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SURVEY

A Comprehensive Step-Wise Survey of Multiple Attribute Decision-Making Mobility Approaches

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ABSTRACT In the context of next-generation mobile networks, mobility control mechanisms are anticipated to provide infrastructures that can adapt to a broad range of requirements enforced by heterogeneous devices and applications. A mechanism that is central to this adaptability is the handover. During this critical phase of mobility lifecycle management, an appropriate technique for selecting the most suitable Point of Attachment (PoA) must be employed to ensure that mobile devices maintain optimal connectivity. Among the various strategies used to tackle the handover decision problem, the Multiple Attribute Decision-Making (MADM) method is one of the most cost-effective, given the benefits provided by its decision-making approach. Despite its popularity, mobility management mechanisms often employ MADM methods without conducting a thorough performance analysis to justify the approach. One of the main reasons for such referenceless handover technique adoptions is the lack of studies that could inform researchers, developers, mobility managers, and operators about the primary differences among available MADM methods. To fill this knowledge gap, in this paper, we conduct a comprehensive review of the literature on MADM methods in the domain of handover decisions. In particular, our contribution includes providing a detailed summary of the step-wise mathematical implementation in addition to a broad discussion of the main MADM methods in the quality-oriented mobility decision domain, thoroughly classifying their characteristics, and analyzing strengths and limitations. We also compare different categories of MADM methods and discuss some open issues and research challenges in this area.

INDEX TERMS 5G, mobility management, handover decision, handoff, multiple attribute decision-making, MADM.

I. INTRODUCTION

In recent years, there has been a significant increase in the number of mobile networks wireless-connected User Equipments (UEs) [1], [2]. This surge is largely due to the proliferation of applications and services influenced by emerging paradigms, such as cloud computing and the Internet of Things (IoT) [3], leading to unprecedented demands for mobile traffic. It is projected that this demand will continue to grow until 2030, at which point global mobile traffic is expected to reach 5016 Exabytes [4], [5].

The increase in UEs has created a further need to develop connectivity, mobility, and data transmission with higher Quality of Service (QoS) assurances. To exacerbate

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the challenges, multiple content services and new network paradigms became recently available: real-time multimedia, video on demand, vehicular communication, e.g., Vehicle-to-Everything (V2X) [6], Massive Machine-Type Communications (MTCs), Multi-Hop Communications (MHCs), and Ultra-Reliable Communications (URCs) [7], to name a few. All these applications have distinct requirements, ranging from ultra-low latency to high connectivity capabilities [7], [8], as is the case with the fog-enabled vehicular networks [9].

In this scenario, researchers consider Next-Generation Mobile Networks (NGMN) architectures based on the advent of Fifth-Generation (5G) networks a significant advance [10]. With rapid speed and ultra-low latency, they are able to handle multiple connections simultaneously [11]. The materialization of 5G serves as a promising alternative to build new network infrastructures in a deployable and elastic manner [12]. Further, the programmability [13] of 5G networks offers new flexibility and cost-effectiveness, critical requirements for new service design and delivery [14], [15].

A main challenge of NGMN systems is that 5G networks will need to cope with increasing demand for wireless network resources, coverage, and capacity. At the same time, 5G networks' QoS will depend on bandwidth (increasingly required by mobile traffic) and spectrum efficiency [16].

One promising approach to the constraints imposed by such a need for 5G capacity is the deployment of Ultra-Dense Small Cells (UDSC) [17]. UDSC techniques have been widely adopted [18], [19] to reliably cope with the high demand for greater capacity, as they allow ad-hoc broadband data service provisioning [20]. UDSC infrastructure can also be merged with traditional macrocell base stations to establish multiple Radio Access Networks (RAN) formed by distinct Radio Access Technologies (RAT), also known as Heterogeneous Networks (HetNets) [21]. We expect these 5G Radio Access Network (RAN) infrastructures to be formed by several wireless network technologies, increasing network management complexity and aggravating the already challenging task of meeting user requirements.

A. PROBLEM STATEMENT

Mobility management, in general, and handover (HO) mechanisms, in particular, will likely be a central concern that will coexist with other design and implementation challenges within such future 5G architectures. In recent papers on handover challenges, opportunities, and solutions, other authors pointed out how the handover procedure is crucial to mobility management in 5G RAN [22], [23], [24].

One key feature of 5G mobility involves selecting the best Point of Attachment (PoA) – as a first selection point or to maintain the best connectivity. The goal of PoA selection is to accommodate running mobile sessions without degrading the user's Quality of Experience (QoE) [25].

Handover decisions and resource allocation have been extensively investigated, especially among networks based on different technologies, that is, Vertical Handovers (VHO) [26], [27]. In this context, we identify in the literature at least ten strategies adopted by decision-making mechanisms for selecting PoA [28], [29], [30]:

1) Traditional
2) Function-based
3) User-centric (UC)
4) Fuzzy Logic (FL)
5) Markov chain
6) Game theory
7) Reputation
8) Context-aware (CA)
9) Machine Learning (ML)
10) Multiple Attribute Decision-Making (MADM)

The need for seamless mobility drives the decision-making strategy in a VHO scenario. A suitable strategy has to provide continuity to UEs while reducing signaling overhead between user mobility and heterogeneous networks and avoiding unnecessary handovers (the so-called "ping-pong" effect) [31], [32], [33]. For this reason, the MADM strategy has been widely adopted in heterogeneous RAT scenarios, where they appear to be the most cost-effective approach [34].

Several solutions have adopted the MADM strategy as the primary decision procedure in VHO. From the standpoint of providing seamless and quality-oriented handover in 5G HetNets, Alhabo and Zhang [35] discuss and design a MADM scheme based on the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) algorithm. Others take hybrid approaches, including employing multiple decision strategies in the PoAs selection mechanism. In this context, the MADM strategy is often chosen because it includes hybrid decision-making with other strategies. For instance, Habbal et al. [36] adopts the Context-aware Multi-attribute RAT (CMRAT) selection, integrating context-aware and MADM strategy to reduce unnecessary handovers and select the most appropriate RAT in an Ultra-Dense Network (UDN).

Although dozens of MADM methods have been introduced, authors still unquestioningly employ them without additional knowledge about their characteristics, features, strengths, and weaknesses. This significant knowledge gap, which we aim to fill, limits researchers to using MADM algorithms arbitrarily, which is our focus.

Our research aims to address these gaps and provide a comprehensive understanding of the existing MADM methods employed in the handover decision problem by thoroughly reviewing the MADM approach. Our study also provides a detailed mathematical step-wise implementation perspective and classifies and compares existing algorithms.

It is of utmost importance to acknowledge that, to the best of our knowledge and proven by a thorough literature review, no previous work offered a broad review of the MADM methods in the context of the handover decision problem with as many details as our survey.

B. CONTRIBUTIONS

We summarize the main research contributions of this article as follows:

(a) Comprehensive review of the literature on MADM decision methods employed in the domain of handover decision problem.
(b) Detailed summary of the step-wise mathematical implementation of each reviewed MADM method, consisting of an elaborate arrangement for supporting researchers with a deeper understanding of the model's fundamentals.
(c) Classification and comparison of the reviewed handover decision solutions that employ the MADM approach, highlighting their main features, characteristics, primary applications, advantages, and limitations.
(d) Broad discussion on current open issues and future research directions in optimizing handover management systems with improved handover decisions supported by MADM facilities.

C. ORGANIZATION OF THIS ARTICLE

The remainder of this paper is structured as follows. Section II introduces mobility management concepts. Section III provides an overview of MADM algorithms and procedures. Section IV, compares our contributions with related surveys. Section V comprehensively describes available MADM methods. Section VI compares different categories of MADM methods and their main applications. Section VII discusses open issues and research challenges. Section VIII concludes the paper with final considerations and hints for future work. In the Appendix, we provide the step-wise mathematical implementation of each reviewed MADM method.

II. BACKGROUND

A. MOBILITY AND MULTIHOMING

In heterogeneous wireless network systems, UEs are equipped with network interfaces based on different communication technologies. These technologies can be used to provide multihomed communication [37]. They are also expected to shape future 5G infrastructures by orchestrating a high number of UEs with different mobility patterns while guaranteeing the connection with several PoAs ubiquitously.

To achieve this goal, mobility management in the 5G scenarios seeks to ensure that the UEs can carry out the handover process among the heterogeneous candidate PoAs while maintaining continuous flow session connections and avoiding interruptions in communication. However, significant problems are arising from mobility in these networks caused by the signaling overhead and high latency resulting from this process. The main reason is the failure to select the best new network during the mobility stage, leading to poor service quality.

Mobility management techniques allow infrastructures to locate a new PoA to deliver data packets to an on-the-go UE while ensuring uninterrupted connection. One of these techniques, known as localization management [38], enables mobile network infrastructures to manage the state of the UE location by employing advanced prediction techniques. This strategy allows for setting thresholds to avoid disconnecting UEs from the PoA and appropriately performing handover procedures.

The handover process takes place in two different ways:

1) Horizontal handover (HHO), which is activated when the UE switches on the network which is connected by another network that shares the same technology (e.g., Wi-Fi to Wi-Fi);
2) Vertical handover (VHO), which occurs when the UE migrates between networks of different technologies (e.g., Wi-Fi to 5G-NR).

Figure 1 depicts a heterogeneous network scenario built under distinct mobile communication technologies so that a moving UE needs to perform different types of handover (i.e., horizontal and vertical handovers) to be continuously connected.

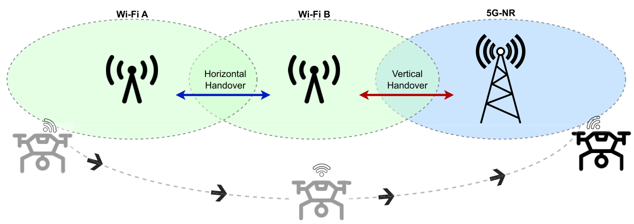

FIGURE 1. Example of a heterogeneous network scenario with a moving UE requiring horizontal and vertical handover control procedures.

From an operational standpoint, handovers can be performed in two different ways:

1) Hard-handover, which occurs when the UE is equipped with only one network interface and has to initially be disconnected from the current PoA and connected to a new network (this operation involves significant losses during the connection);
2) Soft-handover, in which the UE has at least two network interfaces. In this case, an association can be made with the new network before being completely disconnected from the old network, and thus avoid significant losses in the flows of the running mobile sessions.

The handover process can be divided into four phases, namely:

1) Handover initialization: involves detecting changes in connection parameters like the Received Signal Strength Indicator (RSSI), available bandwidth, battery life, etc.;
2) System discovery: in this phase, information is obtained about the applicant networks in the area of coverage of the UE, which is carried out through a request to scan it;
3) Handover decision: this is the selection stage of the new network, where the most suitable PoA is selected based on the information obtained in the previous phase;
4) Handover execution: involves configuring the connection in the new PoA by the results of the decision phase.

TABLE 1. Comparison between VHO handover decision strategies.

VHO strategy	Traditional	Function-based	UC	FL	Markov chain	Game theory	Reputation	CA	ML	MADM
Implementation Complexity	Low	Low	Low	High	Medium	High	Medium	Medium	High	High
Reliability	Low	Medium	Medium	High	High	High	Medium	High	High	High
User-centric	No	Medium	High	Medium	Low	Medium	Medium	High	Medium	Medium
Multi-criteria	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Flexibility	No	High	High	Medium	Medium	Medium	Medium	High	Medium	High

B. MOBILITY DECISION STRATEGIES

The decision phase is a critical factor in keeping the UE well-connected. It requires employing suitable quality-oriented decision strategies to meet the minimum QoS requirements of mobile flow sessions (e.g., delay/loss tolerance, minimum bandwidth, etc.). Moreover, the handover decision mechanism has to deal with the constraints on heterogeneous network deployment, which raises new challenges in mobility management (i.e., unnecessary handovers, signaling overhead, high interference, etc.). In the following, we set out some current strategies for mobility decision-making.

1) TRADITIONAL

The Traditional decision strategy, also known as classic or network-centric strategy [36], compares physical characteristics like RSSI and Signal-to-Noise Ratio (SNR). The operational approach of this strategy works without considering the QoS features of the network [39]. It is unsuitable for scenarios where there is a need to provide quality assurance for the mobile application sessions.

2) FUNCTION-BASED

The Function-based strategy consists of applying mathematical models that can return a numerical value representing the degree of satisfaction of a decision support mechanism that relies on several criteria. In this strategy, decisions are guided by a cost function, usually calculated from the weighted sum of parameters such as QoS, cost, reliability, compatibility, and preference. It is configured to trigger the handover execution process and depends on whether mobility is needed from a predefined threshold. This is often empirically determined through experiments that can assist in adjusting the weights and other variables in the main equation [29].

3) USER-CENTRIC

The main objective of the User-centric (UC) mobility decision strategy is to satisfy the mobile user. It is generally assumed that users are primarily interested in the performance and reliability of the service and are thus responsible for defining the trade-off between quality and cost depending on their needs [40]. In this type of decision strategy, the users are usually responsible for selecting the network that best suits their preferences.

4) FUZZY LOGIC

Fuzzy Logic (FL) is a technique based on degrees of pertinence, where values 0 and 1 delimit the various truth states of a non-quantifiable concept [41]. Fuzzy Logic can provide intelligence to the decision systems by allowing an event to be more accurately characterized. Through this approach, it is possible to estimate the degree of imprecision of real wireless networks [42].

5) MARKOV CHAIN

In the decision-making strategy based on the Markov chain [43], the handover problem is modeled as a Markov Decision Process (MDP), at which point the QoS requirements of mobile sessions determine the reward function. MDP modeling also estimates the optimal strategy regarding the dynamics and diversity of heterogeneous RATs [44].

6) GAME THEORY

In the decision strategy based on the Game theory, the handover problem is designed in the form of a competition between the participants (i.e., UEs and PoAs) [45]. This approach allows each player to select its course of action, such as the appropriate procedures to identify and choose better networks (in the case of UEs). In the case of PoAs, players can trigger functions to maximize network admissions [46].

7) REPUTATION

Reputation-based VHO decision-making [47] considers QoS parameters and running mobile session flow requirements to provide an indicator about expected UE QoE [48], [49]. The decision mechanism is based on two types of agents:

(a) Mobile reputation agent, in charge of collecting performance metrics of previously connected networks;
(b) Network reputation agent, responsible for aggregating already consolidated scores, previously assigned by the mobile reputation agent [50].

8) CONTEXT-AWARE (CA)

Context-aware (CA) decision strategies use the available context information of a wide range of applications and services for UEs [51]. The behavioral adaptation of the system is based on the change in the environmental information that enables context awareness, which assists in handover decision-making.

9) MACHINE LEARNING

The handover decision based on the Machine Learning (ML) strategy uses prior information from the network to assist in decision-making regarding future events [52]. The ML-based approach is classified according to its operation [53], namely:

(a) Supervised learning;
(b) Unsupervised learning
(c) Reinforcement learning

10) MULTIPLE ATTRIBUTE DECISION-MAKING

In formulating a mobility control algorithm based on the MADM approach, the handover decision problem can be expressed in a matrix format called the decision matrix. The matrix element x_{ij} represents the j^{th} attribute of the alternative i^{th} [1].

In the case of a quality-oriented handover decision, the alternatives are the candidate networks, and the attributes are the required quality-of-service parameters. The networks are classified employing scoring techniques that assign different values of importance (i.e., weights) to each parameter.

C. SUMMARY OF HANDOVER DECISION STRATEGIES

Table 1 summarizes features of handover decision strategies such as implementation complexity, reliability, user-centricity, multi-criteria, and flexibility.

Several handover decision strategies are chosen because of their *implementation complexity*. In this respect, MADM, Function-based, and User-Centric approaches are among the most accessible. A handover decision system is considered efficient when it achieves excellence in accurate decision-making and *reliability*. In this respect, several strategies (i.e., traditional, function-based, user-centric, and reputation) have proved inadequate because they do not offer high-reliability prospects. The *user-centric* feature is critical because it can include user interventions through interaction with the decision subsystem. Thus, the user-centric and context-aware strategies are the most significant. The *multi-criteria* support system can be essential for quality-oriented mobility decision-making and may allow QoS analysis. In light of this, the traditional decision-making strategy is unsuitable for this scenario. Instead, it can only depend on features such as the candidate networks' RSSI and SNR. *Flexibility* requires the ability to detach the decision mechanism from the handover management system and readjust to new functionalities and additional parameters. Function-based, User-centered, context-aware, and MADM strategies are most relevant.

The 5G mobile infrastructure, with its diverse requirements, necessitates mobility management systems that can handle the heterogeneity of wireless technologies. The handover decision procedure, in particular, must consider multiple candidate networks with varying attributes. This underscores the need for a handover decision mechanism that can effectively address various constraints, such as flexibility and efficiency. In this crucial context, the MADM approach stands out as the most cost-effective and suitable solution. Its ability to consider multiple attributes simultaneously and make informed decisions based on them sets it apart, making it an effective approach.

The following section outlines the MADM strategy, which is the focal point of this paper.

III. THE MULTIPLE ATTRIBUTE DECISION-MAKING (MADM) APPROACH

Multiple Attribute Decision-Making (MADM) methods are currently employed in the most important mobility control algorithms that tackle handover decision problems. In general, the MADM approach is concerned with choosing an alternative from a set, on the basis of the attributes of each element of the set [54].

Although it has recently caught the attention of the mobile-networking research community, the term MADM has been known for several decades [54]. MADM is a subcategory within the Multiple Criteria Decision-Making (MCDM) set, or Multiple Criteria Decision Analysis (MCDA), a concept popularized in the 1970s [55]. Even today, some authors very often define the MADM theory through MCDM [56]. Since they are known for their high degree of flexibility and adaptability, MADM methods are usually combined with other decision-making strategies (e.g., Fuzzy-MADM – FMADM and Stochastic-MADM), known as Hybrid-MADM.

The modeling of a MADM problem can be roughly divided into three stages [57], namely:

1) Normalization
2) Weighting
3) Ranking

Figure 2 depicts the MADM approach in three stages of operational perspective.

FIGURE 2. MAD problem modeling workflow.

In the rest of this section, we describe these operational stages and report some examples of well-known techniques employed in each.

A. NORMALIZATION STAGE

Considering the varying nature of the alternatives included in a MADM model, the values of the multiple attributes must be standardized to avoid the dominance of the data displayed on different scales. In this way, it is possible to obtain comparable numerical input data on a standard scale [58]. There are several normalization techniques in which procedures meet the MADM requirements. In the following section, we summarize the most common of these:

1) ADDITIVE NORMALIZATION

The additive normalization [59], also known as the Sum method [60], is the most popular method for normalizing the attributes in the MADM approach, mainly due to its simplicity. The normalization process entails dividing the elements of each column of the attribute matrix A by the sum of the respective column, obtaining the normalized matrix A_{norm}:

(a) After defining the decision matrix, it is calculated the normalized values r_{ij}:

$$r_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}}. \tag{1}$$

where:

- x_{ij}: the value of a given attribute j in the network i.
- m: the number of candidate networks.

