPIs

Colour	Definition	Outcome
Green	The option generates an impact assessed with a high level of confidence	The assessment of the impact by the KPI is fully reliable
Yellow	There are uncertainties in the assessment of the impact generated by the option that affects the reliability of the assessment outcome	The assessment of the impact by the KPI is acceptable, even if it can be improved if further information is available
Red	The impact generated by the option is subject to an assessment for which insufficient information is available. The confidence level associated with the KPI assessment is low.	The assessment of the impact by the KPI is not reliable

The qualitative scale identifying the level of confidence with which each KPI is assessed in Table 7.65 is complementary to the assessment of the impact generated by the option under analysis. This synthetic information makes it possible to include in the analysis those impacts for the assessment of which partial information is available, from which it is still possible to extrapolate a sufficiently reliable estimate for the decision-making process. In addition, the confidence level assessment provides the decision-maker with an overview of the state of the analysis and the further steps to deepen and improve the appraisal of the options.

Regarding the contribution towards the smart grid realization given by the project options, the use of the criteria and KPIs that belong to the smart grid deployment merit branch described in section 6.3.1.4 is evaluated. In Table 7.66, the selection process for smart grid realisation criteria done for the case study analysed is described.

Considering the suggestion provided in the JRC guidelines, as described in section 6.2.1.2, several aspects are evaluated for determining the criteria which can be included in the branch for the evaluation of the externality impacts of the planning options. The impacts of the planning options in terms of externalities are evaluated considering through KPIs which belong to the labour market, customer Sphere, and sector coupling areas. In Table 7.67, the selection process for the evaluation criteria related to the externalities is described.

The criteria selected for the MC-CBA appraisal are resumed in Table 7.68; the related hierarchical structure which models the decision-making problem is depicted in Figure 7.13.

Table 7.66. The outcome of the selection process for smart grid realisation criteria (Part 1)

Policy Criterion	**KPI**	**Description**	**Level of confidence**	**Is included in the MC-CBA?**	**Assessment**
Level of sustainability	Reduction of GHG emissions	Reduction of greenhouse gas emissions (GHG)		No	Not Applicable
	Environmental impact	Environmental impact of electricity grid infrastructure		No	In general, the action of building new lines can have a not negligible environmental impact. The installation of the storage device can also have an environmental impact depending on the technology adopted. Although a qualitative evaluation of the environmental impact of the option could be possible, the KPI is excluded from the analysis due to the lack of detailed information.
Capacity of transmission and distribution grids	DERs capacity	Installed capacity of distributed energy resources fed by renewals in distribution networks		No	Since all the planning options considered in the present case study concern the same installed capacity from DERs, the KPI is excluded from the analysis since it is not able to discriminate the options.
	Maximum power injection	Allowable maximum injection of power without congestion risks in transmission networks		No	Not applicable

Table 7.65. The outcome of the selection process for smart grid realisation criteria (Part 2)

Policy Criterion	KPI	Description	Level of confidence	Is included in the MC-CBA?	Assessment
Capacity of transmission and distribution grids	Energy not withdrawn from DERs	Energy not withdrawn from renewable sources due to congestion or security risks		Yes	In the case study, the options involved are based on different strategies regarding the management of the energy produced by the distributed resources. From the planning activity, it is available information about the total energy curtailed from DERs during the planning horizon. The KPI is included in the appraisal; the assessment of the impact is quantitative.
	Reactive power exchange	Reactive power exchanged with the adjacent networks		Yes	The options involved in the case study determine a different reactive power behaviour at the interface between the transmission and the distribution network. Punctual information about the reactive power flows in the planning period is not available; however, the Average power factor at the HV/MV interface is available. The KPI is included in the appraisal; the assessment of the impact is quantitative.
Network connectivity	Tariff calculation	Methods adopted to calculate charges and tariffs		No	Not applicable.
	Operational flexibility	Operational flexibility provided for dynamic balancing of electricity in the network		Yes	The planning option concern a different level of flexible capacity useful for the dynamic balancing of the system. Secondary frequency support is considered in the case study; therefore, the contribution of controllable generators, loads, and storage is included. The KPI is included in the appraisal; the assessment of the impact is quantitative.

Table 7.65. The outcome of the selection process for smart grid realisation criteria (Part 3)

Policy Criterion	KPI	Description	Level of confidence	Is included in the MC-CBA?	Assessment
Security and quality of supply	System adequacy	Ratio of reliably available generation capacity and peak demand		No	Due to the control of demand, generation, and storage, the options are characterised by different values for the peaks of generation and demand. However, no information is available for appraising with confidence this KPI.
	System stability	Stability of the electricity system		Yes	This KPI evaluates the contribution of the planning options in relieving the possible sources of system instability. In this case study, the definition of the KPI is broadened to consider the events that undermine the security of the supply. Therefore, the KPI is evaluated in terms of the residual risk of network constraints violation. The KPI is included in the appraisal; the assessment of the impact is quantitative.
	Duration of interruptions	Duration of interruptions per customer		No	No information is available for appraising this KPI.
	Frequency of interruptions	Frequency of interruptions per customer		No	No information is available for appraising this KPI.
	Voltage quality	Voltage quality performance		Yes	This KPI evaluates the contribution of the planning options in improving the voltage quality. In this case study, information about the average voltage value related to each planning option is available. The KPI is included in the appraisal; the assessment of the impact is quantitative.

Table 7.65. The outcome of the selection process for smart grid realisation criteria (Part 4)

Policy Criterion	**KPI**	**Description**	**Level of confidence**	**Is included in the MC-CBA?**	**Assessment**
Efficiency and service quality	Network losses	Level of losses in networks		Yes	The value of network losses related to each planning option is available in terms of energy losses. An independent KPI for energy losses is used instead of including the energy losses in the monetary assessment, as described in section 7.2.1. The KPI is included in the appraisal; the assessment of the impact is quantitative.
	Load leveling	Ratio between minimum and maximum electricity demand		No	As for the *System adequacy* KPI, no information is available for including this KPI in the evaluation.
	Demand side participation	Demand-side participation in electricity markets and in energy efficiency measures		Yes	The planning options evaluated concern demand-side participation program. The percentage of users involved in the demand-side participation program provides an estimation for this KPI. The KPI is included in the appraisal; the assessment of the impact is quantitative.
	Average loading	Percentage utilisation		No	Average loading of electricity network components No information is available for appraising this KPI.
	Grid components availability	Availability of network components		No	Availability related to planned and unplanned maintenance and its impact on network performances. No information is available for appraising this KPI.
	Availability of network capacity	Actual availability of network capacity with respect to its standard value		No	No information is available for appraising this KPI.