2) MAX-MIN METHOD

The MAX-MIN method normalization process separates the attributes into two categories based on their characteristics (i.e., cost and benefit attributes) [61].

(a) After constructing the decision matrix, calculate the normalized values r_{ij}:

(b) The cost attributes are represented by metrics that need to be minimized. Examples of such metrics include, e.g., packet delay, jitter, and loss rate:

$$r_{ij}^{-} = \frac{x_j^{max} - x_{ij}}{x_j^{max} - x_j^{min}}. \tag{2}$$

(c) Benefit attributes instead identify those that need to be maximized (e.g., available bandwidth):

$$r_{ij}^{+} = \frac{x_{ij} - x_j^{\min}}{x_j^{\max} - x_j^{\min}}, \tag{3}$$

where:

- x_j^{max} and x_j^{min}: the maximum and minimum values of a given attribute j, respectively;
- x_{ij}: the value of a given attribute j in the network i.

3) MAX NORMALIZATION METHOD

The MAX normalization method [62] follows a normalization procedure in which the evaluated criteria are divided by the maximum value among others in the same group. Like the MAX-MIN method, it can include cost and benefit attributes as follows:

(a) After constructing the decision matrix, it is calculated the normalized values r_{ij}:

(b) Normalization of cost attributes:

$$r_{ij}^{-} = 1 - \frac{x_{ij}}{x_j^{\max}}; \tag{4}$$

(c) Normalization of benefit attributes:

$$r_{ij}^{+} = \frac{x_{ij}}{x_j^{\max}} \tag{5}$$

4) SQUARE ROOT METHOD

The Square Root method [63], also known as the vector normalization method [60] or Euclidean normalization method [64], divides each evaluated criteria by its norm:

(a) After constructing the decision matrix, it is calculated the normalized values r_{ij}:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \tag{6}$$

B. WEIGHTING STAGE

Following the workflow depicted in Figure 2, the second stage in the MADM operation flow is the weighting, which consists of defining the values that represent the importance of each attribute by determining its respective weights [65]. Weighting methods can be categorized as subjective and objective:

1) Subjective weighting methods operate by making subjective assessments of the attributes.
2) Objective weighting methods assign weights through models and measures, usually based on mathematical and statistical patterns, without any previous or pre-established information [66].

Table 2 summarizes some current weighting methods (not restricted to the MADM context) by listing their characteristics.

TABLE 2. MADM weighting methods.

Type	MADM weighting method
Subjective	WLS
	AHP
	RW
	CRITIC
	ANP
	TRUST
	WRMA
	M-AHP
	M-ANP
	iTRUST
	FAHP *
	FANP *
	Eigenvector *
Objective	Entropy *
	Standard Deviation *
	Variance *

* Methods not included in this survey because they are outside the scope of the MADM approach.

As this survey focuses on the MADM decision models, we decided to concentrate on providing a more detailed description of the subjective weighting methods, which are mainly carried out by the MADM approach . This study does not cover other hybrid methods (see the note in Table 2), such as those based on fuzzy logic and objective weighting methods. This step-wise mathematical description is provided in the Appendix.

C. RANKING STAGE

After the values of the attributes have been normalized and the weighting process completed, the next stage of MADM involves following the decision-making procedure. This is achieved by employing ranking methods that select the best alternative from those available. In the Appendix, we provide a comprehensive step-wise mathematical description of several available MADM ranking methods.

IV. OVERVIEW OF RELATED SURVEYS

Several studies have reviewed mobility decision strategies in the last decade. Some authors employed a broader review process, which ranges from mobility management concepts, which consider MADM algorithms hastily, to more specific approaches that deal with some specificities of the MADM approach. In the following, we summarize the main characteristics of the related surveys.

In some cases, the authors only provided an overview of the decision-making strategies by giving examples of algorithms and related methods. Following this approach, the studies presented by Ravichandra and Kumar [67], Rajule et al. [68] and Gaikwad and Bhute [69] are similar by showing a superficial overview of several strategies of VHO decisions without providing any details about them.

Another group of studies generically explored basic mobility management concepts and offered a comparative analysis between different approaches. For example, Kassar et al. [29] introduced basic mobility management concepts and compared the techniques. Márquez-Barja et al. [70] provided an overview of the main mechanisms (algorithms, protocols, and tools) available for mobility management in heterogeneous wireless networks. Zekri et al. [28] introduced the basic concepts of mobility management by examining the main protocols and decision-making approaches involved in this process. The authors in Ahmed et al. [71] discuss the state-of-the-art mobility decision techniques in heterogeneous wireless networks by dividing these schemes into five categories and comparing them regarding reliability, input parameters, complexity, and selection of better networks. Pahal and Sehrawat [72] introduces mobility concepts and provides an overview of existing VHO decision-making mechanisms, highlighting decision strategies that employ MADM methods. Similarly, Rao et al. [73] and Manjaiah and Payaswini [74] outlined mobility decision strategies, listing some of the main MADM algorithms. Mamadou et al. [75] provides a classification of RAT decision-making algorithms. Jha and Gupta [76] provides a generalist overview of mobility management in the vertical handover problem scenario. Xiao et al. [77] categorizes existing network selection algorithms by analyzing their advantages and disadvantages.

From a different perspective, some authors focused on analyzing the handover decision strategies regarding specific demands, such as those focused on the user needs and the mathematical modeling of the models. Louta et al. [78] discusses the capabilities of techniques for meeting users' needs and points out essential factors that the mechanisms should consider. Wang and Kuo [63] analyzed the mathematical theories underpinning the modeling of mobility decision mechanisms. The review carried out in Malathy and Muthuswamy [79] focused on studying the techniques in which the modeling allows a large number of parameters to be employed for the performance evaluation of candidate networks. Stanic et al. [80] and Stanic et al. [81] survey the state-of-art of handover decision algorithms regarding mathematical procedures and algorithm modeling.

Another group of works studied the mobility management and handover decision fields for specific communication scenario paradigms. In this respect, Aljeri and Boukerche [82] surveys mobility management in the 5G-enabled vehicular network scenario by presenting solutions for distinct categories of services and applications. Tashan et al. [83] discuss self-optimization handover in 5G networks. Alraih et al. [84] surveys the handover decision challenges in B5G.

Finally, the MADM approach received special attention from a restricted group of researchers, who focused on surveying existing algorithms through generic and individual analysis, classification, evaluation, and comparison. Lahby et al. [65] surveys and compares weighting MADM-based algorithms. Lahby et al. [85] surveys and compares MADM methods by means of its capabilities for selecting networks that best meet the demands of applications requirements. Jadhav and Sambare [86] surveys a few MADM methods and compares their decision performance in terms of packet delay, jitter, and total bandwidth. Obayiuwana and Falowo [87] examines, classifies, and evaluates some of the selected decision algorithms in HWN. Allias et al. [88] used the systematic mapping approach [89] to identify research studies of MADM methods in the vertical handover problem. Kim et al. [90] discusses MADM methods in wireless ad hoc network communication. Yadav et al. [91] surveys and analyzes MADM techniques regarding network selection challenges and trends using MADM.

The analysis of the related literature, in terms of the existing surveys, reveals that previous studies have already dealt with the handover decision specifics. However, in most cases, the authors employed a more generalist approach, thus ignoring the particulars of the MADM domain approach. In this regard, we established a taxonomy, shown in Table 3, to describe and characterize the existing surveys in terms of the key issues addressed and their main contents, thus highlighting the contribution provided in our work. To this end, we employed a methodology developed in our previous works [92], [93]. Table 3 presents the taxonomy.

Table 4 summarizes each related study's benefits, highlighting the key issues. As confirmed by the literature review, most previous surveys were concerned with outlining VHO decision strategies without providing an in-depth analysis that could allow researchers to reproduce the algorithms. The few papers that undertook this kind of analysis [28], [73], [74], [87] were unable to give an overview of the MADM

TABLE 3. Taxonomy of existing surveys: key addressed issues and main content.

Surveys	Key issues	Main contents
Kassar et al. 2008 [29]	Recent research on vertical handover decision strategies.	Providing a classification for the vertical handover decision strategies by showing their characteristics and making a comparison between them to enable a new vertical handover decision-making approach to be adopted.
Louta et al. 2011 [78]	Designing an access network selection mechanism.	Surveying vertical handover schemes, analyzing their features, and discussing their relative merits and weaknesses.
Márquez-Barja et al. 2011 [70]	Employment of algorithms, protocols, and tools in the VHO process.	Description of the VHO process, techniques for connectivity management in vehicular networks, classification of VHO algorithms, comparison, and evaluation of multiple VHO operational features in vehicular networks environments.
Zekri et al. 2012 [28]	Technical challenges in heterogeneous wireless networks.	Surveying the vertical mobility management process, analysis, and comparison of the main vertical handover approaches, multihoming in a heterogeneous environment and an overview of the best known supporting mobility protocols.
Lahby et al. 2012 [65]	Determining the most suitable weights for different criteria in the context of MADM algorithms.	Surveying and comparing five weighting algorithms in four traffic classes.
Ravichandra and Kumar 2013 [67]	The role of VHO algorithms in selecting the most suitable access network.	Classifying and discussing VHD algorithms based on the handover decision criteria.
Rao et al. 2013 [73]	Network selection in a heterogeneous wireless environment.	Surveying essential aspects of the network selection process, decision-making mechanisms, and analyzing and comparing vertical handover approaches.
Wang and Kuo 2013 [63]	Mathematical theories for modeling the network selection problem.	Comparing and discussing the schemes of various mathematical theories and proposing an integrated scheme that relies on using MADM as the core of the selection procedure.
Manjaiah and Payaswini 2013 [74]	Vertical handoff algorithms as the key components of Next-Generation Wireless Networks (NGWN).	Providing an overview of existing MADM algorithms for vertical handoff.
Rajule et al. 2013 [68]	Vertical Decision Algorithms as essential components of heterogeneous wireless networks.	Surveying VHD algorithms designed to meet the QoS requirements of network applications.
Gaikwad and Bhute 2014 [69]	Selection of the appropriate handover decision strategy in next-generation wireless networks.	Providing an overview and categorization of various vertical handoff decision schemes.
Ahmed et al. 2014 [71]	Research initiatives and challenges in the handover decision-making process in heterogeneous wireless networks.	Giving a detailed state-of-the-art account of current VHO decision mechanisms, by categorizing VHO measurement and decision schemes and summarizing their advantages and drawbacks.
Lahby et al. 2015 [85]	Investigating and analyzing the network selection access employing MADM methods.	Surveying, evaluating, and comparing the performance of (eight) MADM methods on the basis of the Always Best Connected principle.
Pahal and Sehrawat 2015 [72]	Handoff decision as the key to appropriately ensuring service continuity and QoS achievement.	Reviewing and discussing the multi-criteria-based algorithms employed in the handoff decision process.
Jadhav and Sambare 2016 [86]	The authors introduced basic concepts of each algorithm, including details of its operation.	Providing a study for the performance understanding of several VHO decision algorithms.
Obayiuwana and Falowo 2017 [87]	MCDM algorithms in the HWN network selection process.	Reviewing and classifying MCDM algorithms, providing step-wise mathematical implementation, and pointing out strengths and weaknesses.
Malathy and Muthuswamy 2018 [79]	Decision schemes to provide seamless handover in NGWN.	Studying and classifying VHO decision schemes for NGWN.
Allias et al. 2018 [88]	Reviews of gaps in research regarding MADM-based VHO schemes.	Providing an overview of VHO MADM algorithms via a systematic mapping approach.
Kim et al. 2019 [90]	Employment of MADM methods in the protocol development of Wireless Ad Hoc Network communication.	Surveying MADM algorithms and categorizing them with planned communication protocols.
Mamadou et al. 2020 [75]	Summarize common design challenges of the applicability of MADM and AI methods.	Providing a taxonomy of decision-making strategies and discussing challenges.
Aljeri and Boukerche 2020 [82]	Discuss mobility management issues in 5G-enabled vehicular networks.	Providing a survey of models of 5G and HetNets HO triggering schemes.
Jha and Gupta 2021 [76]	Improve the handover between Heterogeneous Networks.	Categorizing handover decision strategies.
Tashan et al. 2022 [83]	Study of existing solutions for auto-optimization functions in HO process.	Presenting a comprehensive review examining the state-of-the-art and research challenges.
Alraih et al. 2023 [84]	Investigates challenges in HO management applied in 5G networks.	Presenting detailed background of HO management in heterogeneous scenarios.
Xiao et al. 2023 [77]	Select the best network access, maximize the wireless resource utilization, and provide satisfactory QoS in HetNets scenario.	Classifying and summarizing network selection algorithms, analyzing existing issues and discussing future development.
Stanic et al. 2023 [80] and Stanic et al. 2023 [81]	Find a possibility of a VHO strategy which provides the ABC paradigm for wireless networks	Surveying algorithms and techniques used for VHO RAT selection.
Yadav et al. 2024 [91]	Explore and analyze MADM strategies and challenges in Network Selection using MADM	Provide a description of MADM methods, presenting strengths and limitations.

methods that were employed for VHO in their entirety. The following section is a comprehensive survey of MADM methods, focusing on exploring implementation factors in detail.

TABLE 4. Summary of related survey papers.

Publication	Year	# Considered MADM methods	Methods detailing	# Related papers
Kassar et al. 2008 [29]	2008	4	×	8
Louta et al. 2011 [78]	2011	6	×	10
Márquez-Barja et al. 2011 [70]	2011	5	×	11
Zekri et al. 2012 [28]	2012	4	✓	8
Lahby et al. 2012 [65]	2012	5	×	10
Ravichandra and Kumar 2013 [67]	2013	5	×	3
Rao et al. 2013 [73]	2013	4	✓	8
Wang and Kuo 2013 [63]	2013	5	×	5
Manjaiah and Payaswini 2013 [74]	2013	5	✓	4
Rajule et al. 2013 [68]	2013	2	×	6
Gaikwad and Bhute 2014 [69]	2014	5	×	8
Ahmed et al. 2014 [71]	2014	5	×	12
Lahby et al. 2015 [85]	2015	8	×	5
Pahal and Sehrawat 2015 [72]	2015	6	×	14
Jadhav and Sambare 2016 [86]	2016	9	✓	5
Obayiuwana and Falowo 2017 [87]	2017	11	✓	8
Malathy and Muthuswamy 2018 [79]	2018	6	×	10
Allias et al. 2018 [88]	2018	14	×	9
Kim et al. 2019 [90]	2019	4	×	-
Mamadou et al. 2020 [75]	2020	5	×	-
Aljeri and Boukerche 2020 [82]	2020	3	×	4
Jha and Gupta 2021 [76]	2021	9	✓	-
Tashan et al. 2022 [83]	2022	5	×	-
Alraih et al. 2023 [84]	2023	2	×	15
Xiao et al. 2023 [77]	2023	8	×	4
Stanic et al. 2023 [80]	2023	5	✓	2
Stanic et al. 2023 [81]	2023	8	✓	6
Yadav et al. 2024 [91]	2024	9	✓	9
This survey	**2024**	**46**	✓	**28**

V. MULTIPLE ATTRIBUTE DECISION-MAKING METHODS

Over the years, several new MADM decision techniques have been documented in the literature. This section examines the main mobility decision-making algorithms based on the MADM decision strategy through a comprehensive step-wise mathematical investigation of each method. To better understand, the methods are appropriately organized following their respective categories (i.e., weighting and ranking). These MADM decision techniques find practical application in various mobility decision schemes, which are also described in the following.

A. WEIGHTING METHODS

This section reviews the MADM algorithms employed in the weighting process, as shown in Table 2.

1) WEIGHTED LEAST SQUARE (WLS)

The WLS Weighting method [94], also known as Least Square Weighting (LSW) [95], is a subjective weighting method that involves adopting procedures that are based on a series of linear algebraic equations used simultaneously for the definition of weights [54].

Although it was first designed several years ago, WLS has only recently been adopted in the context of mobility decisions. In Almutairi et al. [96], the authors evaluated the effects of weighting methods on the GRA and DiA methods. The results indicated that WLS selected the most suitable network for the conversational and interactive traffic classes in all the experiments. In contrast, WLS experienced a high-ranking abnormality (approximately 100%) for the background traffic class.

2) ANALYTIC HIERARCHY PROCESS (AHP)

AHP [97] is one of the most commonly employed MADM-based weighting methods. The AHP procedure is based on the eigenvector method [54], a widely used weighting method in decision-making processes [98].

The AHP weighting method has been widely employed in several MADM VHO decision mechanisms. Yang et al. [99] created a Media Independent Handover (MIH) VHO decision-making algorithm supported by AHP to determine the weights of different traffic parameters for Wi-Fi and WiMAX networks. Zekri et al. [100] devised a context-aware VHO decision mechanism comprising an AHP weighting engine and a Fuzzy inference system to achieve flexibility and account for users' needs.

3) RANDOM WEIGHTING (RW)

RW randomly defines the weights of each attribute [101]. The sum of all the defined weights must be equal to 1 [95].

Through an investigation of the most suitable MADM weighting methods in the context of the VHO problem, Lahby et al. [65] conducted a survey and carried out a comparative analysis on several methods (AHP, FAHP, ANP, FANP, and RW) by examining their effects (concerning network selection and ranking abnormality) combined with the TOPSIS ranking method. The simulations were conducted in MATLAB [102] and included a heterogeneous network scenario composed of UMTS, WLAN, and WiMAX networks with applications mapped in four traffic classes [103]. The results prove that RW can reduce the risk of ranking abnormality in approximate values of 45%, 15%, and 35% for conversational, interactive, and streaming traffic classes, respectively. At the end of the evaluation, the authors concluded that RW performed the worst among the methods because it was the only one with divergent results.

Similarly, Almutairi et al. [96] focused on investigating the effects of several weighting methods (AHP, FAHP, ANP, RW, and WLS) combined with the DiA ranking method [104]. Although RW obtained excellent results in some evaluation scenarios, it was insufficient to determine its superiority against the other evaluated methods.

4) CRITERIA IMPORTANCE THROUGH INTERCRITERIA CORRELATION (CRITIC)

CRITIC [105] determines weights by evaluating the contrast intensity and conflicts between the evaluation criteria [106].

In Sgora et al. [106], the authors perform a performance evaluation of several classic MADM methods against the CRITIC method. The results demonstrate that, in terms of QoS and network selection, the VIKOR, combined with AHP, Entropy, and CRITIC, selected the best network.

5) ANALYTIC NETWORK PROCESS (ANP)

ANP belongs to the same family of weighting methods as AHP [107]. The main difference between AHP and the ANP is that, unlike the hierarchical structure used in the AHP, ANP uses a network structure [108], where the decision levels (objectives, criteria, and alternatives) are grouped into clusters. The criteria and alternatives are represented as the nodes of these clusters [109].

In contrast with the linear hierarchy, where each element depends uniquely on itself, the network hierarchy approach allows feedback to be obtained from the network through inner and outer dependence between the components. The operational stages of the ANP are similar to those of the AHP. Through the hierarchical grouping of the elements, though, the ANP can ensure the interdependence of the attributes required for the weighting process. This super matrix reflects the interaction between the elements and clusters of the system [110]. For a definition of the formal theory of the supermatrix principles, see [108].

The authors in Martinez and Ramos [111] proposed a MADM decision mechanism based on the ANP to provide the best network selection. The numerical simulations proved the efficiency of the proposal compared with other traditional methods such as AHP. Reference [112] combined ANP with improved TOPSIS, known as Enhanced-TOPSIS (E-TOPSIS). The assessments based on numerical simulations showed that the proposal outperforms other widely known MADM methods.

6) TRigger-BASED AUTOMATIC SUBJECTIVE weighTing (TRUST)

TRUST was put forward [113] as a subjective weighting method capable of meeting terminal-side and network-side requirements through a network selection procedure involving triggering events. Table 5 illustrates the relationship between triggering network events and the attributes of weights.

TABLE 5. Example of the relationship between trigger events and weights of attributes [113].

Events & Weights				Attributes				
Layer-1		Layer-2		PR	BD	SC	BER	JT
Application QoS levels	0.74	Streaming	0.24		✓			
		Conversational	0.32					✓
		Interactive	0.12			✓	✓	
		Background	0.06					
Customer preferences	0.26	Low price	0.10	✓				
		High security	0.10			✓		
		Large bandwidth	0.06	✓				

As well as setting out their scheme, Wang and Binet [113] also conducted a comparative evaluation considering extensive scenarios and several attributes (9 in total). The assessment results in a MATLAB simulation environment showed that TRUST has more significant benefits than the extensively used eigenvector method.

7) WEIGHTED RATING OF MULTIPLE ATTRIBUTES (WRMA)

WRMA was introduced [114] as a simple method to calculate the attribute weights using a straightforward approach. WRMA operation procedure relies on the definition of the network attributes and traffic type according to the application requirements following the definitions of IEEE 802.11e [115] and IEEE 802.16 [116] standards, as shown in Table 6).

TABLE 6. Example of traffic types supported by WRMA [114].

	Traffic type	802.11e	802.16
T1	Voice	AC_VO	UGS
T2	Video	AC_VI	Rt-VR
T3	Best Effort	AC_BE	Nrt-VR
T4	Background	AC_BK	BE

In Yang and Tseng [117], the authors conducted a performance evaluation of the WRMA-based decision-making scheme through simulations carried out in an MIH version of the network simulator (NS-2) [118]. In addition to the WRMA proposal for handling attribute weighting, TOPSIS was used to rank the networks for handover. The evaluation outcomes proved that the scheme was better than an AHP-SAW handover scheme and the NIST signal handoff model.

8) MULTIPLE AHP (M-AHP)

M-AHP was proposed [119] to deal with some of the problems of the original AHP methods. These problems include the user's preference for certain criteria considered the same for each alternative network. Another problem with the original AHP method is the consistency index, which in most situations is higher than 10% and thus requires a re-computation of the decision matrix. The main difference between M-AHP and the classic AHP is that it follows a procedure that involves constructing the decision matrix. This procedure is based on the experience of a large number of specialists before defining the matrix for the weighting.

Lahby et al. [120] combined the M-AHP weighting method with the e-TOPSIS method. Their evaluation result assessed the scheme's performance, comparing ranking abnormality and the number of handoffs between the two approaches.

9) MULTIPLE ANP (M-ANP)

M-ANP was put forward to improve the ANP method [121]. Following the approach adopted in M-AHP, M-ANP also draws on the experience of multiple experts to carry out the weighting procedure.

In Lahby et al. [121], the authors also evaluated the M-ANP proposal through a performance comparison, which included variations of ANP and TOPSIS.

10) INTELLIGENT TRUST (i-TRUST)

The i-TRUST method was introduced to deal with some limitations of the TRUST method, such as prioritizing specific events, to provide user flexibility [122].

In addition to the i-TRUST scheme, the authors in Alam et al. [122] also conducted a performance evaluation that took account of the particular requirements of Aeronautical Telecommunication Networks (ATN). The assessment outcomes proved that i-TRUST could significantly improve costs, throughput, and resource consumption.

B. RANKING METHODS

This section surveys the MADM algorithms employed in the ranking process. Each method is introduced in terms of its underlying operating concepts. Moreover, there is a step-wise mathematical implementation, followed by an example of its application in a mobility decision scenario.

1) MULTIPLICATIVE EXPONENTIAL WEIGHTING (MEW)

Also referenced as a Weighted Product Method (WPM) [123], MEW calculates the score as a weighted product of the attributes of the candidate networks [124].

MEW was modified by TalebiFard and Leung [125] for interval data use and employed in a dynamic context-aware network selection handover mechanism, which considers the quality of the context, used to penalize alternatives where there were lower standards in data transmission. The evaluation of the results indicated that it had a low computational cost and was subject to fewer effects of the ranking abnormality phenomenon than TOPSIS.

2) ELIMINATION AND CHOICE TRANSLATING PRIORITY (ELECTRE)

The ELECTRE method, first introduced as Elimination and Choice Translating Reality [126], uses the concept of a reference PoA, which expresses the value of the ideal performance in a given attribute [127] and compares it with the values of candidate networks.

Ahmad et al. [128] adopted ELECTRE to devise a QoS-aware VHO mechanism in the context of M2M Heterogeneous Mobile Ad hoc Networks (HetMANET). The assessment revealed that the solution significantly reduces handover frequency and energy consumption.

3) SIMPLE ADDITIVE WEIGHTING (SAW)

SAW [129] is one of the most commonly used MADM methods in the mobility management process [130]. It is frequently referenced as the Weighting Sum Method (WSM) [131]. The basic operation of SAW involves calculating the weighted sum of the metrics, where the score of each candidate network is obtained by normalizing the values of each metric multiplied by the weight of each criterion.

Several studies have used SAW to compare with the effectiveness of other methods and mechanisms [132], [133], [134]. In other cases, SAW was used as a component of hybrid decision schemes, as discussed by Zineb et al. [135].

4) TECHNIQUE FOR ORDER OF PREFERENCE BY SIMILARITY TO IDEAL SOLUTION (TOPSIS)

TOPSIS makes the selection of the best PoA by finding the similarity to an ideal solution (i.e., one that has the best attributes among the candidate networks) and is the farthest from the worst solution (i.e., the one with the worst characteristics among candidate networks) [54].

Singh and Singh [136] evaluated several MADM methods to determine the most appropriate handover decision in a WiMAX-WLAN scenario. After calculating the relative standard deviation, the authors decided TOPSIS was the most suitable for the handover decision.

5) PREFERENCE RANKING ORGANIZATION METHOD FOR ENRICHMENT OF EVALUATIONS (PROMETHEE)

PROMETHEE [137] aims to find a relation of superiority that takes account of the standard sets of criteria. A pairwise comparison is made between the candidate networks for each alternative to evaluate whether one criterion in one network is better than another in a candidate network.

A performance comparison of the differences between SAW, MEW, and PROMETHEE was conducted by Anupama et al. [138]. The simulated results revealed that PROMETHEE was superior to the other methods in selecting networks for interactive, background, and conversational traffic classes.

6) GREY RELATIONAL ANALYSIS (GRA)

GRA [139] computes the best network according to the Grey Relational Coefficient (GRC), which establishes the relation between the reference values (i.e., the best among all those available) of an attribute and the values of the candidate networks.

Song et al. [140] created a MADM-based network selection algorithm that uses FAHP and standard deviation as subjective and objective weighing methods, respectively, and

GRA as the main ranking method. It was concluded from the simulations that the planned model (called FGRA) improved the QoS guarantees and reduced the number of handovers.

7) MULTICRITERIA OPTIMIZATION AND COMPROMISE SOLUTION (VIKOR)

Initially known as VIseKriterijumska Optimizacija I Kompromisno Resenje, VIKOR [141], is based on the similarity between the candidate and ideal networks, a strategy used by other MADM methods.

Baghla and Bansal [142] carried out a performance comparison of the effect of three weighting methods (AHP, ANP, and subjective weighting). The weighting methods were combined with VIKOR to select the best candidate network. The assessment was conducted concerning the ranking abnormality and number of handovers. The results revealed that the ANP method, combined with VIKOR (called V-ANP), performed better than AHP or subjective weighting.

8) COMPLEX PROPORTIONAL ASSESSMENT (COPRAS)

COPRAS is a notable method known for its simple calculations and reliability [143].

The statistical evaluation of MATLAB simulations carried out by Orimolade [144] accounted for ranking performance, consistency, and ranking abnormality factors. The performance of COPRAS is compared with that of SAW, MEW, and TOPSIS. The results suggest that COPRAS can provide an ideal level of ranking consistency and ranking abnormality, but the best results for ranking consistency have yet to be obtained.

9) GRAPH THEORY AND MATRIX APPROACH (GTMA)

GTMA was introduced [145] as an alternative for selecting materials for engineering components by combining the MADM approach with the graph theory [146].

The use of GTMA is observed in the assessments conducted by Kaur et al. [147] in which various MADM methods were analyzed using the MATLAB software to determine the best technique for dealing with the ranking abnormality effects and number of handovers. The results of the evaluations indicated that GTMA outperformed traditional methods like AHP, TOPSIS, and GRA for different types of traffic.

10) WEIGHTED MARKOV CHAIN 1 (WMC1)

The research conducted by Wang et al. [148] devised two methods based on the Markov chain theory [149], namely WMC1 and WMC2. The methods differ from each other in the construction of the Markov chain transition matrix.

Agrawal and Vidhate [150] conducted a comparative study of several MADM methods for network selection in a heterogeneous wireless network scenario. The article compares the WMC1 and traditional techniques like SAW, TOPSIS, GRA, and MEW. The results indicate that WMC1 obtained good performance in data applications of simulations and was able to select the best alternative network.

11) WEIGHTED MARKOV CHAIN 2 (WMC2)

As mentioned above, WMC2 is the second technique developed by [148]. WMC2 follows the same approach as the WMC1, except for constructing the Markov chain transition matrix.

The authors in Wang et al. [148] also conducted a comparative study of WMC1 and WMC2 using the TOPSIS method. The results suggest that the WMC-based techniques obtained an excellent performance in data user and VoIP application simulations and were able to select the best alternative network.

12) DISTANCE TO THE IDEAL ALTERNATIVE (DIA)

DiA was mainly designed [104] to deal with the rank-constrained abnormalities of the TOPSIS method.

As well as devising a method for the proposal, the authors in Tran and Boukhatem [104] also performed a performance comparison between DiA and the well-known SAW, MEW, and TOPSIS. The evaluation results revealed that DiA outperformed TOPSIS in solving the ranking abnormality problem and improved the ranking capabilities of SAW and WP.

13) FULL MULTIPLICATIVE FORM WITH MULTI-OBJECTIVE OPTIMIZATION BY RATIO ANALYSIS (MULTIMOORA)

MULTIMOORA [151] is formed by the Multi-Objective Optimization by Ratio Analysis (MOORA) and the Full Multiplicative Form of Multiple Objectives. This method makes the selection of the best network according to three (3) classification models:

(a) ratio
(b) reference point system and multiplication system
(c) unification of decisions through the dominance theory [152].

In Obayiuwana and Falowo [153], the authors conducted a performance assessment in a heterogeneous network scenario (WLAN, UMTS, and WiMAX). The results indicated that MULTIMOORA could select the best networks when requested by voice, file download, and video-streaming traffic applications.

14) GRA-BASED-NORM_1

Huszak and Imre [154] presented three (3) methods to improve the GRA algorithm and to reduce the ranking abnormality phenomenon. Each new resulting algorithm, called here GRA-based-norm_1, GRA-based-norm_2, and GRA-based-norm_3, employs different normalization techniques based on modified versions of the MAX-MIN method.

Regarding the GRA-based norm_1, normalization is performed by determining minimum and maximum absolute values for the attributes while keeping the normalized values unchanged.

15) GRA-BASED-NORM_2

As mentioned above, the GRA-based-norm_2 algorithm is the second GRA-based method proposed by Huszak and Imre [154]. The normalization procedure differs from the one adopted by the GRA-based-norm_1 algorithm by determining an absolute maximum for cost attributes and a minimum for benefit attributes.

16) GRA-BASED-NORM_3

The GRA-based-norm_3 algorithm is the third GRA-based method proposed by Huszak and Imre [154], as mentioned above. The normalization strategy in GRA-based-norm_3 does not employ minimum and maximum absolute values. In contrast, it uses a normalization function where the normalized value of the best parameter would be equal to 1.

As well as setting out the scheme, the authors [154] also conducted simulation-based performance analysis. The results revealed that, in some cases, the techniques (GRA-based-norm_2 and GRA-based-norm_3) reduced the rank reversal rate from 65% to 99.9%. Otherwise, as a result of the GRA-based-norm_1 technique, the ranking abnormality was eliminated.

17) NOVEL METHOD BASED ON MAHALANOBIS DISTANCE (NMMD)

Lahby et al. [155] introduced NMMD as an alternative to mitigate the ranking abnormality and ping-pong effect issues by adopting the Mahalanobis distance [156] to measure the distance between the ideal and non-ideal solutions.

The authors also performed a performance comparison that included the SAW, MEW TOPSIS, and DiA methods regarding the number of handovers and ranking abnormality. The results revealed that NMMD could reduce the ranking abnormality and ping-pong effects better than the other methods.

18) WEIGHTED AGGREGATED SUM PRODUCT ASSESSMENT (WASPAS)

WASPAS [157] was designed to integrate the decision-making capabilities of the SAW and MEW methods.

WASPAS was the object of a comparative study performed by Yadav et al. [91], which aimed at analyzing the strengths and limitations of MADM algorithms in terms of algorithmic approaches, the cardinality, the importance of decision attributes, and network utilities.

19) VHO-QoS/QoE

The VHO-QoS/QoE method [158] adopts an approach that eliminates values that do not satisfy a minimum requirement for a given attribute. This is achieved by adding a threshold value to each evaluated attribute.

Maaloul et al. [158] also carried out a performance evaluation between the planned solution and classical MADM methods. The results revealed that VHO-QoS/QoE achieved better performance in the number of handovers and handover processing delay.

20) ENHANCED-TOPSIS (E-TOPSIS)

E-TOPSIS [159] is one of the several attempts to improve the ranking performance of the TOPSIS methods by reducing the number of ranking abnormality problems. E-TOPSIS examines the relative importance of both ideal and non-ideal solutions (i.e., negative ideal solutions) to measure their relative closeness to an ideal solution.

The evaluations conducted by Lahby et al. [159] revealed that E-TOPSIS reduced the reversal phenomenon and the number of handovers. The results also suggest that E-TOPSIS provided better alternatives than the SAW, MEW, and TOPSIS to IEEE 802.11e traffic classes.

21) EXTENDED ELITISM FOR BEST SELECTION (E2BS)

E2BS was set out in Silva et al. [160] and is based on the combination of the elitist strategy [161] and the MADM features. In the E2BS approach, the chosen network will be the one that is closest to the elite solution, which is represented by a reference PoA, with attribute values close to the ideal solution (e.g., attributes such as latency and loss equal to zero).

Santos et al. [34] performed a performance analysis of E2BS with the well-known MADM methods (SAW, TOPSIS, GRA, and MEW) in a video streaming scenario. The results, expressed through QoE metrics, demonstrate the superiority of E2BS in selecting the most suitable PoA.

22) NMMD-N1

Four (4) strategies for determining a suitable normalization technique for the NMMD method [155] were introduced by Lahby et al. [162]. Each new resulting MADM algorithm employs different normalization techniques, namely NMMD-N1, NMMD-N2, NMMD-N3, and NMMD-N4. Since the algorithms are based on the NMMD method, the following sections focus on describing the normalization procedure used by each technique.

Concerning the NMMD-N1, the normalization is performed by applying the square root or Euclidean normalization method (see section III for details).

23) NMMD-N2

As mentioned above, the NMMD-N2 algorithm is the second NMMD-based method proposed by Lahby et al. [162]. The normalization strategy employed in NMMD-N2 is based on the MAX-MIN technique (see section III for details).

24) NMMD-N3

The NMMD-N3 algorithm is the third NMMD-based method proposed by Lahby et al. [162], as mentioned above. The normalization strategy employed in NMMD-N3 is based on the MAX technique (see section III for details).

25) NMMD-N4

The NMMD-N4 algorithm is the fourth NMMD-based method proposed by Lahby et al. [162], as mentioned above. The normalization strategy employed in NMMD-N4 is based on additive normalization (see section III for details).

These four NMMD algorithms proposed by Lahby et al. [162] are compared in a performance evaluation with four different traffic types to analyze the ranking abnormality phenomenon and number of handovers. The simulation results indicate that the NMMD performed better when combined with the Euclidean normalization method (NMMD-N1). This was highlighted by the ranking abnormality rate, which was reduced to 30%. NMMD-N4 obtained a good performance for the number of handovers for two (2) traffic types.

26) GRA-TOPSIS

Sasirekha et al. [163] combined the GRA and TOPSIS methods, thus giving rise to the GRA-TOPSIS method.

In addition to introducing the new method, the authors [163] also compared the performance of GRA-TOPSIS by employing the FAHP technique to weigh the attribute values. Additionally, the efficiency of the proposed model (i.e., the combination of FAHP and GRA-TOPSIS) was compared with a hybrid formed with AHP and GRA-TOPSIS. The results revealed that adopting the FAHP led to a more significant improvement during the pair-wise comparison stage, thus resulting in a better network selection.

27) MeTHODICAL

MeTHODICAL [164] is based on an optimization technique that enables users to specify a wide range of heuristics to achieve different goals.

Sousa et al. [164] also evaluated MeTHODICAL by assessing it in terms of the accuracy of path optimization, performance, and accuracy of heuristics. Furthermore, the influence of the distance configurations was considered in the assessment. By including MADM methods such as TOPSIS, NMMD, and DiA, MeTHODICAL performance proves its superiority in optimal path selection, accuracy, and precise heuristic selection. The evaluations also show that MeTHODICAL does not suffer from the ranking abnormality.

28) EVALUATION BASED ON DISTANCE FROM AVERAGE SOLUTION (EDAS)

EDAS was proposed by Keshavarz Ghorabaee et al. [165] for inventory classification purposes. EDAS classification process follows the similarity distance approach. It computes the distance between each candidate alternative and an average solution to find the best result.

EDAS was considered by Yadav et al. [91] in the same comparison study that analyzed the WASPAS technique.