Table 7.65. The outcome of the selection process for smart grid realisation criteria (Part 5)

Policy Criterion	KPI	Description	Level of confidence	Is included in the MC-CBA?	Assessment
Contribution to cross-border electricity markets	Interconnection demand rate	Ratio between interconnection capacity of a Member State and its electricity demand		No	Not applicable.
	Interconnection exploitation	Exploitation of interconnection capacities		No	Not applicable.
	Congestion rents	Congestion rents across interconnections		No	Not applicable.

Table 7.67. The outcome of the selection process for externality criteria (Part 1)

Externality Criterion	KPI	Description	Level of confidence	Is included in the MC-CBA?	Assessment
Labour market	Employment	Measure the impact of the option in terms of job creation or loss.			The spillover effects on the labour market represent a relevant externality impact. Therefore, it is of interest to identify the segments where jobs could be created or lost either directly or considering the induced effects. The planning options considered will have a temporary and permanent employment impact; however, the available information does not allow a reliable assessment of this impact. Therefore, this impact is not considered in the analysis.
	Gap in skills	Measure the impact of the option in terms of the qualification needed to perform the roles			Among the externalities in terms of jobs, it is relevant to estimate the possible need to retrain the staff employed. The planning options considered will have an employment impact; however, the available information does not allow a reliable assessment of this impact. Therefore, this impact is not considered in the analysis.
	Market Dynamics	Measures the impact in terms of the creation of new opportunities for third parties			The smart grid initiative can enable new services and applications which can represent a business opportunity for third parties (e.g. aggregators). The set of planning options considered in this case study consider the exploitation of the flexibility provided by grid users through aggregators. The KPI is included in the appraisal; the assessment of the impact is qualitative.

Table 7.66. The outcome of the selection process for externality criteria (Part 2)

Externality Criterion	KPI	Description	Level of confidence	Is included in the MC-CBA?	Assessment
Customer Sphere	Customer inclusion	Measures the effects of the planning options on the customer engagement in the electric sector practices			For the initiative to be economically and socially sustainable, end-users must be informed in a transparent manner of the management mechanisms adopted and the tangible benefits (economic benefits, greater freedom of choice in the market, greater awareness of consumption). The planning options considered will impact customer inclusion; however, the available information does not allow a reliable assessment of this impact. Furthermore, it could represent a double-counting with respect to the KPI *Demand-side participation*. Therefore, this *Customer inclusion* is not considered in the analysis.
	Time saved and lost by costumers	Measures the impact in terms of the time saved or lost by consumers due to the planning option			The analysis of time lost or saved by consumers and network users aims to capture the impact of the initiative on the stakeholders' quality of life. Due to the functionality and the services which can potentially be enabled, the planning options considered will have an impact in terms of *Time saved and lost by costumers*; however, even if some payback effect is considered in the demand side participation, the overall available information does not allow a reliable assessment of this impact. Therefore, this impact is not considered in the analysis.

Table 7.66. Outcome of the selection process for externality criteria (Part 3)

Externality Criterion	KPI	Description	Level of confidence	Is included in the MC-CBA?	Assessment
Customer Sphere	Social acceptance	Measures how well the initiative is accepted or tolerated by society			Social acceptance is crucial for the success of the initiatives, particularly for the ones that bring innovation. To illustrate, low social acceptance could be related to lacks of transparency, benefit-sharing, inclusion, environmental sustainability [32]. Considering the options under analysis, social acceptance can be evaluated in qualitative terms based on the actions of each initiative. To illustrate, options A1 and A2 could have low and medium social acceptance due to the new lines built. A3 could also have a medium social acceptance due to the environmental concerns related to the installation of storage devices. Since the effects on the daily life habits due to the demand response policy, considering the typical behaviour modelled by the diffusion of innovation curve [195], [196], A4 could have a low social acceptance at the beginning. In contrast, a medium and high social acceptance as the time passes. However, the available information does not allow a reliable assessment of this impact. Therefore, this impact is not considered in the analysis.
	Privacy and security	Measures the impact in terms of privacy and security standards			The options under analysis have an impact in terms of privacy and security since information about the energy supply is used as well as remote control of the supply is allowed. However, the initiative should develop measures to ensure data privacy and cyber-security. Although a qualitative analysis should be possible, the available information does not allow a reliable assessment of this impact. Therefore, this impact is not considered in the analysis.

Table 7.66. Outcome of the selection process for externality criteria (Part 4)

Externality Criterion	KPI	Description	Level of confidence	Is included in the MC-CBA?	Assessment
Sector coupling	Effects on the transportation sector	Measures the cross-sector impacts, the coupling with the transportation sector			Due to the electrification policies, the options could have an impact on the transportation sector. Demand-side management policies could influence the transportation sectors since it may involve electric cars. Although a qualitative analysis should be possible, the available information does not allow a reliable assessment of this impact. Therefore, this impact is not considered in the analysis.
	Effects on the heating and cooling sector	Measures the cross-sector impacts, the coupling with the heating and cooling sector			Due to the electrification policies, the options could have an impact on the transportation sector. The demand-side management policies could influence the heating and cooling sector since it may involve the installation of new loads such as heat pumps and combined heat and power systems. Although a qualitative analysis should be possible, the available information does not allow a reliable assessment of this impact. Therefore, this impact is not considered in the analysis.

Table 7.68. Selected evaluation criteria

Branch	**Criterion**	**KPI**		**Evaluation type**	**Evaluation metric**
Economic branch	Financial viability	rTOTEX	Reduction of TOTEX, total discounted expenditures	Quantitative	Reduction of TOTEX without losses
Smart grid branch	Network capacity	KPI_{A1}	Energy not withdrawn from DERs	Quantitative	Total energy curtailed from DERs during the planning horizon
		KPI_{A2}	Reactive power exchange	Quantitative	Average power factor at the HV/MV interface
	Network connectivity	KPI_{B1}	Operational flexibility	Quantitative	Power capacity of controllable generators, loads, and storage
	Security and quality of supply	KPI_{C1}	System stability	Quantitative	Residual risk of network constraints violation
		KPI_{C2}	Voltage quality	Quantitative	Average voltage value
	Service and grid operation	KPI_{D1}	Network losses	Quantitative	Energy losses
		KPI_{D2}	Demand-side participation	Quantitative	Percentage of users involved in the demand side management
Externality branch	Labour market	KPI_{E1}	Market Dynamics	Qualitative	Possibility of aggregation services (yes, no)

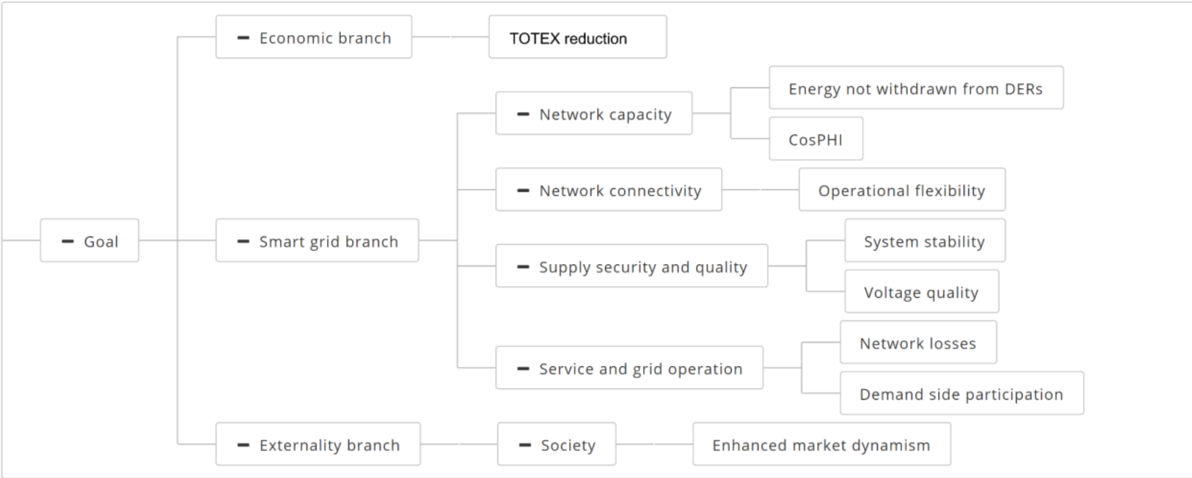

Figure 7.13. Decision tree of the decision-making problem

7.4.6.3 Result of the evaluation

The decision-making problem of identifying the most valuable smart distribution planning approach applied to the system described in this case study is addressed by exploiting subjective and objective procedures, as well as the Decision Theory-based methodology proposed in section 5.4. The structure of the decision-making problem is depicted in Figure 7.13, the related decision matrix, which contains the attributes of the options with respect to the evaluation criteria is represented in Table 7.69.

Table 7.69. Decision matrix of the decision-making problem

	rTOTEX [k€]	KPI_{A1} [GWh/y]	KPI_{A2} [cosϕ]	KPI_{B1} [kW]	KPI_{C1} [risk/year]	KPI_{C2} [pu]	KPI_{D1} [MWh]	KPI_{D2} [%]	KPI_{E1} [-]
A1	0	0	0.844	0	0	0.9972	2.88	0	0
A2	22670.2	0	0.875	0	4.5	0.9995	3.89	0	0
A3	3886.3	0	0.875	1500	12.8	0.9995	4	0	0
A4	27204.3	2	0.881	11090	19.1	0.9983	4.32	15	1

The algorithms exploited in the MC-CBA framework for addressing this case study are the subjective weighting method, Shannon's Entropy, Standard Deviation, and Ideal Point objective weighting methods MiniMax Regret Multi-Criteria method.

To obtain the appraisal of the planning options according to the subjective weighting method, the decision matrix in Table 7.69 is normalised according to the automated procedure described in section 6.4.3. Hence, the scoring stage is addressed, the global priorities (or normalised scores) of the options are calculated; the result of the scoring stage is reported in Table 7.70.

Table 7.70. Global priorities (or normalised scores) of the planning options

	rTOTEX	KPI_{A1}	KPI_{A2}	KPI_{B1}	KPI_{C1}	KPI_{C2}	KPI_{D1}	KPI_{D2}	KPI_{E1}
A1	0.0348	0.3214	0.0372	0.0493	0.3786	0.0367	0.7059	0.0833	0.0833
A2	0.3720	0.3214	0.2580	0.0493	0.3183	0.4266	0.1246	0.0833	0.0833
A3	0.2212	0.3214	0.2580	0.3733	0.2677	0.4266	0.1126	0.0833	0.0833
A4	0.3720	0.0357	0.4468	0.5280	0.0354	0.1101	0.0568	0.7500	0.7500

The set of planning options are evaluated considering the evaluation criteria of the structure of the decision-making problem according to the procedure described in section 6.4. Tree different weight schemes are used for the evaluation according to the subjective weights (Table 7.71, Table 7.72, Table 7.73).

The first weight scheme is characterised by assigning to the three branches the same relevance. The first weight scheme and the corresponding global priorities for the KPIs are reported in Table 7.71.

Table 7.71. Weight scheme n.1 – equal relevance of the three branches

Weight scheme n.1			
Branch	**Local priority**	**KPIs**	**Global priorities**
Economic	0.3333	rTOTEX	0.3333
		KPI_{A1}	0.0417
		KPI_{A2}	0.0417
		KPI_{B1}	0.0833
Smart grid	0.3333	KPI_{C1}	0.0417
		KPI_{C2}	0.0417
		KPI_{D1}	0.0417
		KPI_{D2}	0.0417
Externality	0.3333	KPI_{E1}	0.3333

The second weight scheme is characterised by the economic branch that accounts for half. The second weight scheme and the corresponding global priorities for the KPIs are reported in Table 7.72.