29) TOPSIS-NORM1

Senouci et al. [166] recommended four (4) methods to improve the TOPSIS algorithm and thus reduce the negative effects of the normalization procedure on the way alternative candidate networks are ranked. Each new resulting algorithm, namely TOPSIS-norm1, TOPSIS-norm2, TOPSIS-norm3, and TOPSIS-norm4, employs the MAX-MIN method (see section III for details) in different ways.

Concerning the TOPSIS-norm1, normalization consists of replacing the original TOPSIS normalization strategy with the original implementation of the MAX-MIN method.

30) TOPSIS-NORM2

The TOPSIS-norm2 algorithm is the second TOPSIS-based method proposed by Senouci et al. [166], as mentioned above. The normalization strategy in TOPSIS-norm2 keeps the normalized values unchanged by configuring maximum and minimum absolute values for each considered attribute.

31) TOPSIS-NORM3

As mentioned above, the TOPSIS-norm3 method is the second TOPSIS-based method proposed by Senouci et al. [166]. The normalization procedure adopted by the TOPSIS-norm3 determines an absolute maximum for cost attributes and a minimum for benefit attributes.

32) TOPSIS-NORM4

The TOPSIS-norm4 algorithm is the third TOPSIS-based method proposed by Senouci et al. [166], as mentioned above. The normalization strategy in TOPSIS-norm4 dynamically sets maximum and minimum attributes by deriving the values from network parameters. With this approach, the best attributes' normalized values will equal 1.

Senouci et al. [166] also conducted a performance evaluation, revealing that the new techniques could reduce and eventually eliminate the ranking abnormalities.

33) UTILITY FUNCTION-BASED TOPSIS

Senouci et al. [167] put forward a new TOPSIS-based scheme, here called Utility Function-based TOPSIS, which employs utility functions to normalize the decision matrix values. This aims to eliminate the effects of ranking abnormality and optimize the TOPSIS ranking process.

The authors also conducted a comparative analysis [167] to evaluate the effects of ranking abnormality and ranking performance contrasted with the classic TOPSIS method. The results reveal that the new method can reduce the impact of ranking abnormality and select better networks than the original.

34) SIMPLIFIED AND IMPROVED MULTIPLE ATTRIBUTES ALTERNATE RANKING (SI-MAAR)

SI-MAAR was set out by Chandavarkar and Guddeti [168] to eliminate the dependence on normalization and weighting procedures and reduce the rank reversal problem.

In addition to introducing the new technique, the authors [168] also conducted a performance evaluation of SI-MAAR employing classical MADM methods. The results proved that SI-MAAR can provide more reliable network alternatives than TOPSIS, SAW, MEW, and GRA.

35) MODIFIED-SAW (M-SAW)

Bendaoud et al. [169] introduced M-SAW, a modified version of the SAW method, intending to improve the performance of the original implementation.

Furthermore, an experimental evaluation [169] showed that M-SAW outperforms the classical MADM method, including the original SAW algorithm.

36) TOPSIS-BASED UTILITY

Lahby and Sekkaki [170] introduced a hybrid approach consisting of a joint operation of the TOPSIS algorithm and a utility function

The TOPSIS-based utility approach was evaluated [170], and the results revealed that the employed mechanism reduces the effect of some well-known handover problems, such as reversal rank and the ping-pong effect.

37) MODIFIED GRA (MGRA)

Du et al. [171] put forward MGRA, which consists of a GRA-based decision mechanism that covers both the user preferences and the status of the candidate networks.

In addition to proposing the MGRA, the authors assessed [171] its performance regarding network load balancing and unnecessary handovers.

38) MODIFIED-MULTIPLICATIVE EXPONENT WEIGHTING (M2EW)

A modified version of the MEW algorithm, M2EW, was introduced by Jumantara et al. [172]. Improvements in M2EW are achieved by employing the Euclidean distance technique in the alternative ranking procedure.

The evaluations proved [172] that M2EW had a better performance than SAW and the original MEW algorithms for the background traffic class.

39) EUCLIDEAN DISTANCE-BASED NETWORK SELECTION ALGORITHM (EDBNS)

Kumari and Sravani [173] proposed five (5) new MADM methods, namely:

1) Euclidean Distance-Based Network Selection Algorithm (EDBNS)
2) Rank Reversal Technique-Based Algorithm (RRTA)
3) Parameter-Based Network Selection Algorithm (PBNSA)
4) Oliver Blume Algorithm Method (OBAM)
5) Similarity-Based Network Selection Algorithm (SBNSA)

The EDBNS ranking procedure is based on the Euclidean distance from the decision matrix to the ideal and the non-ideal matrix. The other four methods are examined below.

40) RANK REVERSAL TECHNIQUE-BASED ALGORITHM (RRTA)

RRTA [173] jointly employs the TOPSIS similarity concept and the cost function to determine the best alternative network [174].

41) PARAMETER-BASED NETWORK SELECTION ALGORITHM (PBNSA)

The PBNSA [173] adopts the PROMETHEE preference structure, which is based on the superiority analysis between the attributes and the Euclidean distance concepts to determine the degree of preference among them.

42) OLIVER BLUME ALGORITHM METHOD (OBAM)

OBAM [173] applies a cost function that inputs the elements of an ideal matrix consisting of the maximum and minimum values for each attribute set. In the ranking state, OBAM selects the alternative with the minimum cost.

43) SIMILARITY-BASED NETWORK SELECTION ALGORITHM (SBNSA)

SBNSA [173] is based on quantifying a disagreement index of the alternatives concerning the ideal and non-ideal solutions for defining the best alternative.

44) ENHANCED-MOORA (E-MOORA)

E-MOORA enhances the MOORA method [175] by incorporating vector normalization for benefit and cost attributes to overcome the ranking abnormality phenomenon.

Palas et al. [175] carried out a performance evaluation to validate the efficiency of the method in terms of minimizing unnecessary HO, radio link failure, and user throughput when compared to traditional MADM methods, such as GRA and TOPSIS.

45) COMBINED COMPROMISE SOLUTION (COCOSO)

COCOSO [176] was designed by combining the Exponential Weighted Product technique (EWP) and the SAW technique.

The evaluation presented by Mefgouda and Idoudi [176] was performed to demonstrate the efficiency of COCOSO in terms of rank reversal ratio by performing simulations using conversational, streaming, background, and interactive traffic. The results demonstrated that COCOSO outperformed SAW and TOPSIS.

46) OPPORTUNE CONTEXT-AWARE NETWORK SELECTION (OCANS)

OCANS [177] relies on the user-centric approach, in which the user performs decisions based on pre-defined preferences.

Honarvar et al. [177] evaluated the efficiency of OCANS regarding QoS, battery efficiency, and security. The results showed that OCANS outperformed traditional methods such as TOPSIS and SAW.

VI. MADM CATEGORIZATION AND CHARACTERISTICS

This section classifies, compares, and discusses the different ranking MADM algorithms and their main applications. Table 7 summarizes the state-of-the-art ranking techniques into six (6) main categories, as follows:

A. VALUE MEASUREMENT-BASED

In this category, the ranking procedure involves calculating the utility function of the considered attributes using both sum-based and multiplicative-based techniques. These simple calculations define the final ranking, eliminating the need for complex, computer-intensive processes to select the best alternative among the candidate networks.

The categories here include traditional methods like SAW and MEW, and other methods often used in different areas, such as the multiple attribute utility theory (MAUT) and multiple attribute value theory (MAVT). These methods offer significant benefits, allowing for the compensation of good value criteria with other less favorable values.

Despite their drawbacks, such as the cognitive challenge and time consumption of preference elicitation, these methods have proven to be highly effective in interactive and conversational traffic applications, serving as a reliable tool for network selection.

B. GREY SYSTEM-BASED

The grey system contains uncertain information in grey numbers or variables [178]. The grey theory was devised as a mathematical theory with concepts of grey sets and designed to solve uncertainty problems. This category includes methods that use a grey system procedure to obtain the final rank, usually employing discrete data with poor, incomplete, and uncertain information.

The more widely known MADM strategy in this category is the traditional GRA and all the GRA-based methods (e.g., M-GRA, GRA-based, and GRA-TOPSIS). An advantage of this set of methods is the satisfactory results obtained when handling small amounts of data and many factor variables [179].

At the same time, its drawback is that it lacks self-learning, self-organizing, and self-adapting or processing nonlinear information [180]. These methods obtained the best performance when networks were selected for the use of streaming traffic applications [171], [181].

C. SIMILARITY DISTANCE-BASED

Mathematical distances are often used to measure the distance between two points. This category includes the MADM techniques, which use mathematical distances (e.g., Euclidean and Manhattan) to compare and calculate the distance from an alternative to an ideal solution (i.e., a referential alternative with the attribute values that can supply the objectives of the decision). An advantage of this set of methods is that they include a limitless number of alternatives and evaluated attributes [182].

Nevertheless, similarity distance methods can be regarded as goal programming methods [183], and, following, these methods are too complex to allow appropriate weights to be set [184]. Traditional methods like TOPSIS and VIKOR are included in this set. These methods obtained the best performance in network selection for applications with streaming and conversational traffic types [87], [168], [185], [186], [187].

D. OUTRANKING-BASED

This group of methods is characterized by its degree of dominance, which means that the value of an attribute may dominate other alternatives. The procedure consists of a pairwise comparison for each criterion to find the preference of one alternative to another [188], [189]. The advantage of this group of methods, which includes traditional strategies like ELECTRE and PROMETHEE, is that it avoids making compensation between attributes and the normalization process [182].

However, the Outranking-based methods may require more computational resources than another set of methods owing to their complexity [168], and the outranking may make it difficult to detect the benefits and drawbacks of each alternative [190]. This set of methods is most suitable for evaluating applications employing conversational, interactive, and data traffic [181], [191], [192], [193].

E. MARKOV CHAIN-BASED

The Markov chain approach, owing to its ability to integrate dependent heuristic methods for applications, is an attractive method for vertical handover using multiple decision factors (attributes) [148]. This method builds a Markov transition decision matrix [194] and uses a stationary distribution to rank the alternatives. It is a category that includes methods combining the concepts of MADM and the Markov chain, which are two types of vertical handover algorithms.

An advantage of the Markov chain-based approach is that it has a better user control consideration for the final decision allowed by the MADM concepts (while the traditional Markov methods lack user control consideration [28]). On the other hand, Wang and Kuo [63] thought that, in several scenarios, this approach is best suited to calling admission control and not to network selection where it lacks precision.

The methods based on the Markov chain obtain the best performance in network selection if used in conversational traffic applications [148], [150].

F. USER-CENTRIC/MADM HYBRID

This category includes methods that combine MADM and User-centric approaches. Similar to Markov chain-based, the pros of this approach are that it has a better user control consideration for the final decision allowed by the MADM concepts. However, like the Markov chain approach, implementing this category is a very complex task [177].

G. DISCUSSION

Several MADM methods were designed decades ago for general calculation purposes. Years later, they were employed in mobility decision mechanisms. As they were increasingly used, it became evident that they applied to specific network service scenarios, as proved by evaluations and experiments.

Table 8 provides a glance into the historical context of MADM ranking methods and summarizes the algorithms presented in section V through their characteristics in terms of:

(a) being arranged in the order of the year when they were devised;
(b) their original goal (i.e., if the algorithm was proposed with mobility decision purposes);
(c) their main usage scenarios.

As shown in Table 8, the first methods, employed in the 1960s, had a goal that differed from the mobility decision. For several years, their primary application was to support research in diverse fields such as energy and fuels, operations research and management science, business management, economics, and environmental sciences and ecology. This panorama underscores the versatility and adaptability of these methods.

Moreover, several research papers have been published over the years in the literature, as well as a significant number of books and book chapters directly related to the MADM approach [54], [195], [196]. However, it was only in 2008 that we had the first MADM method (DiA), designed to deal with the mobility decision problem (although classic methods such as SAW and TOPSIS had already been employed in handover decision-making early). After this, MADM was established as an efficient and promising solution that could be used in the area of handover decisions, and this led to the creation of several new algorithms.

VII. OPEN ISSUES AND CHALLENGES

Although the facilities in the handover decision process provided by the MADM approach offer many mobility management benefits, several challenges still need to be solved. Previous studies examined many of the mobility decision algorithms.

In this section, we point out several research challenges that, in our opinion, remain to be addressed to ensure an accurate deployment and improvement of future MADM mobility-based mechanisms.

A. RANKING ABNORMALITY

The ranking abnormality phenomenon, referred to as rank reversal, is caused by changes to normalized attribute values. This phenomenon leads to inconsistencies in classification [154]. The most common occurrence of ranking abnormality is eliminating an alternative from the pool, causing the ranking to change.

Several studies have tried to mitigate the effects of such ranking abnormality phenomenon on the main MADM methods by modifying known strategies or developing new techniques, e.g., DiA [104], NMMD [155] and more recently, SI-MAAR [168]. As another example, Lahby et al. [112] proposed the E-TOPSIS, which updates the final result by considering the relative importance of each candidate network's positive and negative solutions.

Normalization techniques are known to be ineffective against ranking abnormality in some methods, such as the AHP [200]. Extensive investigation is still needed to mitigate ranking abnormality, mainly concerning its ranking efficiency compared to the other existing methods. Thus, in addition to validating the reduction or absence of ranking abnormality, new schemes must show they can outperform existing solutions.

B. NETWORK SELECTION BASED ON USER SATISFACTION

New network selection decision-making systems are expected to satisfy user requirements (and not only their preference parameters) for a given service or application. Such constraint satisfaction can be guaranteed by employing the most appropriate handover decision methods for a specific running traffic class or, in other words, hiring the best MADM method for traffic class QoS requirements.

For instance, consider an in-transit mobile device running real-time multimedia applications. The main challenge here is, *which MADM method makes the best handover decision to meet user requirements?* Based on previous evaluations [65], [85], [87], [112], [130], [154], [166], [191], [197], [201], [202], [203], the most appropriate method cannot be selected by merely statistical or numerical/sensitive analysis.

Analyzing user satisfaction with a given service or application (using QoE metrics [204]) has been found to be the most effective among the main ways of determining network performance. Since the volume of Internet multimedia traffic, such as video-on-demand, has skyrocketed recently [205], analyzing multimedia applications' QoE has become essential in gauging overall system acceptability.

We previously [34] evaluated MADM methods in a mobility scenario by assessing how their decisions impacted users' QoE, notably the Structural Similarity Index (SSIM) and Video Quality Metric (VQM) [206]. Promising results helped fill this research gap, but there is still much to analyze. We evaluated only the SAW, TOPSIS, E2BS, GRA, and MEW methods in a horizontal handover scenario (Wi-Fi). For this reason, the new mobility decision solutions using MADM methods should employ mechanisms that can select the most appropriate method to meet the needs of a specific scenario and user requirement. Methods differ in applicability, as shown in Table 8.

C. LIMITING UNNECESSARY HANDOFFS (PING-PONG EFFECT)

The ping-pong effect, well-known in mobile networks, occurs when the UE performs many handovers in a limited period.

TABLE 7. Categorization of MADM ranking methods.

Categories	Decision methods	Description	Advantages	Limitations
Value Measurement based	SAW, M-SAW, VHO-QoS/QoE, MEW, M2EW, E-MOORA, COCOSO and WASPAS	The decision relies on a utility function (e.g., sum function, product function, etc.)	Simple calculations define the selected network with the best attributes, a bad performance of one criterion can be compensated by excellent performance of other available criteria.	It does not make comparisons with the best attribute values, and the preference elicitation can be cognitively challenging, and time-consuming.
Grey System-based	GRA, GRA-based-norm #(1-3), M-GRA and GRA-TOPSIS	The decision is based on the grey system.	The capacity to deal with unknown information allows satisfactory results to be achieved from small amounts of data and many portions of variables.	It lacks self-learning, self-organizing, and self-adaptation; weak processing of nonlinear information.
Similarity Distance-based	TOPSIS, TOPSIS-norm #(1-4), Utility Function-based TOPSIS and TOPSIS-based utility, E2BS, VIKOR, NMMD and NMMD-N#(1-4), MeTHODICAL, MULTIMOORA, E-TOPSIS, EDBNS, COPRAS, DiA, SI-MAAR, PBNSA, RRTA, SBNSA, OBAM, EDAS and GTMA	It is based on estimating mathematical distances to an ideal point (e.g., Mahalanobis, Euclidean, Pearson, Chebyshev, etc.).	Calculate the distance between all alternative networks and the ideal network solution (e.g., network with the best attributes); consider a non-limited number of alternatives and attributes.	It lacks consistent judgment, leading to an unsuitable weighting setting.
Outranking-based	PROMETHEE and ELECTRE	Selects the alternative that has higher preference than the others available.	Selects the alternative that has higher preference over the others. The methods in this category can avoid compensation between criteria and normalization, maintaining the original values.	It is difficult to implement; outranking makes it challenging to determine the strengths and weaknesses of the value of alternatives.
Markov chain methods	WMC1, WMC2	Consists of a MADM method combined with the Markov chain approach.	It allows better user consideration in the final decision, by considering the decision attributes.	It is difficult to implement and has low decision precision in several network selection scenarios.
User-Centric Methods	OCANS	Consists of a MADM method combined with the User-Centric approach.		

This causes extended latency, increases energy consumption, and reduces flow rate/throughput. It is mainly caused by frequent movement of the UE between different PoAs or even by the wide variation of the RSSI in a PoA coverage area [207].

Numerous solutions have been introduced, but only some authors have employed evaluations in network simulators/emulators. This knowledge gap prevents validating the impact of proposed solutions, especially in HetNets, which are increasingly common in 5G infrastructures. Examples of critical applications in this context are those who have fast-moving requirements [208], rely on cellular networks [31], or use a vehicular network infrastructure such as those driven by smart car network services [209].

D. OPEN PROBLEMS IN ATTRIBUTE RANKING

Our analysis found work analyzing inconsistencies in the ranking procedures of some MADM methods. In particular, Tran and Boukhatem [201] noticed abnormalities in methods such as SAW. Another example is the case observed when an attribute set has elements with similar values, i.e., similar scores between alternatives, which leads methods such as MEW to inconsistent final score calculation.

Obayiuwana and Falowo [87] noted less efficient ranking score calculation when decision-making employed only a few attributes (e.g., three). On the other hand, with a more significant number of alternatives (e.g., ten), ranking score calculation proved more accurate. However, a large number of alternatives increases computational overhead and handover latency. An interesting open question would be the analysis of these tradeoffs across several novel (5G) applications that would benefit from more responsive and delay-sensitive mobility management solutions.

E. RAPID EVALUATION PROTOTYPING

Several studies have evaluated MADM methods in different scenarios. Although this is a well-established research path with numerous existing valuable studies, we could not find a standardized way to accelerate innovation through devices that could provide rapid prototype implementations. Hence, evaluations have yet to be made in simulated wireless

TABLE 8. Characteristics of the main MADM ranking methods.

Method	Year	Mobility purposes	Main application
MEW	1960	×	Interactive, conversational and streaming traffic [130, 197]; data and cost applications [185].
ELECTRE	1966	×	Data traffic [191]; cost traffic [185]; conversational and streaming [181, 192].
SAW	1967	×	Interactive and conversational [168, 191].
TOPSIS	1981	×	Background and interactive traffic [168, 186]; conversational, streaming and data service [197–199].
PROMETHEE	1985	×	Conversational, background and interactive traffic [138].
GRA	1989	×	Low delay and bandwidth-intensive applications [168, 186]; conversational and streaming [181].
VIKOR	1990	×	Conversational and cost applications [185]; interactive traffic [85].
COPRAS	1994	×	Data, conversational and video traffic [144].
GTMA	2006	×	Reduction of ranking abnormality and number of handovers [147].
WMC1 WMC2	2008	✓	Data and conversational traffic [148, 150].
DiA	2008	✓	Reduction of ranking abnormality and number of handoffs for common traffic classes (background, interactive, streaming and conversational) [159].
MULTIMOORA	2010	×	Conversational, streaming and background traffic [153].
GRA-based-norm_1 GRA-based-norm_2 GRA-based-norm_3	2010	✓	Streaming traffic (better than original GRA), by employing different normalization techniques [34].
NMMD	2012	✓	Background traffic (ranking abnormality and reduction of number of handovers) [155].
WASPAS	2012	×	Data connection applications [91].
VHO-QoS/QoE	2013	✓	Conversational traffic [158].
E-TOPSIS	2013	✓	Background, interactive, streaming and conversational traffic [112].
E2BS	2014	✓	Streaming applications [34].
NMMD-N1 NMMD-N2 NMMD-N3 NMMD-N4	2014	✓	Background, streaming, interactive and conversational traffic (by employing the Euclidean normalization) [162].
GRA-TOPSIS	2015	✓	Scenarios with several network criteria [163].
MeTHODICAL	2015	✓	Application requirement-aware scenarios and reduction of ping-pong effect [164].
EDAS	2015	×	Uncertainty problems and various application scenarios [91].
TOPSIS-norm1 TOPSIS-norm2 TOPSIS-norm3 TOPSIS-norm4	2016	✓	Reduction of ranking abnormality [166].
Utility Function-based TOPSIS	2016	✓	Reduction of ranking abnormality [167].
SI-MAAR	2016	✓	Reduction of ranking abnormality [168].
M-SAW	2017	✓	Conversational, streaming and best-effort traffic applications [169].
TOPSIS-based utility	2017	✓	Reduction of ranking abnormality and ping-ping effect for common traffic classes [170].
M-GRA	2017	✓	Reduction in the number of handovers for conversational and streaming traffic applications [171].
M2EW	2017	✓	Background traffic [172].
EDBNS	2017	✓	Delay sensitive applications [173].
RRTA	2017	✓	Delay and packet loss sensitive applications [173].
PBNSA	2017	✓	Delay and bandwidth sensitive applications [173].
OBAM	2017	✓	Delay, jitter, loss, and bandwidth sensitive applications [173].
SBNSA	2017	✓	Cost and bandwidth sensitive applications [173].
E-MOORA	2021	✓	Improve network selection in number of handovers, radio link failure, energy efficiency and mean throughput [175].
COCOSO	2021	✓	Improve reduction of ranking abnormality [176].
OCANS	2022	✓	Improve network selection for low battery, high QoS, secure, and mixed applications. Fails in economy applications [177].

network scenarios with real features. Researchers are trying to overcome this problem by employing network simulators and emulators, such as NS-2 [118], NS-3 [210], and Mininet-WiFi [211]. Moreover, MADM methods are expected to face several evaluation scenarios that provide perspectives on QoE.

Few existing virtual network testbeds (e.g., GENI [212]) focus on wireless networks. Those who exist mainly have components designed to test reprogrammable radios but lack testing facilities that would enable innovation even in mobility management in general and MADM methods, in particular, in real scenarios.

VIII. CONCLUSION

This paper outlines a comprehensive survey of MADM methods used in the handover decision problem. First, we performed a thorough literature review of MADM methods employed in the context of the handover decision problem. In addition to the methods review, we present a detailed step-wise mathematical implementation of each MADM method in an appendix. Then, the reviewed handover decision solutions utilizing the MADM approach are classified and compared based on their main features, characteristics, primary applications, advantages, and limitations. Lastly, the paper broadly discusses the current open issues and future research directions for optimizing handover management systems with improved handover decisions supported by MADM facilities, highlighting their potential impact on real-world decision-making scenarios.

In future work, we intend to perform algorithmic computational complexity analysis of the MADM methods to evaluate their scalability and efficiency. Furthermore, we will investigate the impact of MADM handover decision methods on the user experience, considering applications with stringent QoE requirements (e.g., video streaming).

APPENDIX

This Appendix provides a detailed step-by-step mathematical implementation guide for each reviewed MADM technique. We have designed this detailed arrangement to assist researchers with a more thorough comprehension of the model's underlying principles.

A. WEIGHTING METHODS

1) WLS

(a) Construction of the pair-wise comparisons matrix A [57]:

$$A = \begin{bmatrix} a_{1,1} & a_{1,2} & \cdots & a_{1,j} \\ a_{2,1} & a_{2,2} & \cdots & a_{2,j} \\ \vdots & \vdots & \vdots & \vdots \\ a_{i,1} & a_{i,2} & \cdots & a_{i,j} \end{bmatrix} \quad (7)$$

where:

- $a_{ii} = 1$;
- $a_{ji} = \frac{1}{a_{ij}}$.

Since the comparison matrix A can be constructed manually, the value of a_{ij} can be assigned as an integer number between 1 and 9, which means that the higher the value, the greater the importance of the i^{th} criteria over the j^{th}. This step can repeat until the matrix A ensures user experience.

(b) Calculation of weights through modelling optimization problems [57], [59]:

$$\min_w \sum_{i=1}^{N}\sum_{j=1}^{N}(a_{ij}w_j - w_i)^2 \quad s.t. \sum_{i=1}^{N} w_i = 1 \quad (8)$$

where:

- a_{ij}: the ij^{th} element in the matrix A;
- w_i: the i^{th} element in a w vector, which will be defined.

(c) As described by Bikmukhamedov et al. [57], this mathematical modeling, shown in equation (8), requires a considerable amount of computational resources. Considering this, an alternative kind of optimization is proposed, which involves formulating it in a matrix form:

$$\min_w \{diag(ww^T)^T * diag(A^TA) - 2w^TAw + Nw^Tw\}$$
$$s.t.\ e^Tw = 1 \quad (9)$$

where:

- $e = [1 \ldots 1]^T \in \mathbb{R}^{N\times 1}$;
- $diag()$: operator that nulls all matrix elements except the main diagonal.

(d) Following the approach expressed in equation (10), the problem can be solved by analytically adopting Lagrangian multipliers [57]:

$$L(w,\lambda) = F(w) - \lambda * h(w) \quad |$$
$$F(w) = diag(ww^T)^T * diag(A^TA) - 2w^TAw + Nw^Tw$$
and
$$h(w) = e^Tw - 1 \quad (10)$$

Thus, the w weight vectors can be defined as follows [57]:

$$\frac{\partial L(w,\lambda)}{\partial w} = 2diagA^TA - 2Aw - 2A^Tw + 2Nw - \lambda e$$
$$\implies w = (2diag(A^TA) - 2A - 2A^T + 2NI_N)^{-1}\lambda e$$
$$(2diag(A^TA) - 2A - 2A^T + 2NI_N) \implies B$$
$$\frac{\partial L(w,\lambda)}{\partial \lambda} = -e^Tw + 1 = 0 \implies e^Tw = 1$$
$$\implies e^TB^{-1}\lambda e = 1$$
$$\implies \lambda = \frac{1}{e^TB^{-1}e}$$
$$w = \frac{(diag(A^TA) - A - A^T + NI_N)^{-1}e}{e^T(diag(A^TA) - A - A^T + NI_N)^{-1}e} \quad (11)$$

where I_N corresponds to the $N \times N$ identity matrix.

2) AHP

(a) Definition of the AHP hierarchy: this top-to-bottom hierarchy represents a decision-making problem that can be split into upper levels (the goals of the decision-making process) and lower levels (the attributes included in this problem) [213]. In this case, when the aim is to select the best network, the criteria are represented by the QoS attributes, and the alternatives are defined by the networks that need to be evaluated for selection;

(b) A pairwise comparison between attributes of the comparison matrix. This matrix of size $N \times N$ depends on the importance (values ranging between 1 and 9) given to each attribute. Table 9 shows the possible values and their respective descriptions:

TABLE 9. Example of AHP degree of preference [120].

Degree of preference	Description
1	Equal preference
3	Moderately preference
5	Strong preference
7	Very strong preference
9	Absolutely preference
2, 4, 6, 8	Intermediate values

$$A = \begin{bmatrix} 1 & x_{12} & \cdots & x_{1j} \\ x_{21} & 1 & \cdots & x_{2j} \\ \vdots & \vdots & \vdots & \vdots \\ x_{i1} & x_{i2} & \cdots & x_{ij} \end{bmatrix} \quad (12)$$

where:

- $1, 2 \cdots i$: the number of attributes;
- $1, 2 \cdots j$: the number of attributes;
- x_{ij}: the degree of importance of an attribute i of an attribute j:

$$x_{ij} = \frac{1}{x_{ji}} \quad s.t. \quad i = j; x_{i,j} = 1. \tag{13}$$

(c) Normalization of the elements in the matrix A, resulting in a normalized comparison matrix A_{norm}:

$$y_{ij} = \frac{x_{ij}}{\sum_{i=1}^{N} x_{ij}} \tag{14}$$

where N is the number of compared QoS attributes.

(d) Calculation of the weights of each attribute:

$$w_i = \frac{\sum_{i=1}^{N} y_{ij}}{N} \quad s.t. \sum_{i=1}^{N} w_i = 1 \tag{15}$$

(e) Evaluation of to what extent the comparison conforms to the Consistency Ratio (CR):

$$CR = \frac{CI}{RI} \tag{16}$$

$$CI = \frac{\lambda_{max} - N}{N - 1} \tag{17}$$

$$\lambda_{max} = \frac{\sum_{i=1}^{n} b_i}{n} \quad s.t. \quad b_i = \frac{\sum_{j=1}^{n} W_i * a_{ij}}{W_i} \tag{18}$$

where:

- λ_{max}: is the largest eigenvalue of A_{Norm} [214]. As the AHP is an eigenvector-based method, it requires the eigenvalue of the matrix A to calculate the weight of attributes;
- RI: the Random Index (RI) associated with the number of considered criteria, as defined in Table 10.

TABLE 10. The value of RI associated with the number (N) of considered criteria [120].

N	2	3	4	5	6	7	8	9	10
RI	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49

(f) Definition of a consistent comparison: a weighting process is considered consistent when the CR is less than 0.1 (i.e., 10%) [215].

3) RW

(a) Definition of attribute weights (the sum of all weights must be equal to 1):

$$\sum_{i=1}^{n} w_i = 1 \tag{19}$$

where w_i represents the weights of each attribute i.

4) CRITIC

(a) Construction of a $M \times N$ decision matrix [87], where M represents the number of candidate networks and N the number of attributes:

$$D = \begin{bmatrix} x_{1,1} & x_{1,2} & \cdots & x_{1,j} & \cdots & x_{1,N} \\ x_{2,1} & x_{2,2} & \cdots & x_{2,j} & \cdots & x_{2,N} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ x_{i,1} & x_{i,2} & \cdots & x_{i,j} & \cdots & x_{1,N} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ x_{M,1} & x_{M,2} & \cdots & x_{M,j} & \cdots & x_{M,N} \end{bmatrix} \tag{20}$$

(b) Normalization of the decision matrix elements:

$$r_{ij} = \frac{x_{ij} - x_j^{worst}}{x_j^{best} - x_j^{worst}} \tag{21}$$

where:

- x_j^{best}: the best value of the j^{th} attribute;
- x_j^{worst}: the worst value of the j^{th} attribute.

(c) Calculation of the standard deviation of each normalized attribute.

(d) Construction of a $n \times n$ square matrix formed by r_{jk} elements. The matrix is calculated using the linear correlation coefficient between vectors x_j and x_k. If the attributes are similar, the value of the linear correlation coefficient equals 1, thus resulting in a diagonal value of 1.

(e) Measurement of the extent to which the j^{th} attribute does not have scope in the decision-making domain:

$$\sum_{k=1}^{m}(1 - r_{jk}) \tag{22}$$

(f) Assessment of the degree of relevance for each attribute:

$$C_j = \sigma_j \sum_{k=1}^{m}(1 - r_{jk}) \tag{23}$$

where:

- σ_j: the standard deviation of the j^{th} attribute;
- r_{jk}: the correlation coefficient between the vectors x_j and x_k. These vectors represent the values, mapped in a [0, 1] scale, of j and k attributes;
- m: the number of attributes.

(g) Calculation of the weight of the attribute j^{th}:

$$W_j = \frac{C_j}{\sum_{k=1}^{m} C_k} \tag{24}$$

5) ANP

(a) Construction of the pairwise comparison matrix, which compares the criteria in the entire system by determining the degree of importance that one criterion has about another criterion concerning user preferences. This involves using the values ranging from 1 to 9 (as shown in Table 9), which are defined for a given attribute [159]:

$$A = \begin{bmatrix} 1 & x_{1,2} & \cdots & x_{1,j} \\ x_{2,1} & 1 & \cdots & x_{2,j} \\ \vdots & \vdots & \vdots & \vdots \\ x_{i,1} & x_{i,2} & \cdots & x_{i,j} \end{bmatrix}$$
$$s.t.\ x_{ji} = 1, \forall\, i = j \text{ or } x_{ji} = \frac{1}{x_{ij}}, \forall\, i \neq j \quad (25)$$

where x_{ij} represents the degree of importance of an attribute i under an attribute j.

(b) Normalization of the elements in the matrix A, resulting in a normalized comparison matrix A_{norm}. Similar to AHP, the normalized decision matrix construction procedure is defined in equation (14);

(c) Definition of the weights of each attribute, according to equation (15);

(d) Evaluation of the CR, according to equations (16), (17) and (18);

(e) Construction of the supermatrix, used to deal with the relationship of feedback and interdependence with the elements [216]. The outcome of this judgment will make it possible to assign the value 0 to the pairwise comparison in the event of no interdependent relationship being determined. Otherwise, an unweighted supermatrix will be formed [217]:

$$W = \begin{array}{c} \\ C_1 \\ \\ \\ C_k \\ \\ \\ C_n \end{array} \begin{array}{c} e_{11} \\ \vdots \\ e_{1_{m1}} \\ \vdots\ e_{k1} \\ \vdots \\ e_{k_{mk}} \\ \vdots\ e_{n1} \\ \vdots \\ e_{n_{mn}} \end{array} \overset{\begin{array}{ccccc} C_1 & \cdots & C_k & \cdots & C_n \\ e_{11} \cdots e_{1_{m1}} & & e_{k1} \cdots e_{k_{mk}} & & e_{n1} \cdots e_{n_{mn}} \end{array}}{\begin{bmatrix} W_{11} & \cdots & W_{1k} & \cdots & W_{1n} \\ \vdots & & \vdots & \vdots & \vdots \\ W_{k1} & \cdots & W_{kk} & \cdots & W_{kn} \\ \vdots & & \vdots & \vdots & \vdots \\ W_{n1} & \cdots & W_{nk} & \cdots & W_{nn} \end{bmatrix}}, \quad (26)$$

where:

- C_i: a given m cluster ($n = 1 \cdots n$);
- e_{nm}: a given element n in a cluster m;
- W_{ij}: the eigenvector of the influence of compared elements in different clusters.

6) TRUST

(a) Identification of ongoing network events (and their respective relative importance) combined with the selection procedure (see Table 5);

(b) Construction of an EA $k \times n$ matrix, which includes the network attributes (n) and network events (k):

$$EA = \begin{bmatrix} c_{1,1} & c_{1,2} & \cdots & c_{1,n} \\ c_{2,1} & c_{2,2} & \cdots & x_{2,n} \\ \vdots & \vdots & \vdots & \vdots \\ c_{k,1} & c_{k,2} & \cdots & c_{k,n} \end{bmatrix} \quad (27)$$

where:

- $i = 1 \ldots k$: a set of handover trigger events;
- $j = 1 \ldots n$: a set of considered attributes;
- Each c_{ij}: the effect of an event i on an attribute j. This variable can be assumed as 1 (True) or 0 (False).

(c) Construction of a diagonal TF matrix which displays the number (k) of ongoing events i at the time of the network selection procedure:

$$TF = \begin{bmatrix} tf_{1,1} & 0 & \cdots & 0 \\ 0 & tf_{2,2} & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & \cdots & tf_{k,n} \end{bmatrix} \quad (28)$$

where:

- k: non-negative integer;
- tf_{ij}: the current state (i.e., True or False) of an event i.

(d) Calculation of the weights (based on the eigenvector method) following the events and description of the weighting relationship (see Table 5):

$$W_E = [we_1, we_2 \ldots we_k] \quad (29)$$

where we_k represents the weight of an event k.

(e) Classification of events at two levels of hierarchy (as shown in Table 5), namely: *(i)* W_E1 representing the upper level or layer 1; and *(ii)* W_E2i representing the bottom level or layer 2:

1. W_E1 representing the upper level or layer 1:

$$W_E1 = [we1_1, we1_2, \ldots we1_k1] \quad (30)$$

2. W_E2i representing the bottom level or layer 2:

$$W_E2i = [we2i_1, we2i_2, \ldots we2i_k2] \quad (31)$$

Where i represents the group i within an event j (e.g., type of traffic).
Therefore, the values of the weights of an j^{th} event in a given group i^{th} can be calculated:

$$we_{ij} = we1_i * we2i_j \quad (32)$$

(f) The calculation of the final subjective weights:

$$W_S = [ws_1\ ws_2\ \ldots\ ws_n] = W_E * TF * EA \quad (33)$$

(g) At this point, the weight of the j^{th} attribute can be calculated:

$$ws_j = \sum_{i=1}^{k} we_i * tf_{ii} * c_{ij} \quad (34)$$

7) WRMA

(a) Establishment of a state table consisting of information about the considered network attributes;

(b) Traffic type assignment by traffic class definitions (see Table 6);

(c) Map network applications at priority levels to achieve effectiveness in the attribute weighting process. This mapping process involves classifying the applications into priority levels ranging from 1 to 8 so that the lowest and the highest levels can be determined;

(d) Weight assignment based on the relationship between attributes and priority levels. At this point, it is necessary to conduct a sensitive and subjective analysis of the importance of a given attribute (e.g., delay) to a particular network application (e.g., real-time multimedia streaming), represented by the appropriate traffic type, which is carried out by employing the priority levels described in the previous stage. Table 11 provides an example of the attribute weight assignment adopted by WRMA;

TABLE 11. Example of attributes' weight assignment [114].