Table 7.72. Weight scheme n.2 – the economic branch accounts for half

Weight scheme n.2			
Branch	**Local priority**	**KPIs**	**Global priorities**
Economic	0.5	rTOTEX	0.5000
		KPI_{A1}	0.0313
		KPI_{A2}	0.0313
		KPI_{B1}	0.0625
Smart grid	0.25	KPI_{C1}	0.0313
		KPI_{C2}	0.0313
		KPI_{D1}	0.0313
		KPI_{D2}	0.0313
Externality	0.25	KPI_{E1}	0.2500

The third weight scheme is characterised by assigning to all the KPIs the same relevance. The third weight scheme and the corresponding global priorities for the KPIs are reported in Table 7.73.

Table 7.73. Weight scheme n.3 – equal weight for all the KPIs

Weight scheme n.3			
Branch	**Local priority**	**KPIs**	**Global priorities**
Economic	0.1111	rTOTEX	0.1111
		KPI_{A1}	0.1111
		KPI_{A2}	0.1111
		KPI_{B1}	0.1111
Smart grid	0.7778	KPI_{C1}	0.1111
		KPI_{C2}	0.1111
		KPI_{D1}	0.1111
		KPI_{D2}	0.1111
Externality	0.1111	KPI_{E1}	0.1111

The partial scores of the alternatives of the decision-making problem for the three branches are calculated according to the procedure described in section 6.4. The results obtained are presented in Table 7.74. Among the set of alternatives, A4 and A2 are the options that achieve the highest economic performances. In terms of contribution towards the smart grid realisation, option A4 is the most valuable, followed by the alternative A3. In terms of externality impact, also, in this case, the most valuable alternative is A4.

Table 7.74. Partial scores of the set of alternatives

Alternative	Economic score	Smart grid merit score	Externality score
A1	0.0350	0.2081	0.0833
A2	0.3705	0.2030	0.0833
A3	0.2241	0.2764	0.0833
A4	0.3705	0.3125	0.7500

The overall scores achieved by the alternatives calculated for all the three subjective weight schemes are presented in Table 7.75. In all three appraisals, the alternative A4 achieves the highest overall score; hence, it is the most valuable alternative according to the MC-CBA methodology based on subjective criteria weights.

Table 7.75. The overall score of the alternatives according to the three subjective weight schemes

	Weight scheme n.1	Weight scheme n.2	Weight scheme n.3
Alternative	**Overall score**	**Overall score**	**Overall score**
A1	0.1088	0.0904	0.1923
A2	0.2189	0.2568	0.2263
A3	0.1946	0.2020	0.2386
A4	0.4777	0.4509	0.3428

The appraisal of the planning options according to the objective methods for weighting the evaluation criteria is based on the normalised decision matrix in Table 7.76 for Shannon's entropy and the Standard Deviation method, and on the decision matrix in Table 7.77 for the Ideal Point method. Table 7.76 is obtained according to the procedure described in section 4.2.2.1.1, while Table 7.76 is obtained according to the procedure described in section 4.2.1.

Table 7.76. Normalised decision matrix of global priorities according to the frequency

	rTOTEX	KPI_{A1}	KPI_{A2}	KPI_{B1}	KPI_{C1}	KPI_{C2}	KPI_{D1}	KPI_{D2}	KPI_{E1}
A1	0.0348	0.3214	0.0372	0.0493	0.3786	0.0367	0.7060	0.0833	0.0833
A2	0.3720	0.3214	0.2580	0.0493	0.3183	0.4266	0.1246	0.0833	0.0833
A3	0.2212	0.3214	0.2580	0.3733	0.2677	0.4266	0.1126	0.0833	0.0833
A4	0.3720	0.0357	0.4468	0.5281	0.0354	0.1101	0.0568	0.7501	0.7501

Table 7.77. Normalised decision matrix according to the min-max interval

	rTOTEX	KPI_{A1}	KPI_{A2}	KPI_{B1}	KPI_{C1}	KPI_{C2}	KPI_{D1}	KPI_{D2}	KPI_{E1}
A1	0	1	0	0	1	0	1	0	0
A2	0.8333	1	0.8378	0	0.7644	1	0.2986	0	0
A3	0.1429	1	0.8378	0.1353	0.3298	1	0.2222	0	0
A4	1	0	1	1	0	0.4783	0	1	1

The weight schemes for the evaluation criteria calculated according to Shannon's Entropy, Standard Deviation, and Ideal Point method are presented in Table 7.80. Since these techniques are based on a similar principle, Shannon's Entropy and the Standard Deviation method produce a confrontable pattern for the KPIs weights. The KPIs achieving the highest score are those for which the alternatives have the greatest diversity in attribute values. Therefore KPI_{D1}, KPI_{D2} KPI_{E1} are the criteria that, more than others, are able to discriminate the alternatives. The weight schemes in Table 7.80 highlight that the Ideal Point method is based on a completely different approach compared to Shannon's Entropy and Standard Deviation methods. The criteria KPI_{D1}, KPI_{D2}, and KPI_{E1} belong to the set of less important criteria; conversely, the most important criteria are KPI_{A1} and KPI_{A2}.

Table 7.78. Weight schemes for the KPIs obtained according to the objective weight schemes

	Shannon's Entropy	**Standard Deviation**	**Ideal Point**
KPIs	**Weight**	**Weight**	**Weight**
rTOTEX	0.0664	0.0785	0.1036
KPI_{A1}	0.0574	0.0701	0.1826
KPI_{A2}	0.0680	0.0821	0.1735
KPI_{B1}	0.1277	0.1178	0.0665
KPI_{C1}	0.0608	0.0736	0.1214
KPI_{C2}	0.0980	0.1011	0.1436
KPI_{D1}	0.1568	0.1498	0.0871
KPI_{D2}	0.1825	0.1635	0.0609
KPI_{E1}	0.1825	0.1635	0.0609

The appraisal of the planning alternatives considering the weight schemes in Table 7.80 obtained by means of the objective methods produces three overall rankings which are presented in Table 7.79. According to Shannon's Entropy and the Standard Deviation Methods, the weights obtained produce overall rankings in which is option A4 the one which achieves the highest overall score. The overall score obtained by A4 is almost two times the score obtained by the remaining options. The Ideal Point methods weight generates an overall ranking in which the overall scores of the alternatives are close; nevertheless, the option achieves the highest overall score A4.

Table 7.79. The overall score of the alternatives according to the objective weight schemes

Alternative	Shannon's Entropy Overall score	Standard Deviation Overall score	Ideal Point Overall score
A1	0.1981	0.1993	0.1948
A2	0.1768	0.1902	0.2656
A3	0.2038	0.2115	0.2628
A4	0.4213	0.3990	0.2767

In Table 7.80 is presented the outcome of the analysis of the stability of the five overall rankings produced by considering the five weight schemes studied. The subjective weight schemes n.1 and n.2 are characterised by the highest value of the stability index $\boldsymbol{\eta}$. The Ideal Point weighting method produces the overall ranking characterised by the lowest stability; indeed, the alternatives achieve close overall scores. For the sake of completeness, Table 7.81 provides the range of values for the criteria weights within which the stability of the first position of the overall ranking is guaranteed.

Table 7.80. Ranking stability indicator of the weight schemes analysed

	Weight scheme n.1	Weight scheme n.2	Weight scheme n.3	Shannon's Entropy	Standard Deviation	Ideal Point
$\boldsymbol{\eta}$	0.7645	0.7644	0.3449	0.4449	0.4117	0.2339

Table 7.81. Range of invariance for the first position of the overall rankings

		rTOTEX	KPI_{A1}	KPI_{A2}	KPI_{B1}	KPI_{C1}	KPI_{C2}	KPI_{D1}	KPI_{D2}	KPI_{E1}
Weight scheme n.1	W_{low}	0.0785	0.0098	0.0098	0.0196	0.0098	0.0098	0.0098	0.0098	0.0785
	Weight	0.3333	0.0417	0.0417	0.0833	0.0417	0.0417	0.0417	0.0417	0.3333
	W_{up}	0.5881	0.0736	0.0736	0.1470	0.0736	0.0736	0.0736	0.0736	0.5881
Weight scheme n.2	W_{low}	0.1178	0.0074	0.0074	0.0147	0.0074	0.0074	0.0074	0.0074	0.0589
	Weight	0.5000	0.0313	0.0313	0.0625	0.0313	0.0313	0.0313	0.0313	0.2500
	W_{up}	0.8822	0.0552	0.0552	0.1103	0.0552	0.0552	0.0552	0.0552	0.4411
Weight scheme n.3	W_{low}	0.0728	0.0728	0.0728	0.0728	0.0728	0.0728	0.0728	0.0728	0.0728
	Weight	0.1111	0.1111	0.1111	0.1111	0.1111	0.1111	0.1111	0.1111	0.1111
	W_{up}	0.1494	0.1494	0.1494	0.1494	0.1494	0.1494	0.1494	0.1494	0.1494
Shannon's Entropy	W_{low}	0.0369	0.0319	0.0378	0.0709	0.0338	0.0544	0.0870	0.1013	0.1013
	Weight	0.0664	0.0574	0.0680	0.1277	0.0608	0.0980	0.1568	0.1825	0.1825
	W_{up}	0.0960	0.0829	0.0983	0.1845	0.0879	0.1416	0.2265	0.2636	0.2636
Standard Deviation	W_{low}	0.0462	0.0412	0.0483	0.0693	0.0433	0.0595	0.0881	0.0962	0.0962
	Weight	0.0785	0.0701	0.0821	0.1178	0.0736	0.1011	0.1498	0.1635	0.1635
	W_{up}	0.1109	0.0989	0.1159	0.1663	0.1039	0.1427	0.2114	0.2308	0.2308
Ideal Point	W_{low}	0.0794	0.1399	0.1329	0.0509	0.0930	0.1100	0.0667	0.0466	0.0466
	Weight	0.1036	0.1826	0.1735	0.0665	0.1214	0.1436	0.0871	0.0609	0.0609
	W_{up}	0.1279	0.2254	0.2141	0.0820	0.1498	0.1771	0.1075	0.0751	0.0751

The MC-CBA methodology based on the Regret Theory presented in section 5.3.7.6 is also used in this case study for addressing the decision-making problem of identifying the most valuable planning option among the set of four alternatives developed according to different planning approaches. The Regret Theory-based MC-CBA methodology proposes the solution to the decision-making problem without requiring to define a specific weight scheme for the evaluation criteria. The decision matrix of the alternatives for the Regret Theory-based MC-CBA methodology is in Table 7.82, which is calculated from Table 7.69 according to the procedure described in section 4.2.1.

Table 7.82. Decision Matrix of the forth case study normalised according to the min-max method

Alternative	rTOTEX	KPI_{A1}	KPI_{A2}	KPI_{B1}	KPI_{C1}	KPI_{C2}	KPI_{D1}	KPI_{D2}	KPI_{E1}
A1	0	1	0	0	1	0	1	0	0
A2	0.8333	1	0.8378	0	0.7644	1	0.2986	0	0
A3	0.1429	1	0.8378	0.1353	0.3298	1	0.2222	0	0
A4	1	0	1	1	0	0.4783	0	1	1

The additional constraints used for the optimisation model are the non-dominance and non-exclusion constraints. Therefore, each entry of the weight vector can assume values within the interval (7.18), where *m* is the number of the evaluation criteria in this case equal to 9.

$$w_{k,j} \in [0.001m^{-1}, 0.5) \tag{7.19}$$

Moreover, the optimisation assumes that all possible weight space points are characterised by the same probability (ε=0).

The initial point of the optimisation problem is identified by solving the brute force model approach with step size Δw = 0.05. Then, for each alternative in the set, the regret maximisation problem is solved analytically. This problem is converted into a minimization problem by changing the sign of the objective function and is solved in the Matlab environment using the Interior Point method, which allows solving constrained nonlinear optimisation problems. The results of the optimisation problems are the maximum regrets determined by the alternatives in their worst-case scenario. The overall solution of the decision-problem is the alternative that presents the minimum-maximum regret value. The assessment results are in Table 7.83, which present the maximum value of regret achieved by the alternative under analysis. According to the Regret Theory-based MC-CBA methodology, the most valuable alternative is A4 which achieves the lowest value of maximum regrets in its worst scenario.