Traffic type	Attribute #1	Attribute #2	Attribute #n
T1	2	4	1
T2	7	3	5
T3	1	3	4
T4	3	2	6

(e) Calculation of the final weight values by dividing the weight value of each attribute by the sum of all the attributes of a given traffic type:

$$w_i = \frac{x_i}{\sum_{i=1}^{n} x_i} \tag{35}$$

where x_i identifies the value of each attribute for the traffic type i.

8) M-AHP

(a) Calculation of weights based on the experience of a given expert i using the pairwise comparison matrix, according to equation (12):

$$W_{AHP_i} = [a_{i1}, a_{i2}, \ldots, a_{im}] \ s.t. \sum_{j=1}^{m} a_{ij} = 1; i = 1 \ldots n \tag{36}$$

(b) Calculation of the final weights for each attribute, achieved through the geometric mean of the values of an attribute from the perspective of different experts:

$$W_{M-AHP} = [c_1, c_2, \ldots, c_m] \quad s.t. \ c_j = \sqrt[n]{\prod_{j=1}^{n} a_{ij}} = 1; i = 1 \ldots m, \tag{37}$$

where:

- m: the attributes;
- n: the experience of each of the experts;
- c_j: the geometric mean of the weights obtained for a given attribute j by an expert i.

9) M-ANP

(a) Construction of the pairwise comparison matrix to determine the importance degree of criterion regarding user preferences. This procedure uses the 1-9 range values to define the degree of importance of (see Table 9). The construction of this comparison matrix is expressed in equation (25);

(b) Normalization of the elements in the comparison matrix following equation (14);

(c) Calculation of weights according to the experience of a given expert i:

$$W_{ANP_i} = [a_{i1}, a_{i2}, \ldots, a_{im}] \ s.t. \sum_{j=1}^{m} a_{ij} = 1; i = 1 \ldots n \tag{38}$$

(d) Calculation of the final weights for each attribute, obtained through the geometric mean of values of an attribute, obtained from a given expert:

$$W_{M-ANP} = [c_1, c_2, \ldots, c_m] \quad s.t. \sqrt[n]{\prod_{j=1}^{n} c_j} = 1; j = 1 \ldots m] \tag{39}$$

where:

- m: the attributes;
- n: the experience of each of the experts;
- c_j: the geometric mean of the weights obtained for a given attribute j by an expert i.

(e) Construction of the supermatrix, as suggested by the equation (26).

10) i-TRUST

(a) Determine the relative importance of a requirement defined by a user:

$$RQ = [r_1, r_2, \cdots, r_k] \tag{40}$$

where:

- k: the number of requirements;
- r_k: the importance of a requirement k. These values range between a and b;
- a and b: the least and highest importance values, respectively. Intermediate values ($a \leq x < b$) represents a mid-level importance between both values, $s.t.$ $\{(a, b) \in \mathbb{R} : (a, b) \geq 0 \ \& \ b > a\}$.

(b) Definition of a binary vector from the user requirements defined in equation (40), where each element $bv_k = 1$ for all non-zero elements in RQ:

$$BV = [bv_1, bv_2, \cdots, bv_k] \tag{41}$$

(c) Construction of a diagonal matrix from the binary vector BV:

$$D = \begin{bmatrix} d_{11} & \cdots & 0 \\ \vdots & \vdots & \vdots \\ c_{k1} & \cdots & c_{kk} \end{bmatrix} \tag{42}$$

where:

- $d_{ii} = bv_i$;
- $d_{ij} = 0, \forall i \neq j$.

(d) Construction of a correspondence $k \times m$ matrix, which displays the relationship between attributes (m) and requirements (k):

$$EA = \begin{bmatrix} c_{11} & c_{12} & \cdots & c_{1m} \\ c_{21} & c_{22} & \cdots & x_{2m} \\ \vdots & \vdots & \vdots & \vdots \\ c_{k1} & c_{k2} & \cdots & c_{km} \end{bmatrix} \quad (43)$$

where c_{ij} represents the effect of a given requirement k on the attribute j, assuming values of 1 or 0.

(e) Definition of the base weight vector, consisting of the base weight of the k^{th} attribute, which is manually defined by the operator. These weight values can be defined jointly using the eigenvector and the AHP methods:

$$W_B = [wb_1, wb_2, \cdots, wb_k] \quad (44)$$

where wb_k represents the base weight of an attribute k.

(f) Calculation of a new base weight vector, which reflects the relative importance of user requirements:

$$W_E = (W_B \odot RQ) \cdot D \cdot EA) \quad (45)$$

where $\odot$ identifies the element-wise multiplication operator.

(g) Calculation of the final weighting vector by adding a x_f scalar to the base weighting vector W_E. This scalar will replace all the zero values with non-zeros elements:

$$W_S = [w_{s1}, w_{s2}, \cdots, w_{sm}] = f(W_E^*) \quad (46)$$

where $f(\cdot)$ consists of the normalization function, which is applied as follows:
For benefit attributes:

$$v_{ij} = 1 - \frac{|x_{ij} - max_i(x_{ij}))|}{max_i(x_{ij}) - min_i(x_{ij})} \quad (47)$$

For cost attributes:

$$v_{ij} = 1 - \frac{|x_{ij} - min_i(x_{ij}))|}{max_i(x_{ij}) - min_i(x_{ij})} \quad (48)$$

where v_{ij} represents the normalized values, where the first equation normalizes benefit attributes and the second normalizes cost attributes.

(h) Calculation of the final subjective weight:

$$w_{sj} = \frac{\sqrt{w_{ej}^*}}{\sum_{j=1}^{m} \sqrt{w_{ej}^*}} \quad (49)$$

where:

- w_{ej}^*: j^{th} element of the normalized vector (W_E^*);
- m: the number of attributes.

(i) Construction of the final weighting vector (w_j) by merging the subjective and objective weight vectors, as described in the previous steps.

$$w_{oj} = \sqrt{\sum_{i=1}^{n} \frac{(x_{ij} - \bar{x_j})^2}{n\bar{x_j}}} \;\; s.t. \;\; \bar{x_j} = \frac{1}{n}\sum_{i=1}^{n} x_{ij} \quad (50)$$

$$w_j = \frac{w_{sj} \cdot w_{oj}}{\sum_{j=1}^{n}(w_{sj}) \cdot w_{oj}} \quad (51)$$

where n represents the number of alternatives.

B. RANKING METHODS

1) MEW

(a) Construction of the decision matrix, as expressed in equation (20);

(b) Normalization of the attribute values:
For cost criterion:

$$r_{ij} = \frac{x_j^{min}}{x_{ij}} \quad (52)$$

For benefit criterion:

$$r_{ij} = \frac{x_{ij}}{x_j^{max}} \quad (53)$$

(c) Calculation of scores of candidate networks:

$$S_i = \prod_{j=1}^{N} r_{ij}^{w_j} \quad (54)$$

where S_i represents the score of the network, which considers the values of the normalized attributes r_{ij} and their weights w_j. The weights will be negative values ($-w_j$) if a given attribute j is a cost attribute.

(d) Definition of the best network, which is obtained by finding the highest value of S_i:

$$A_{MEW}^* = arg \max_{i \in M} S_i \quad (55)$$

2) ELECTRE

(a) Construction of the decision matrix, as suggested by the equation (20).

(b) Calculation of the difference of the values between the attributes of the candidate networks and the referenced PoA:

$$r_{ij} = x_{ij} - x_j^{ref} \quad (56)$$

where x_j^{ref} identifies the reference PoA.

(c) Normalization of attribute values:

$$\hat{r_{ij}} = \frac{\max_{i \in M} r_{ij} - r_{ij}}{\max_{i \in M} r_{ij} - \min_{i \in M} r_{ij}} \quad (57)$$

where $\max_{i \in M} r_{ij}$ and $\min_{i \in M} r_{ij}$ represent the largest and smallest values obtained in equation (56), respectively.

(d) Application of weights for each attribute:

$$\tilde{r}_{ij} = w_j * \hat{r}_{ij} \quad (58)$$

(e) Calculation of the coefficients of agreement ($CSet(k, l)$) and disagreement ($DSet(k, l)$). These coefficients represent the superiority and inferiority of a given attribute j of the network k, respectively, for the same attribute in the network l:

$$CSet_{kl} = j|\tilde{r}_{kj} >= \tilde{r}_{lj} \tag{59}$$

$$DSet_{kl} = j|\tilde{r}_{kj} < \tilde{r}_{lj} \tag{60}$$

(f) Calculation of the concordance matrix:

$$C_{kl} = \sum_{j \in CSet_{kl}} w_j \tag{61}$$

(g) Calculation of the discordance matrix:

$$D_{kl} = \frac{\sum_{j \in DSet_{kl}} |\tilde{r}_{kj} - \tilde{r}_{lj}|}{\sum_{j \in N} |\tilde{r}_{kj} - \tilde{r}_{lj}|} \tag{62}$$

(h) Calculation of the agreement index of the network (i), which represents the degree of dominance of a network i over its alternatives:

$$\tilde{C}_i = \sum_{j \in N, j \neq i} C_{ij} - \sum_{j \in N, j \neq i} C_{ji} \tag{63}$$

(i) Calculation of the disagreement index (i), which represents the degree of the weakness of a network i compared with its alternatives:

$$\tilde{D}_i = \sum_{j \in N, j \neq i} D_{ij} - \sum_{j \in N, j \neq i} D_{ji} \tag{64}$$

(j) Choice of the alternative that has the best and worst agreement ($\tilde{C}_i$) and disagreement ($\tilde{D}_i$) indexes. An average for these two rankings is estimated if no alternative is found with these features. The alternative with the highest average will be considered the best network.

3) SAW

1) Construction of the decision matrix, as suggested by the equation (20).
2) Calculation of each cost and benefit criterion, as expressed in equations (2) and (3), respectively.
3) Application of the weights of each attribute:

$$\hat{a}_{ij} = w_j * r_{ij} \tag{65}$$

where:

- w_j: the weights of each attribute j;
- r_{ij}: the normalized values of an attribute j from an alternative i in the decision matrix.

4) Final calculation of the score by adding the total sum of the values of all the attributes:

$$S_i = \sum_{j=1}^{N} \hat{a}_{ij} \tag{66}$$

5) Selection of the best network based on the higher score:

$$A^*_{SAW} = arg \max_{i \in M} S_i \tag{67}$$

4) TOPSIS

(a) Construction of the decision matrix, as suggested by the equation (20).
(b) Normalization of attribute values, following the square root normalization, expressed in equation (6).
(c) Application of the respective weights for the construction of a weighted normalized decision matrix:

$$v_{ij} = w_j * r_{ij} \tag{68}$$

(d) Calculation of the positive (A^+) and negative (A^-) ideal solutions:

$$A^+ = (\max_{i \in M} v_{ij} | j \in J), (\min_{i \in M} v_{ij} | j \in J') \tag{69}$$

$$A^- = (\min_{i \in M} v_{ij} | j \in J), (\max_{i \in M} v_{ij} | j \in J') \tag{70}$$

where:

- A^+ and A^-: calculated according to the best and worst values for the attributes;
- v_{ij}: the weighted value of an attribute j in the network i.

(e) Calculation of positive (S_i^+) and negative (S_i^-) distance solutions:

$$S_i^+ = \sqrt{\sum_{j \in N} (v_{ij} - v_j^+)^2} \tag{71}$$

$$S_i^- = \sqrt{\sum_{j \in N} (v_{ij} - v_j^-)^2} \tag{72}$$

(f) Calculation of similarity between candidate networks and the ideal network:

$$c_i^* = \frac{s_i^-}{s_i^+ - s_i^-} \tag{73}$$

(g) Selection of the best network based on the highest score.

$$A^*_{TOP} = arg \max_{i \in M} c_i^* \tag{74}$$

5) PROMETHEE

(a) Construction of the decision matrix, as suggested by the equation (20).
(b) Calculation of the difference between the attribute values in the set of candidate networks based on pairwise comparisons:

$$d_k(a_i, a_j) = g_k(a_i) - g_k(a_j) \tag{75}$$

where:

- k: the attributes;
- i and j: the networks that are being compared;
- $g_k(a)$: the value of the attribute k for the network i.

(c) Enforcement of a preference function to determine the degree of superiority of a given attribute in the network i when compared with the same attribute in the network j as a function of $d_k(i, j)$:

$$P_k(i, j) = [d_k(i, j)] \tag{76}$$

TABLE 12. PROMETHEE preference functions [219].

Number	Description	Equation
1	Usual criterion	$p(d_k) = \begin{cases} 0 & \text{if } d_k \leq 0 \\ 1 & \text{if } d_k > 0 \end{cases}$
2	U-shape criterion (quasi-criterion)	$p(d_k) = \begin{cases} 0 & \text{if } d_k \leq p_k \\ 1 & \text{if } d_k > p_k \end{cases}$
3	V-shape criterion	$p(d_k) = \begin{cases} 0 & \text{if } d_k \leq 0 \\ \frac{d_k}{p_k} & \text{if } 0 \leq d_k \leq p_k \\ 1 & \text{if } d_k > p_k \end{cases}$
4	Level criterion	$p(d_k) = \begin{cases} 0 & \text{if } d_k \leq q_k \\ \frac{1}{2} & \text{if } q_k < d_k \leq p_k \\ 1 & \text{if } d_k > p_k \end{cases}$
5	V-shape with indifference criterion (linear)	$p(d_k) = \begin{cases} 0 & \text{if } d_k \leq q_k \\ \frac{d_k - q_k}{p_k - q_k} & \text{if } q_k < d_k \leq p_k \\ 1 & \text{if } d_k > p_k \end{cases}$
6	Gaussian criterion	$p(d_k) = \begin{cases} 0 & \text{if } d_k \leq 0 \\ 1 - e^{-\frac{d_k^2}{2s^2}} & \text{if } d_k > 0 \end{cases}$

Table 12 shows the possibilities PROMETHEE considers for the preference equation [218].
where:

- q_k and p_k: the threshold values of indifference and preference. These values are the largest and the smallest for each attribute obtained in equation (75);
- s: an intermediate value between p and q.

(d) Calculation of the global preference index:

$$\pi(a_i, a_j) = \sum_{k=1}^{q} P_k(a_i, a_j) w_k \tag{77}$$

(e) Calculation of positive and negative preference flow values (outranking flows):

$$\phi^+(a_i) = \frac{1}{n-1} \sum_{a_j \in A} \pi(a_i, a_j) \tag{78}$$

$$\phi^-(a_i) = \frac{1}{n-1} \sum_{a_j \in A} \pi(a_j, a_i) \tag{79}$$

where A represents the set of candidate networks.

(f) Selection of the best network based on the calculation of the preference flow value:

$$\phi(a_i) = \phi^+(a_i) - \phi^-(a_i) \tag{80}$$

6) GRA

1) Construction of the decision matrix, as suggested by the equation (20).
2) Normalization of network parameters using the MAX-MIN principle, based on equations (2) and (3).
3) GRC calculation:

$$\Gamma_{0,i} = \sum_{j=1}^{N} \frac{\Delta_{\min} + \zeta \Delta_{\max}}{\Delta_i + \zeta \Delta_{\max}} \tag{81}$$

$$\Delta_i = |x_{0j} - r_{ij}| \tag{82}$$

$$\Delta_{\max} = \max_{i \in M} \Delta i, \quad \Delta_{\min} = \min_{i \in M} \Delta i \tag{83}$$

where:

- Δ_i: the grey relational space, which makes the difference between the normalized values r_{ij} and the reference value x_{0j};
- $\Delta_{\max}$ and $\Delta_{\min}$: the largest and smallest values of Δ_i for each attribute;
- ζ: the value of the coefficient of distinction (it is usually assigned to the value of 0.5 [220]);
- M: the number of candidate networks.

4) Classification of candidate networks according to GRC values. The best network will be the one with the highest GRC value:

$$A^*_{GRA} = arg \max_{i \in M}(w_j * \Gamma_{0,i}) \tag{84}$$

7) VIKOR

(a) Construction of the decision matrix, as suggested by the equation (20).
(b) Normalization of attributes based on equation (6).
(c) Identification of the best (F_j^+) and worst (F_j^-) values of each attribute set:

$$F_j^+ = (\max_{i \in M} |j \in N_b), (\min_{i \in M} |j \in N_c) \tag{85}$$

$$F_j^- = (\min_{i \in M} |j \in N_b), (\max_{i \in M} |j \in N_c) \tag{86}$$

where:

- N_b: the set of benefit attributes;
- N_c: the set of cost attributes.

(d) Calculation of the measurement of utility (S_i) and the regret measure (R_i) [221]:

$$S_i = \sum_{j \in N} w_j * \frac{(F_j^+ - x_{ij})}{F_j^+ - F_j^-} \tag{87}$$

$$R_i = \max_{j \in N} \left[w_j * \frac{(F_j^+ - x_{ij})}{F_j^+ - F_j^-} \right] \tag{88}$$

(e) Calculation of the final score (Q_i) to determine the best network:

$$Q_i = v \left(\frac{S_i - S^+}{S^- - S^+} \right) + (1 - v) \left(\frac{R_i - R^+}{R^- - R^+} \right) \tag{89}$$

where:

- $S^+ = \min_{i \in M} S_i$;
- $S^- = \max_{i \in M} S_i$;
- $R^+ = \min_{i \in M} R_i$;
- $R^- = \max_{i \in M} R_i$;
- v: a value of superiority of the evaluated attribute (this value is estimated between 0 and 1).