Table 7.83.Maximum regret of alternatives on the related worst scenario

Alternative	Maximum Regret	Final Rank
A1	0.9993	4
A2	0.9991	3
A3	0.9990	2
A4	0.9987	1

The vector in Table 7.83 represents the weighting scheme related to the worst-case scenario of the planning option A4. The worst-case vector shows that option A4 achieves the lowest overall score when the KPIs with respect to which it has the lower values of attribute have high relevance. For the sake of completeness, the overall ranking of all the alternative considering the weighting scheme of the worst-case scenario of option A4 is presented in Table 7.85.

Table 7.84. Weight schemes related to the worst-case scenarios

	rTOTEX	KPI_{A1}	KPI_{A2}	KPI_{B1}	KPI_{C1}	KPI_{C2}	KPI_{D1}	KPI_{D2}	KPI_{E1}
Weight	0.0001	0.3265	0.0001	0.0001	0.3394	0.0001	0.3334	0.0001	0.0001

Table 7.85. Overall Ranking of the alternatives in the worst-case scenarios of A4

Alternative	Overall score	Regret
A_1	0.9993	0.0000
A_2	0.6858	0.3135
A_3	0.5128	0.4865
A_4	0.0006	0.9987

As shown in Table 7.85, according to the MMR method, the most valuable alternative is A4. According to the performance values, A4 achieves the highest values of attributes in five criteria over nine, while it presents the lowest attributes in three criteria over nine. Therefore, A4 represents the most valuable solution considering most of the evaluation criteria selected for addressing the decision-making problem. The worst-case scenario for A4 is described by the weighting scheme in which the KPIs KPI_{A1}, KPI_{C1}, and KPI_{D1} have the highest relevance; these are the KPIs on which A4 is the less valuable alternative of the set. Nevertheless, due to its attribute values, A4 is the option of the set that achieves the least maximum regret. According to the MMR method, the second-best alternative is A3.

7.5 Lesson learned from the case studies

The four case studies presented in this chapter aim to provide proof of concept for the application of the MC-CBA-based methodology on the decision-making problems regarding the future electric distribution sector. Due to the new functionalities and services introduced by the smart grid paradigm and the use of the flexibility provided by third-party owned assets connected to the grid, the impacts caused by upgrading plans for the distribution cross the power system borders. More interests than those of the DSO proposing the upgrading plan are involved and have to be considered at the planning stage. The novel functionalities and services enabled will influence daily life habits and create new business opportunities. Therefore, it is of utmost interest to improve the distribution sector planning activities by broadening the assessed impacts. The most valuable distribution planning alternative in which flexibility competes with network expansions have to be identified considering several different and conflicting than the only minimisation of the reinforcement costs. As suggested by the current guidelines, the compliance with the objectives defined by the current policies and the impacts in terms of externalities have to be assessed with confidence and included in the overall analysis. In general, these impacts are not tangible; hence, they are not easy to quantify and monetise. Although a monetary equivalent can be calculated for some of the possible impacts, the values obtained could lack in reliability. Tools that base the appraisal on output-based indicators that nature could be quantitative and qualitative have been proposed to outclass this drawback. The use of multi-criteria analysis methodologies combined with the cost-benefit analysis allows the appraisal of the planning options while simultaneously considering all the impacts generated irrespective of their tangible or intangible nature. The multi-criteria analysis framework provides a systematic procedure for addressing complex decision-making problems. It is considered an acknowledged approach in several sectors in which the options have typically relevant impacts on society. Moreover, the perspective of all stakeholders of planning initiatives can be introduced, minimising the risk of biasing the decision-making process.

The MC-CBA approach proposed in section 6.3 is based on recent guidelines for the smart grid project assessment. These fundamentals grant validity to the proposed approach. The scientific novelty of the proposed MC-CBA approach is the formalisation of the JRC guidelines' assessment procedure. The formalisation of the MC-CBA approach in line with the JRC guidelines represents one of the contributions of the dissertation.

The MC-CBA approach follows and completes the guidelines' recommendation; furthermore, a mathematical procedure is proposed for solving in a systematic and automated decision-making problem modelled according to the JRC guidelines. The strengths and weakness of the procedure are analysed. On the one hand, the main strengths of the procedure are the support provided to the decision-maker in analysing and decomposing the decision-making problem and in solving it since the high complexity related to problems characterised by a large number of options and criteria. On the other hand, the main drawback is the requirement of eliciting the criteria weight. Determining the evaluation criteria relevance is crucial since the considerable influence that criteria weights have in solving the decision-making problem. The weighting criteria techniques have been extensively studied to outclass this drawback; however, no subjective, objective or integrated methodology has been found able to provide the necessary improvements. In the later stage, Decision Theory rules have been investigated to identify the most suitable decision rule to be combined with the proposed MC-CBA methodology. Among the available decision rules, the MiniMax Regret rule of the Regret Theory is found the most effective rule to be combined with the MC-CBA methodology. By taking advantage of the optimisation model built on the combination of the decision rule and the MC-CBA aggregation function, the decision-making problem is solved without requiring the evaluation criteria' elicitation of weight. However, the Regret Theory-based MC-CBA can include the preferences on the evaluation criteria relevance expressed by stakeholders in terms of constraints for the optimisation model.

The Regret Theory-based MC-CBA is one of the contributions of this dissertation. The MC-CBA framework for smart grid initiatives' assessment represents a general-purpose support tool for the decision-makers in smart grids. It aims to support system operators and regulatory bodies for smart grid projects appraisal by complying with the novel context requirements. The research activity on the decision-making support for the appraisal of smart grid initiative represents part of the Italian contribution to the International Smart Grid Action Network (ISGAN) Annex 3. ISGAN is the short name for the International Energy Agency (IEA) Technology Collaboration Programme (TCP) for a Co-operative Programme on Smart Grids. It is also an initiative of the Clean Energy Ministerial (CEM) and formally established at CEM2 in Abu Dhabi, in 2011 as an Implementing Agreement under the IEA framework. ISGAN represents a strategic platform to support high-level government attention and action for the accelerated development and deployment of smarter, cleaner electricity grids worldwide. ISGAN Annex 3 is devoted to cost-benefit and socio-economic analyses of smart grids and related regulatory policies. From these analyses, toolkits and recommendation are developed to inform smart grid policy at global, regional, national, and sub-national levels and deployment priorities at the project- and utility-scales. In this context, the research activity presented in this dissertation led to the development of the software version of the MC-CBA framework, which is available at the address: https://smartgrideval.unica.it/.