The best network will be the one with the lowest value of Q_i.

$$A^*_{VIK} = arg \min_{i \in M} Q_i \tag{90}$$

8) COPRAS

(a) Construction of the decision matrix, as suggested by the equation (20).
(b) Calculation of the normalized decision matrix employing equation (6).
(c) Calculation of the weighted normalized decision matrix following the equation (65).
(d) Calculation of benefit (S_i^+) and cost attributes (S_i^-):

$$S_i^+ = \sum_{j=1}^{v} \hat{a}_{ij} | j \in j^{\max} \tag{91}$$

$$S_i^- = \sum_{j=1}^{v} \hat{a}_{ij} | j \in j^{\min} \tag{92}$$

(e) Calculation of the relative importance (prioritization) of the alternatives:

$$Q_i = S_i^+ + \frac{\min S_i^- \sum_{j=1}^{v} S_i^-}{S_i^- \sum_{j=1}^{v} \frac{\min S_i^-}{S_i^-}} \tag{93}$$

(f) Calculation of the utility value (N_i) ranking:

$$N_i = \frac{Q_i}{Q_{max}} \tag{94}$$

(g) Selection of the best network in terms of the highest utility value:

$$N_{TOP} = arg \max_{i \in M} N_i \tag{95}$$

9) GTMA

(a) Construction of the decision matrix, as suggested by the equation (20).
(b) Normalization of attribute values based on the linear normalization for cost attributes and benefit attributes, respectively:

$$nv_{ij} = \frac{\min(D_j)}{D_j} \tag{96}$$

$$nv_{ij} = \frac{D_j}{\max(D_j)} \tag{97}$$

(c) Construction of the pair-wise relative comparison matrix, representing the relative importance between the different network parameters. The relative importance depends on the application traffic type:

$$P = \begin{bmatrix} - & \cdots & p_{1j} \\ \vdots & \ldots & \vdots \\ p_{i1} & \cdots & - \end{bmatrix} \tag{98}$$

where:

- p_{ij}: determine the relative importance of the i^{th} attribute over the j^{th} attribute, which is based on the GTMA scale, as presented in Table 13;
- p_{ji}: determine the relative importance of the j^{th} attribute over the i^{th} attribute:

$$p_{ji} = 1 - p_{ij} \tag{99}$$

(d) Construction of the Performance Attribute Matrix (PAM) by incorporating the values of each candidate network and the P matrix for all attributes:

$$PAM_i = \begin{bmatrix} nv_{1j} & \cdots & p_{1j} \\ \vdots & \ldots & \vdots \\ p_{i1} & \cdots & nv_{ij} \end{bmatrix} \tag{100}$$

(e) Calculation of the final score of each alternative network by applying the permanent function [222]:

$$S_i = Per(PAM_i) \tag{101}$$

TABLE 13. Comparison between the Saaty's and the GTMA scales.

Description	Saaty	GTMA
Equal preference	1	0.5
Moderate preference	3	0.590
Strong preference	5	0.665
Very strong preference	7	0.745
Absolute preference	9	0.865
Intermediate values	2,4,6,8	0.545, 0.627, 0.705, 0.805

10) WMC1

(a) Compilation of a ranking list (T_q) for each decision factor q (i.e., the included attributes), with attributes sorted by order of quality (i.e., from best to worst):

$$T_q = [p_1 \geq p_2 \geq p_3 \geq \ldots \geq p_M] \tag{102}$$

(b) Construction of the Markov chain transition matrix (MC) by initializing a matrix of a given size $M \times M$ with all the elements equal to zero, in which mc_{ij} represents the conditional probability that a transition will occur from alternative p_i to alternative p_j.
(c) Update of the mc_{ij} elements in the matrix MC for each rank T_q:

$$mc_{ij} = mc_{ij} + \frac{w_q}{T_q(p_i)} \; if \; T_q(p_i) \geq T_q(j) \tag{103}$$

where represents the normalized weight of the decision factor q.
(d) Calculation of the stationary probability distribution π that sorts the candidate networks:

$$\pi_j = \sum_{i=1}^{M} \pi_i \, mc_{ij} \tag{104}$$

where π_j represents a (row) vector whose elements are probabilities summing to 1 and $\pi_j = \pi_j \times MC$.
(e) The best network will be the one with the highest value of π_j:

$$\pi_{TOP} = arg \max_{j \in M} \pi_j \tag{105}$$

11) WMC2

As discussed in section V, WMC2 follows the same approach as the WMC1, except for constructing the Markov chain transition matrix, which is performed as follows:

(a) Update mc_{ij} elements in the matrix MC for each rank T_q: if $p_i, p_j \in P$ and $\tau_q(p_i) > \tau_q(p_j)$:

$$mc_{ij} = mc_{ij} + \frac{w_q}{N} \tag{106}$$

if $p_i, p_j \in P$ and $\tau_q(p_i) = \tau_q(p_j)$:

$$mc_{ij} = mc_{ij} + \frac{N - \tau_q(p_i) + 1}{N} * w_q \tag{107}$$

12) DiA

(a) Construction of the decision matrix, as suggested by the equation (20).
(b) Calculation of the normalized decision matrix following equation (6).
(c) Calculation of the weighted normalized decision matrix following the equation (68).
(d) Calculation of positive (a_j^+) and negative (a_j^-) ideal values of each attribute following equations (69) and (70), respectively.
(e) Calculation of the Manhattan distance [223] between the candidate network attribute values and the positive (D_i^+) and negative (D_i^-) ideal solutions:

$$D_i^+ = \sum_{j=1}^{m} |v_{ij} - a_j^+| \tag{108}$$

$$D_i^- = \sum_{j=1}^{m} |v_{ij} - a_j^-| \tag{109}$$

where:
- a_j^+: the best value for each attribute set;
- a_j^-: the worst value for each attribute set.

(f) Find the Positive Ideal Alternative (PIA) by considering the minimum value (D_i^+) and the maximum value (D_i^-):

$$\min D^+ = \min D_i^+ = \min_i \sum_{j=1}^{m} |v_{ij} - a_j^+| \tag{110}$$

$$\max D^- = \max D_i^- = \max_i \sum_{j=1}^{m} |v_{ij} - a_j^-| \tag{111}$$

(g) Selection of the best network, which is expressed by the shortest distance to the PIA:

$$R_i = \sqrt{(D_i^+ - \min D^+)^2 + (D_i^- - \max D^-)^2} \tag{112}$$

13) MULTIMOORA

(a) Construction of the decision matrix, as suggested by the equation (20).
(b) Normalization of attribute values following equation (6).
(c) Calculation of the weighted normalized decision matrix following the equation (68).
(d) Calculation of the first classification model, based on the ratio system for each alternative:

$$y_i = \sum_{j=1}^{k} x_{ij}^* - \sum_{j=k+1}^{N} x_{ij}^* \tag{113}$$

where:
- $j = 1 \ldots k$: the set of benefit attributes;
- $j = (k+1) \ldots N$: the set of cost attributes.

(e) Calculation of the second classification model, which is based on the reference point, and is obtained through the Chebyshev distance [224]:

$$y_i^* = \min_i(\max_j |r_j - x_{ij}^*|) \tag{114}$$

where r_j identifies the best value for a particular attribute. If it is a cost attribute, then it is expressed as the lowest value of this attribute.

(f) Calculation of the third classification model [225]:

$$A_i = \prod_{j=1}^{k} r_{ij}^{w_j} \tag{115}$$

$$B_i = \prod_{j=k+1}^{N} r_{ij}^{w_j} \tag{116}$$

$$U_i = \frac{A_i}{B_i} \tag{117}$$

where:
- A_i: the product of attributes to be maximized (e.g., benefit attributes);
- B_i: the product of attributes to be minimized (e.g., cost attributes);
- U_i: the overall utility of the i^{th} alternative (i.e., candidate network) [225].

(g) Selection of the best network, which process is based on the dominance in the three classification models (i.e., ratio, reference point, and multiplication systems).

14) GRA-BASED-NORM_1

The GRA-based-norm_1 operating stages are the same as GRA (see Appendix B6 for details), except for the normalization procedure, which is as follows:

$$x_{ij}^{*-} = \frac{E_{max_j} - x_{ij}}{E_{max_j} - E_{min_j}} \tag{118}$$

$$x_{ij}^{*+} = \frac{x_{ij} - E_{min_j}}{E_{max_j} - E_{min_j}} \tag{119}$$

where E_{max_j} and E_{min_j} represent the absolute maximum and minimum values of the attributes, where the first is equal to the highest value of an attribute among the networks and the second is equal to 0.

15) GRA-BASED-NORM_2

The GRA-based-norm_2 operating stages are the same as GRA (see Appendix B6 for details), except for the normalization procedure, which is as follows:

$$x_{ij}^{*-} = \frac{E_{max_j} - x_{ij}}{E_{max_j} - l_j} \quad (120)$$

$$x_{ij}^{*+} = \frac{x_{ij} - E_{min_j}}{u_j - E_{min_j}} \quad (121)$$

where:

- E_{max_j} and E_{min_j}: the absolute maximum and minimum values of the attributes, where the first is equal to the highest value of an attribute among the networks and the second is equal to 0;
- u_j: the maximum value of a given j attribute;
- l_j: the lowest value of a given j attribute.

16) GRA-BASED-NORM_3

The GRA-based-norm_3 operating stages are the same as GRA (see Appendix B6 for details), except for the normalization procedure, which is as follows:

$$x_{ij}^{*-} = \frac{l_j}{x_{ij}} \quad (122)$$

$$x_{ij}^{*+} = \frac{x_{ij}}{u_j} \quad (123)$$

where:

- u_j: the maximum value of a given j attribute;
- l_j: the lowest value of a given j attribute.

17) NMMD

(a) Construction of the decision matrix, as suggested by the equation (20).
(b) Normalization of attributes by employing both the MAX technique, through equations (4) and (5) and the Square root method, using equation (6).
(c) Application of the weights of each attribute using equation (65).
(d) Calculation of the Mahalanobis distance between the alternative networks to find the best values for each attribute:

$$D_M(A_i) = [D_{i1}, D_{i2} \ldots D_{im}] \quad (124)$$

$$D_M(x) = (x-u)^T * S^{-1} * (x-u) \quad (125)$$

where:

- A_i: the alternative networks;
- u: the best values for each attribute.

(e) Definition of the best network:

$$C_i = \frac{\sum_{j=1}^{m} D_{ij}}{m} \quad (126)$$

where m represents the number of attributes.

18) WASPAS

(a) Calculation of the Q_i^1 score based on the SAW method (see Appendix B3 for details).
(b) Calculation of the Q_i^2 score based on the MEW method (see Appendix B1 for details).
(c) Calculation of the WASPAS final score Q_i, which consists of a combination of the SAW and MEW scores computation:

$$Q_i = \lambda Q_i^1 + (1-\lambda) Q_i^2 \quad (127)$$

where:

- Q_i^1 and Q_i^2: represent the scores of the SAW and MEW methods;
- λ: a constant with a value between 0 and 1 ($0 \leq \lambda \leq 1$). It is employed to determine which scores will more significantly impact the WASPAS final score Q_i.

19) VHO-QoS/QoE

(a) Construction of the decision matrix, as suggested by the equation (20).
(b) Normalization of attributes:

$$\hat{a}_{ij} = \frac{a_{ij} - a_j^{th}}{\bar{a}_j - a_j^{th}} \quad (128)$$

where:

- a_j^{th}: the minimum (for benefit attributes) or maximum (for cost attribute) threshold value for a given attribute;
- $\bar{a}_j$: the highest value for benefit criteria (or the lowest for cost criteria).

At this point, the normalized matrix can assume three types of values:

- Positive ($\hat{a}_{ij} > 0$): the value is greater than the defined threshold (i.e., it meets the minimum requirements);
- Zero ($\hat{a}_{ij} = 0$): the value of the attribute meets the threshold value (i.e., the minimum requirement);
- Negative ($\hat{a}_{ij} < 0$): the value is insufficient (compared with the threshold).

(c) Selection of the network based on the highest score:

$$NSF_i = \max_{i \in m} \sum_{i \in m}^{n} w_j \hat{a}_{ij} \quad (129)$$

20) E-TOPSIS

(a) Construction of the decision matrix, as suggested by the equation (20).
(b) Normalization of attribute values following equation (6).
(c) Application of the weights of each attribute, as expressed in equation (68).
(d) Calculation of the positive (A_i^+) and negative (A_i^-) ideal solutions following equations (69) and (70).
(e) Calculation of positive (S_i^+) and negative (S_i^-) distances following equations (71) and (72).

(f) Calculation of the relative closeness to an ideal solution:

$$c_i^* = \frac{s_i^+ * \lambda_1 + s_i^- * \lambda_2}{s_i^+ - s_i^-} \tag{130}$$

where:

- λ_1: the relative importance of the positive solution;
- λ_2: the relative importance of the negative solution.

(g) Selection of the best network, depending on the highest score, by employing equation (74).

21) E2BS

(a) Construction of the decision matrix, as suggested by the equation (20).

(b) Normalization of attribute values:

$$x_{ij} = \frac{x_{ij} - \bar{x}_j}{\sigma_j} \tag{131}$$

where:

- $\bar{x}_j$: the arithmetic mean of the attributes;
- σ: the standard deviation of the attributes.

(c) Application of the weights of each normalized attribute $\| x_{ij} \|$:

$$v_{ij} = w_j * \| x_{ij} \| \tag{132}$$

(d) Calculation of the final score of each candidate PoA:

$$d_{ij} = \sqrt{\sum_{j=1}^{n} (v_{ij} - r_{ij})^2} \tag{133}$$

(e) Definition of the best candidate network in terms of the highest score:

$$S = MaxScore(d) \tag{134}$$

22) NMMD-N1

The NMMD-N1 operating stages are the same as the NMMD (see Appendix B17 for details), except for the normalization procedure, which is based on the Euclidean normalization method, as shown in the equation (6).

23) NMMD-N2

The NMMD-N2 operating stages are the same as the NMMD (see Appendix B17 for details), except for the normalization procedure, which is based on the MAX-MIN normalization method, as expressed in the equations (2) and (3).

24) NMMD-N3

The NMMD-N3 operating stages are the same as the NMMD (see Appendix B17 for details), except for the normalization procedure, which is based on the Max normalization method, presented in the equation (4) and (5).

25) NMMD-N4

The NMMD-N4 operating stages are the same as the NMMD (see Appendix B17 for details), except for the normalization procedure, which is based on the additive normalization method, as defined in equation (1).

26) GRA-TOPSIS

(a) Construction of the decision matrix, as suggested by the equation (20).

(b) Normalization of attribute values based on equation (6).

(c) Calculation of the positive (A^+) and negative (A^-) ideal solutions following equations (69) and (70).

(d) Calculation of the GRC of each candidate network for the positive ($r(A^+(j), A_i(j))$) and negative ($r(\check{A}(j), A_i(j))$) ideal solutions:

$$r(A^+(j), A_i(j)) = \frac{\min_i \min_j |A^+(j) - A_i(j)| + \zeta \max_i \max_i |A^+(j) - A_i(j)|}{|A^+(j) - A_i(j)| + \zeta \max_i \max_i |A^+(j) - A_i(j)|} \tag{135}$$

$$r(A^-(j), A_i(j)) = \frac{\min_i \min_j |A^- - A_i(j)| + \zeta \max_i \max_i |A^+ - A_i(j)|}{|A^- - A_i(j)| + \zeta \max_i \max_i |A^- - A_i(j)|} \tag{136}$$

where:

- $|A^+(j) - A_i(j)|$: the grey relational space, which determines the difference between the normalized values $A_i(j)$ and the positive ideal solution value $A^+(j)$;
- $|A^-(j) - A_i(j)|$: the grey relational space, which makes the difference between the normalized values $A_i(j)$ and the negative ideal solution value $A^-(j)$;
- ζ: the value of the coefficient of distinction (it is usually assigned to the value of 0.5 [220]).

(e) Calculation of the grade of grey relation of each candidate network for the positive and negative ideal solutions:

$$r(A^+, A_i) = \sum_{j=1}^{n} \omega_j r(A^+(j), A_i(j)) \tag{137}$$

$$r(A^-, A_i) = \sum_{j=1}^{n} \omega_j r(A^-(j), A_i(j)) \tag{138}$$

(f) Definition of the relative closeness of distance of an alternative network disclosure to the positive ideal solution:

$$C_i = \frac{r(A^+, A_i)}{r(A^-, A_i)} \tag{139}$$

where:

(g) Selection of the best candidate network by ranking the alternatives according to their relative closeness to each other (the one with the greater value of C_i will be selected).

27) MeTHODICAL

(a) Construction of the decision matrix, as suggested by the equation (20).

(b) Normalization of attribute values employing the MAX-MIN method.

(c) Calculation of the weighted normalized decision matrices for costs and benefits:

$$\hat{B}_{i,b} = b_b \times \bar{B_{i,b}} \tag{140}$$
$$\hat{K}_{i,c} = k_c \times \bar{K_{i,c}} \tag{141}$$

where:
- $\bar{B_{i,b}}$: the elements of the benefit attributes matrix;
- b_b: the weight of a determined benefit attribute b;
- $\bar{K_{i,c}}$: the elements of the cost attributes matrix;
- k_c: the weight of a determined cost attribute c.

(d) Calculation of the ideal benefits $B_j \in B$ and the ideal cost solution $K_j \in K$:

$$I(\hat{B}_j) = \max\{\hat{B}_{ij} | i = 1, 2, \cdots, n\} \tag{142}$$
$$I(\hat{K}_j) = \min\{\hat{K}_{ij} | i = 1, 2, \cdots, n\} \tag{143}$$

(e) Calculation of the MeTHODICAL distance to determine the distance of each path (i.e., alternative network) and the ideal benefit and cost solutions:

$$\Delta(\hat{M}_i) = \sum_{j=1}^{B} \left[\frac{[I(\hat{M}_j) - \hat{M}_{ij}]^2}{[I(\hat{M}_j) - A(\hat{M}_j)] + \Phi} \right] \tag{144}$$

In the selection path context, the MeTHODICAL distance equation assumes two new values, i.e., for benefits ($\Delta(\hat{B}_i)$) and cost attributes ($\Delta(\hat{K}_i)$), respectively:

$$\Delta(\hat{B}_i) = \sum_{j=1}^{B} \left[\frac{[I(\hat{B}_j) - \hat{B}_{ij}]^2}{[I(\hat{B}_j) - A(\hat{B}_j)] + \Phi} \right] \tag{145}$$
$$\Delta(\hat{K}_i) = \sum_{j=1}^{K} \left[\frac{[I(\hat{K}_j) - \hat{K}_{ij}]^2}{[I(\hat{K}_j) - A(\hat{K}_j)] + \Phi} \right] \tag{146}$$

where:
- $A(\hat{B}_j) = m(\hat{B}_j) + v(\hat{B}_j)$ s.t. m = mean, v = variance;
- $A(\hat{K}_j) = m(\hat{K}_j) + v(\hat{K}_j)$;
- $I(\hat{B}_j) = \max\{\hat{B}_{ij} | i = 1, 2, \cdots, n\}$;
- $I(\hat{K}_j) = \min\{\hat{K}_{ij} | i = 1, 2, \cdots, n\}$;
- B_{ij}: the benefit attribute;
- K_{ij}: the cost attribute;
- $\Phi = 0.01$.

(f) Calculation of scores for each candidate network:

$$s_i = \sqrt{\alpha \times \Delta(\hat{B}_i) + (1 - \alpha) \times \Delta(\hat{K}_i)} \tag{147}$$

where α enables the differentiation between the benefit and cost distances.

(g) Calculation of score for the current time (t) for each network:

$$S_{i,t} = S_i + v(S_i, S_{i,(t-z)}) \tag{148}$$

(h) Selection of the best alternative by ordering the score vector. The selected network will be the one with the lowest score:

$$r_i = order(s_{i,t}) \tag{149}$$

28) EDAS

(a) Definition of an average solution matrix:

$$Av_j = [av_{ij}]_{m \times n} = \left[\frac{\sum_{i=1}^{n} x_{ij}}{n} \right] \tag{150}$$

where:
- m: number of attributes;
- n: number of alternatives.