However, a software package prototype that implements the proposed decision-making approach has been devised for testing purposes. The description of the web-based software development is out of the scope of the thesis which focuses on the conceptual formalisation and validation of the proposed decision-making approach. However, considering the prototype developed in MATLAB environment that implements the MC-CBA approach based on Decision Theory (used in the case studies 3 and 4 of the dissertation), the computation time is considered reasonable in the case of decision-making problems characterised by nine criteria and one thousand options. As expected, the computational time increases as the size of the decision-making problem (defined by the number of criteria and number of alternatives) increase. In a virtual machine equipped with Windows Server 2012 R2 64-bit, RAM 41.2 GB, Intel(R) Xeon(R) CPU E5-1620 0 @ 3.60GHz with four logical cores, the overall computational time is about three minutes for up to 16 options, lower than five minutes for less than 64 alternatives, about eight minutes for 128 alternatives, about 14 minutes for 256 alternatives, about half an hour for 512 alternatives. The computational time achieves about 3 hours in the case of 1024 alternatives; it has been considered still a reasonable computational time. The observed computational time is mainly related to the initialisation stage, made with a step length of 0.05. The time required for solving the pure optimisation problem is about 1% of the overall computational time. For this reason, research efforts are ongoing for reducing the computational burden of the initialisation stage; future publications will cover this topic. Regarding the realistic case studies analysed during the PhD period, the prototypal version of the software has shown reasonable computational time since the observed typical size of the real decision-making problem in the context of smart grid initiatives has been characterised by no more than 4-6 alternatives and a maximum number of criteria about 10.

The four case studies present the MCA, and the joined MC-CBA methodologies application to appraise smart grid initiatives. The objective is to provide a decision support tool able to identify initiatives valuable to promote smart grids and then the energy transition. The first case study described presents the use of MCA in smart grid distribution planning. A set of thousands of Pareto optimal planning options produced by an innovative multi-objective optimisation planning methodology is analysed in an automated way using the MC-CBA approach. This case study proves the capability of the proposed approach of analysing a huge set of options and, then, solving complex decision-making problems involving comparing the traditional network reinforcement measures with the exploitation of flexibility from storage devices. In providing the solution, the proposed methodology enhances the objectivity of the assessment by rejecting personal biases and outclasses the shortcoming related to the monetisation of all the impacts, as required by CBA. The first case study outline that the proposed MC-CBA approach can be looped on the option generation tool to improve the design stage and complete the planning process. The proposed MC-CBA approach can be integrated into a unique planning procedure formed by two stages: the design stage in which the planning options are devised and the appraisal stage in which the devised options are evaluated. The proposed MC-CBA methodology represents this second stage in which the planning options are assessed, and the best planning option in the set is identified. In the second case study, the decision-making problem is reshaped according to the international guidelines on smart grid project assessment. The MC-CBA methodology adopted formalises the recommendation of the JRC guidelines for the appraisal of smart grid project, the evaluation criteria identified to belong to the relevant area of interest for impacts: economic, smart grid realisation, externalities. The modelled decision-making problem is then solved by exploiting the AHP-based automated procedure, simplifying the analysis and rejecting personal biases. In the third case study are addressed the shortcomings related to the definition of the evaluation criteria relevance. Since the significant influence of the criteria weights on the solution proposed for the decision-making problem, the most acknowledged weighting techniques are used for testing their effectiveness. This activity highlights that the objective and integrated techniques cannot relieve the shortcoming; however, these techniques provide support in identifying the set of relevant criteria useful for discriminating among the planning option. The third case study's main contribution is the application of the proposed Regret Theory-based MC-CBA methodology in decision—making problems concerning smart distribution planning. The proposed approach identifies the most valuable option eliminating the need to determine weights. It allows avoiding the related cognitive burden and the biases it may provoke. However, personal information on the relevance of the criteria can be included. The fourth case study extents the proof of concept; all the techniques employed in the precedent case studies are exploited on a decision-making problem for smart distribution planning in which different planning approaches are used. The devised planning options concern the competition between the traditional network reinforcement with flexibility measures. The MC-CBA approach and the Regret Theory-Based MC-CBA methodology are exploited to compare the performance achieved by the planning options. The impacts produced by the alternatives based on traditional planning approaches are compared according to an output-based mechanism with the impacts expected from third-party flexibility exploitation. The proposed Regret Theory-Based MC-CBA provides support to the decision-maker to identify the most valuable option; In real decision-making problems, the stakeholders’ perspective modelled in terms of constraints for the minimax optimisation problem lead to identifying the option that achieves the highest degree of consensus.

The management of uncertainties plays a crucial role in long-term planning activities, and it has been considered in the formalisation of the proposed MC-CBA methodology. The proposed MC-CBA methodology solves a selection problem by identifying the best planning option among the evaluation set. Regarding the parameters that are directly related to the MC-CBA methodology, a sensitivity analysis can be performed on the values of the options' attributes under appraisal. The sensitivity analysis on the options' attributes allows defining attributes values ranges to which correspond the invariance of the outcome provided by the MC-CBA methodology. The proposed MC-CBA methodology is flexible and can be evolved to include a stochastic approach to address the uncertainties on attribute values. The uncertainties on the values of the attributes of the options can be modelled in the MC-CBA methodology by using fuzzy sets, as formalised in [197]. Considering the uncertainties related to the value to be assigned to the criteria weight, the MC-CBA approach based on the Decision Theory proposed in the dissertation addresses the topic through the use of the optimisation technique. Instead of requiring a specific weight vector of possibly high uncertainty, this approach requires as input a range of possible criteria weights values. Other parameters related to the scenarios, load growth, prices, among others, pertain to the procedure for designing the planning options; therefore, these parameters are out of the focus of the MC-CBA methodology. The mentioned uncertainties have to be adequately managed by the strategy used for the planning option design. However, since the relevance of proper management of uncertainties for a satisfactory planning activity, it is fundamental that the planning options are devised using design tools based on stochastic approaches for all relevant parameters.