(b) Computation of the Positive Distance from Average (PDA) and the Negative Distance from Average (NDA):

$$PDA = [pda_{ij}]_{m \times n} = \left\{ \frac{\max(0, (x_{ij} - av_{ij}))}{av_{ij}} \right\}, \quad if \ \forall c_j \in AT_1$$
$$PDA = [pda_{ij}]_{m \times n} = \left\{ \frac{\max(0, (av_{ij} - x_{ij}))}{av_{ij}} \right\}, \quad if \ \forall c_j \in AT_2 \tag{151}$$
$$NDA = [pda_{ij}]_{m \times n} = \left\{ \frac{\max(0, (av_{ij} - x_{ij}))}{av_{ij}} \right\}, \quad if \ \forall c_j \in AT_1$$
$$NDA = [pda_{ij}]_{m \times n} = \left\{ \frac{\max(0, (x_{ij} - av_{ij}))}{av_{ij}} \right\}, \quad if \ \forall c_j \in AT_2 \tag{152}$$

where:
- AT_1: the set of benefit attributes;
- AT_2: the set of cost attributes.

(c) Computation of the weighted sum of PDA and NDA:

$$SP_i = \sum_{i=1}^{n} w_j \times pda_{ij} \tag{153}$$
$$SN_i = \sum_{i=1}^{n} w_j \times nda_{ij} \tag{154}$$

(d) Computation of the normalized value of SP and SN:

$$NSP_i = \frac{(SP_i)}{\max_i(SP_i)} \tag{155}$$
$$NSN_i = 1 - \frac{(SN_i)}{\max_i(SN_i)} \tag{156}$$

(e) Calculation of the final score of each network:

$$AS_i = \frac{1}{2}(NSP_i + NSN_i) \tag{157}$$

29) TOPSIS-NORM1

The TOPSIS-norm1 operating stages are the same as TOPSIS (see Appendix B4 for details), except for the normalization procedure, which is based on the original MAX-MIN normalization method (see section III for more information).

30) TOPSIS-NORM2

The TOPSIS-norm2 operating stages are the same as TOPSIS (see Appendix B4 for details), except for the normalization procedure, which is as follows:

$$r_{ij}^{+} = \frac{x_{ij} - A_{min_j}}{A_{max_j} - A_{min_j}} \tag{158}$$

$$r_{ij}^{-} = \frac{A_{max_j} - x_{ij}}{A_{max_j} - A_{min_j}} \tag{159}$$

where:

- r_{ij}^{+} and r_{ij}^{-}: benefit and cost criteria, respectively;
- A_{min_j} and A_{max_j}: the absolute maximum and minimum values for each attribute (i.e., the smallest and highest values these attributes can achieve) [226].

31) TOPSIS-NORM3

The TOPSIS-norm3 operating stages are the same as TOPSIS (see Appendix B4 for details), except for the normalization procedure, which is as follows:

$$r_{ij}^{+} = \frac{x_{ij} - A_{min_j}}{max_j(x_{ij}) - A_{min_j}} \tag{160}$$

$$r_{ij}^{-} = \frac{A_{max_j} - x_{ij}}{A_{max_j} - min_j(x_{ij})} \tag{161}$$

where:

- r_{ij}^{+} and r_{ij}^{-}: benefit and cost criteria, respectively;
- A_{min_j} and A_{max_j}: the absolute maximum and minimum values for each attribute (i.e., the smallest and highest values that these attributes can achieve) [226].

32) TOPSIS-NORM4

The TOPSIS-norm4 operating stages are the same as TOPSIS (see Appendix B4 for details), except for the normalization procedure, which is as follows:

$$r_{ij}^{+} = \frac{x_{ij} - D_{min_j}}{D_{max_j} - D_{min_j}} \tag{162}$$

$$r_{ij}^{-} = \frac{D_{max_j} - x_{ij}}{D_{max_j} - D_{min_j}} \tag{163}$$

where:

- r_{ij}^{+} and r_{ij}^{-}: benefit and cost criteria, respectively;
- $D_{max_j} = max_j(x_{ij})$;
- $D_{min_j} = min_j(x_{ij})$;

The values of D_{max_j} and D_{min_j} are updated when an alternative is included. However, no changes will be performed if an alternative is removed.

33) UTILITY FUNCTION-BASED TOPSIS

(a) Construction of the decision matrix, as suggested by the equation (20).

(b) Normalization of attribute values following the utility function approaches described in Table 14.
where:
  - L: the maximum achievable value of $f(x)$ (usually assumes the value of 1);

TABLE 14. TOPSIS normalization utility functions [167].

Description	Equation
Increasing diminishing marginal utility	$f(x) = L - (L - b)e^{(-k(x-a))}$
Decreasing diminishing marginal utility	$f(x) = L - e^{(k(x-a))}$
Monotonic utility	$f(x) = \begin{cases} 1 - \frac{x}{u} & \text{if } x \leq u \\ 0 & \text{if } x > u \end{cases} f(x)$

  - k: the growth rate (k):

$$k = \frac{-\ln(1-p)}{(Target\ point - a)},\ 0 < p < 1 \tag{164}$$

  - b: the $y-intercept$, which means the point where the utility function crosses the y-axis;
  - a: the $x-intercept$, where the function value reaches a particular value (also known as the basic point). In this context, it is the minimum requirement to run a given service;
  - *Target point*: the recommended value for a smooth service;
  - p: an inversely proportional value to the distance between the *Target point* and a sufficient value for accommodating new demands, namely *Saturation point*;
  - u: the maximum value the user is willing to spend;
  - e: an Euler's number constant.

(c) Application of the respective weights for the construction of a weighted normalized matrix, as suggested by equation (68).

(d) Calculation of the positive (A_i^{+}) and negative (A_i^{-}) ideal solutions through equations (69) and (70).

(e) Calculation of the positive (S_i^{+}) and negative (S_i^{-}) ideal solutions following equations (71) and (72).

(f) Measurement of the relative closeness to the ideal solution, as suggested by equation (73).

(g) Selection of the best network by obtaining the highest relative closeness.

34) SI-MAAR

(a) Construction of the decision matrix, as suggested by the equation (20).

(b) Construction of the closeness index matrix (also called utility matrix):

$$CI_{ij} = \frac{a_{ij}}{(a_{ij} + e_j)} \tag{165}$$

where e_j indicates the expected value for a particular attribute [226].

(c) Calculation of the positive (A^{+}) and negative (A^{-}) ideal solutions:

$$(A^{+}) = \{A_1^{+}, A_2^{+}, \cdots, A_m^{+}\} \tag{166}$$

$$(A^{-}) = \{A_1^{-}, A_2^{-}, \cdots, A_m^{-}\} \tag{167}$$

where:

- A^{+}: the best values for an attribute.

- A^+: the worst values for an attribute.

(d) Calculation of the positive and negative scores of each alternative by employing the Euclidean distance technique:

$$ED_i^+ = \sqrt{\sum_{j=1}^{m}(CI_{ij} - A_j^+)^2} \quad (168)$$

$$ED_i^- = \sqrt{\sum_{j=1}^{m}(CI_{ij} - A_j^-)^2} \quad (169)$$

(e) Selection of the best network:

$$Score_i = \frac{ED_i^-}{ED_i^+ + ED_i^+} \quad (170)$$

35) M-SAW

(a) Construction of the decision matrix, as suggested by the equation (20).

(b) Division of the matrix into a set of vector columns, where each vector represents a specific criterion. For each attribute vector, networks are ranked according to their values:

$$income_{ij} = (\alpha - k_{ij}) * w_j \;\; s.t. \;\; k_{ij} = \min(Vect_{ij}) \quad (171)$$

where α indicates the number of candidate networks.

(c) The final result will be achieved with the sum of all the incoming values a given alternative receives:

$$R_i = \sum_{j=1}^{m} income_{ij} \quad (172)$$

36) TOPSIS-BASED UTILITY

(a) Construction of the decision matrix, as suggested by the equation (20).

(b) Normalization of the attribute values by using the square root normalization.

(c) Application of the respective weights for the construction of a weighted normalized matrix, as expressed in equation (68).

(d) Calculation of the positive (A_i^+) and negative (A_i^-) ideal solutions, according to the equations (69) and (70).

(e) Calculation of the positive (S_i^+) and negative (S_i^-) ideal solutions following equations (71) and (72).

(f) Measurement of the relative closeness to the ideal solution based on equation (73).

(g) Estimate of the user satisfaction:

$$U(x) = \alpha * \left[\frac{1}{1 + e^{-a(x-b)}} - \beta\right]$$
$$s.t. \;\; \alpha = \frac{(1 + e^{ab})}{e^{ab}} \; ; \beta = \frac{1}{(1 + e^{ab})} \quad (173)$$

where:

- a: the negative ideal solution;
- b: the positive ideal solution;
- x: the relative closeness to the ideal solution;
- e: a constant of the exponential utility function.

(h) Selection of the most suitable network by employing the ranked values of $U(x)$.

37) MGRA

(a) Construction of the decision matrix, as suggested by the equation (20).

(b) Normalization of network attributes following the MAX-MIN technique.

(c) Calculation of the GRC value, as expressed in equations (81), (82) and (83).

(d) Calculation of the positive (r_i^+) and negative (r_i^-) scores of each alternative:

$$r_i^+ = \sum_{j=m}^{m} = w_j \gamma_{ij}^+ \quad (174)$$

$$r_i^- = \sum_{j=m}^{m} = w_j \gamma_{ij}^- \quad (175)$$

where:

- γ_{ij}^+: the set of benefit attributes;
- γ_{ij}^-: the set of cost attributes.

(e) Ranking of candidate networks: the best network will be the one with the highest value of E_i:

$$E_i^* = \frac{r_i^-}{\sqrt{(r_i^+)^2 - (r_i^-)^2}} \quad (176)$$

38) M2EW

(a) Construction of the decision matrix, as suggested by the equation (20).

(b) Normalization of attributes values according to equations (52) and (53).

(c) Enforcement of a weighted improvement of both the benefit and cost matrix:

$$w_i = \frac{b_i}{\sum_{i=1}^{N} w_i} \;\; s.t. \;\; \sum_{i=1}^{N} w_i = 1 \quad (177)$$

(d) Calculation of the score of candidate networks following equation (54).

(e) Calculation of the alternative network ranking by dividing the vector S_i by the Euclidean weight value of each vector S, which represents the alternative preference of the vector S_i.

39) EDBNS

(a) Construction of the decision matrix, as suggested by the equation (20).

(b) Construction of the positive (I^+) and negative (I^-) ideal matrix:

$$I^+ = [i_{11}, i_{12}, \cdots, i_{1n}] \quad (178)$$

$$I^- = [i_{11}, i_{12}, \cdots, i_{1n}] \quad (179)$$

(c) Calculation of the distance between the decision matrix from the positive ideal matrix:

$$C_i^+ = \sqrt{\sum_{j=1}^{n}(D_{ij} - I^+)^2} \tag{180}$$

(d) Calculation of the distance between the decision matrix from the negative ideal matrix:

$$C_i^- = \sqrt{\sum_{j=1}^{n}(D_{ij} - I^-)^2} \tag{181}$$

(e) Normalization of the values of C_i:

$$C = \frac{C_i^{+/-}}{mean} \tag{182}$$

where *mean* is the mean between all values of C^+ or C^-.

(f) Calculation of the positive (S_i^+) and negative (S_i^-) solutions:

$$S_i^+ = \begin{bmatrix} C_{11} \\ \vdots \\ C_{M1} \end{bmatrix} \tag{183}$$

$$S_i^- = \begin{bmatrix} C_{11} \\ \vdots \\ C_{M1} \end{bmatrix} \tag{184}$$

(g) Selection of the best alternative network, which will be the one with the highest value of C_k:

$$C_k = \frac{S^-}{S^- + S^+} \tag{185}$$

40) RRTA

(a) Construction of the decision matrix, as suggested by the equation (20).
(b) Normalization of the attribute values following equation (6).
(c) Calculation of the weighted normalized decision matrix according to equation (68).
(d) Selection of the best and worst values for each attribute, as expressed in equations (69) and (70).
(e) Calculation of the distance measurement between the positive and negative ideal solutions, and the alternative solutions:

$$S_i^+ = \sqrt{\sum_{j=1}^{n} \frac{(v_j^+ - v_{ij})^2}{w_j}} \tag{186}$$

$$S_i^- = \sqrt{\sum_{j=1}^{n} \frac{(v_j^- - v_{ij})^2}{w_j}} \tag{187}$$

(f) Selection of the best alternative network in terms of the cost function:

$$C = \frac{S^-}{S^- + S^+} \tag{188}$$

41) PBNSA

(a) Construction of the decision matrix, as suggested by the equation (20).
(b) Definition of the function of preference, as shown in Table 12.
(c) Definition of a preference index for each pair of available alternatives:

$$n = V(a_i, a_j) = W_j * p_j(a_i) - g_k(a_j) \tag{189}$$

(d) Calculation of the distances (S_i^+ and S_i^-) between each pair and the positive and negative ideal points:

$$S_i^+ = \sqrt{\sum_{j \in N}(v_{ij} - v_j^+)^2} \tag{190}$$

$$S_i^- = \sqrt{\sum_{j \in N}(v_{ij} - v_j^-)^2} \tag{191}$$

(e) Selection of the best alternative network in terms of the relative approach degree of each scheme to the ideal points:

$$C_i = \frac{S_i^-}{S_i^- + S_i^+}, 0 < C_i^+ < 1, i \in m \tag{192}$$

42) OBAM

(a) Construction of the decision matrix, as suggested by the equation (20).
(b) Construction of the weighted matrix according to equation (68).
(c) Construction of the ideal matrix I from each considered attribute's minimum and maximum values.
(d) Selection of the best alternative network in terms of the cost function C_i:

$$C_i = \prod_i (\frac{D_{ij}}{I_j}) * w_{ij} \tag{193}$$

43) SBNSA

(a) Construction of the decision matrix, as suggested by the equation (20).
(b) Normalization of the attribute values employing the square root technique.
(c) Construction of the weighted normalized matrix according to equation (68).
(d) Definition of the positive (B_j^+) and negative (B_j^-) ideal solutions:

$$B_j^+ = \max(V_{ij}) \tag{194}$$

$$B_j^- = \min(V_{ij}) \tag{195}$$

(e) Calculation of the positive (θ_j^+) and negative (θ_j^-) solutions degree between each alternative:

$$\theta_j^+ = \frac{\sum_{j=1}^{m} V_{ij} * B_j^+}{(\sum_{j=1}^{m} V_{ij}^2)^{0.5} * (\sum_{j=1}^{m}(B_j^+)^2)^{0.5}} \tag{196}$$

$$\theta_j^- = \frac{\sum_{j=1}^m V_{ij} * B_j^-}{(\sum_{j=1}^m V_{ij}^2)^{0.5} * (\sum_{j=1}^m (B_j^-)^2)^{0.5}} \quad (197)$$

(f) Calculation of the degree of similarity between the alternatives and the positive and negative ideal solutions:

$$k_i = \theta_j^+ * v_{ij} \quad (198)$$

$$l_i = \theta_j^- * v_{ij} \quad (199)$$

(g) Calculation of the total performance index for each alternative:

$$o_i^+ = \frac{k_i}{B_j^+} \quad (200)$$

$$o_i^- = \frac{l_i}{B_j^-} \quad (201)$$

(h) Ranking and selection of the best network:

$$Q_i = \frac{o_i^+}{o_i^+ + o_i^-} \quad (202)$$

44) E-MOORA

(a) Construction of the decision matrix, as suggested by the equation (20);
(b) Normalization of the attribute values employing the square root technique.
(c) Calculation of the performance value:

$$Y_i = \Sigma_{j=1}^g (W_j \times N_{ij}) - \Sigma_{j=g+1}^5 (W_j \times N_{ij}) \quad (203)$$

where:

- W_j: the attribute weight;
- N_{ij}: each element of the normalized decision matrix N;
- g: the benefit attribute's set;
- $g+1$: the cost attribute's set.

45) COCOSO

(a) Construction of the decision matrix, as suggested by the equation (20).
(b) Normalization of attribute values employing the MAX-MIN technique.
(c) Computation of the weighted comparability sequence S_i for each alternative by following the equation (66).
(d) Computation of the power weight of comparability P_i for each alternative:

$$P_i = \sum_{j=1}^m w_j^{r_{ij}} \quad (204)$$

(e) Calculate of the relative weights:

$$k_{ia} = \frac{P_i + S_i}{\sum_{i=1}^n (P_i + S_i)} \quad (205)$$

$$k_{ib} = \frac{S_i}{\min_i(S_i)} + \frac{P_i}{\min_i(P_i)} \quad (206)$$

$$k_{ic} = \frac{\lambda(S_i) + (1-\lambda)(P_i)}{\lambda \max(S_i) + (1-\lambda)\max(P_i)} \quad (207)$$

where:

- k_{ia}: the sum of MEW (P_i) and SAW (S_i) scores;
- k_{ib}: the sum of the relative scores produced by MEW (P_i) and SAW (S_i) compared to the best scores;
- k_{ic}: the compromise between MEW and SAW scores;
- λ: a constant, usually set to 0.5.

(f) Ranking of the alternatives:

$$k_i = (k_{ia}k_{ib}k_{ic})^{\frac{1}{3}} + \frac{1}{3}(k_{ia}k_{ib}k_{ic}) \quad (208)$$

(g) Selection of the best alternative, which will be the one with the highest score.

46) OCANS

(a) Construction of the decision matrix, as suggested by the equation (20).
(b) Normalization of attribute values based on the sigmoid and the piecewise linear functions [227]:

$$u_ij = f_i(a_{ij}) = \frac{(\frac{a_i}{\mu_i})n_i}{1 + (\frac{a_i}{\mu_i}n_i)} \quad (209)$$

$$u_i = f_i(a_i) = \frac{ramp(a_i - X_{li}) - ramp(a_i - X_{ui})}{(X_{ui} - X_{li})} \quad (210)$$

where:

- a_i: the value of the j network attribute;
- u_i: the value of the normalized j network attribute;
- n_i: the slope tuning parameter of the sigmoid function;
- μ_i: the mid-range of a_i;
- $ramp$: a ramp function [228].

(c) Calculation of the utility value $U_i^{(a)}$, which represents the score of the candidate network:

$$U_i^{(a)} = \prod_{i \in A_j} (u_i)^{w_i^a} \quad (211)$$

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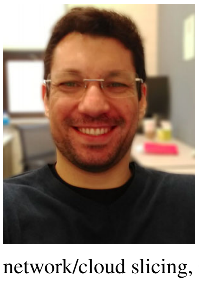

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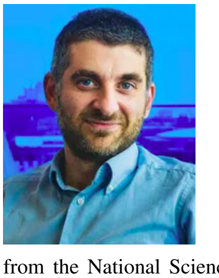

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