8 CONCLUSION AND FUTURE WORK

This thesis investigates the topic of the ongoing power system transformation by focusing on the distribution system. The massive diffusion of non-programmable renewable energy sources dispersedly connected to the distribution system causes severe operation problems and gives a leading role to the flexibility of demand, generation, and network configuration. Facing the consequences of the power system transformation at a reasonable cost by taking advantage of the available opportunities without jeopardising the electric supply's security and quality requires updating the planning and operation practices.

In this context, the thesis aims to contribute to the appraisal of smart grid initiatives. The traditional and innovative distribution system planning approaches are discussed to identify the key points. The innovative distribution system planning approaches are characterised by the competition of traditional network reinforcement and the flexibility provided by the assets connected to the distribution system. Due to the introduction of flexibility and smart grid paradigms, the novel enabled functionalities and services will influence daily life habits and create new business opportunities. Therefore, it is of utmost interest to improve the distribution sector planning activities by broadening the assessed impacts. In fact, more criteria than minimising reinforcement costs have to be considered in selecting the most valuable planning alternative. The impacts generated by a smart grid initiative are not always easy to quantify and monetise. Although a monetary equivalent can be calculated for some impact, the values obtained could lack reliability. Tools that base the appraisal on output-based quantitative and qualitative indicators are proposed to outclass this drawback.

An approach for the appraisal of smart grid initiative based on the combination of multi-criteria analysis and cost-benefit analysis (MC-CBA) is proposed in the thesis to contribute to the distribution sector planning. The proposed approach is based on recent guidelines for the smart grid project assessment. These fundamentals grant validity to the proposed approach. The scientific novelty of the proposed MC-CBA approach is the formalisation of the JRC guidelines for smart grid project assessment. It represents one of the contributions of this dissertation. The MC-CBA approach follows and completes the guidelines recommendation. Furthermore, the dissertation proposes a mathematical procedure for solving the decision-making problem systematically and automatedly. The use of multi-criteria analysis methodologies combined with the cost-benefit analysis allows the appraisal of the planning options while simultaneously considering all the impact generated irrespective of their nature. The multi-criteria analysis framework provides a systematic procedure for addressing complex decision-making problems. It represents an acknowledged tool used in several sectors in which the options are intertwined with the public sector. Moreover, the perspective of all stakeholders of planning initiatives can be introduced to minimise the risk of biasing the decision-making process.

One of the main advantages of the proposed procedure is the support provided to the decision-maker in analysing and decomposing the decision-making problem. The need for practical decision support tools grows as increases with the complexity of the problems. The MC-CBA allows considering simultaneously tangible and intangible impact evaluated through a set of possibly conflicting criteria. This aspect includes the appraisal externalities and impacts without requiring to express them in monetary terms.

A further contribution of this thesis is the proposed Regret Theory-based MC-CBA methodology, which is an evolutionary step of the presented MC-CBA approach. To overcome the analysed issues related to the criteria weight determination, the use of an optimisation technique combined with Regret Theory is proposed in this dissertation. The methodology indicates the best alternative by eliminating the need for criteria weight determination. The result provided by the optimisation model built on the decision rule considers the multiplicity of the possible points of view; partial information on the relevance of the criteria can be provided to limit the eligible region in which the alternatives are evaluated.

The case studies developed present the use of the multi-criteria analysis and the MC-CBA approach for project appraisal in the smart grid context. In all case studies, the planning alternatives include flexibility measures that compete with traditional network reinforcement.

The MC-CBA framework for the assessment of smart grid initiatives represents a general-purpose support tool for the decision-makers in the context of smart grids. It aims to support system operators and regulatory bodies for smart grid projects appraisal by complying with the novel context requirements. The research activity on the decision-making support for the appraisal of the smart grid initiatives represents part of the Italian contribution to the International Smart Grid Action Network (ISGAN) Annex 3. ISGAN Annex 3 is devoted to cost-benefit and socio-economic analyses of smart grids and related regulatory policies. From these analyses, toolkits and recommendation are developed to inform smart grid policy at global, regional, national, and sub-national levels and deployment priorities at the project- and utility-scales. The research activity presented in this dissertation led to the development of the software version of the MC-CBA framework, which is available at the address: https://smartgrideval.unica.it/.

Future work on the decision-making support for the appraisal of smart grid initiative regards the definition of a standardised methodology for appraising the impacts generated by smart grid initiatives and, in particular, the initiatives that make use of flexibility. Since the great diversity among flexibility services and the assets which can provide the same support, it is of interest to develop a standardised appraisal approach. The use of a standard set of metrics for evaluating smart grid initiatives developed in different contexts allows comparisons and development of best practices. Moreover, the MC-CBA evaluation approach proposed supports identifying and estimating impacts related to the electricity sector. However, strategic planning activities may involve different infrastructure types that may result in correlated or competing effects. Sector-coupled planning activities may involve the coordinated implementation of electricity, energy, transport and telecommunications infrastructure. In general, Power-to-X initiatives are of increasing interest in both industrial and civil sectors. The objective of planning is to optimally integrate the different infrastructures to maximise system efficiency and minimise unsuccessful overlaps. To identify the best infrastructure development option, it is necessary to use decision support tools that can capture the complexity of interventions and the correlations between impacts. Sector-coupled initiatives, which involve the interaction of heterogeneous infrastructures and systems, produce significant externalities and impacts whose effects cannot always be monetised with sufficient accuracy. In this context, the characteristics of multi-criteria analysis, whose evaluation of initiatives is based on performance indicators, make it possible to compare heterogeneous impacts caused by different infrastructures. The multi-criteria analysis approach allows a system evaluation to compare alternatives characterised by a different development level of the infrastructure initiatives. Therefore, multi-criteria approaches have the potential to be used for the appraisal of sector-coupled and power-to-X initiatives.

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