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MADM-based network selection and handover management in heterogeneous network: A comprehensive comparative analysis

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ABSTRACT

As radio access technologies, processing speeds, and multimode interfaces of low-powered portable devices continue to advance, the future of wireless communication is envisioned to offer pervasive network coverage, high data rates, and a wide spectrum of services while maintaining high mobility. High data rates, wide range of services, huge connectivity, capacity, and good geographic coverage are being provided by the ultra-dense deployment of small base stations (BSs) in heterogeneous wireless networks (HWN). But dense deployment of small BSs, high mobility, network heterogeneity, imbalanced traffic, and dynamic user preferences lead to frequent handover. Network overhead, excessive energy consumption, and a decrease in service quality and user satisfaction can be due to frequent handover. So, handover management is one of the crucial challenges in the implementation of 5G and beyond in HWNs for ensuring seamless connectivity, energy efficiency, and the required quality of services and experiences. The effectiveness of handover decisions in HWNs relies on the implementation of a suitable network selection mechanism. Multi-attribute decision-making (MADM) is being used to model and analyze appropriate network selection complexities by considering a broad spectrum of intricate and conflicting decision criteria for efficient handover decisions in HWN. This article extensively explores, compares, and analyzes vital MADM techniques utilized for modeling appropriate network selection strategies in terms of algorithmic strategies, cardinality, types and significance of decision attributes, and network utilities. This article also examines, analyzes, and recognizes the recent mobility management challenges and trends in utilizing MADM strategies to tackle network selection issues in high-speed HWNs.

1. Introduction

In the industry 5.0 scenario, cellular networks alone are not enough to support a wide range of emerging services with always best connectivity at a reasonable cost. It needs the integration of non-cellular wireless networks with cellular networks. This coexistence of cellular and non-cellular networks yields a heterogeneous wireless network (HWN), which has the potential to provide higher data rates, greater coverage, increased network capacity, lower battery consumption, ultra-reliability, and low-latency communication at a lower cost than a traditional cellular network. Fig. 1 demonstrates an HWN architecture. Future generation HWN supports a variety of services such as the internet of things (IoT), device-to-device (D2D), and vehicular-to-everything (V2X) with enhanced mobility during roaming [72]. High

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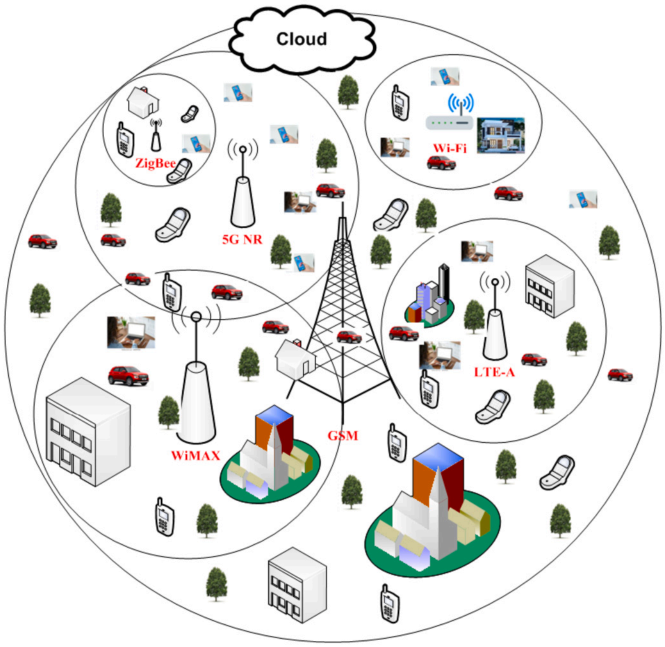

Fig. 1. Heterogeneous Wireless Network Infrastructure.

data requires a wide range of bandwidth, which ensures the satisfaction of users' requirements. Due to the availability of wider bandwidths in millimeter waves, a wide range of bandwidth can be achieved by utilizing the millimeter-wave (mm-wave). These bands include range between 10 GHz to 300 GHz [78]. Current Fifth Generation (5G) network implementations use frequency range between 28 GHz and 38 GHz. The frequencies up to 120 GHz can be used for 6G network implementations in the future. There are numerous advantages to using mm-wave bands for next-generation wireless technology. But it also has created a number of challenges related to mobility management which make mobile communication systems more complex than traditional systems [4], [33].

Several factors have led to the increased complexity of mobility management in mobile communication, which has become increasingly difficult to manage. The utilization of millimeter wave technology is the first and most crucial aspect. To compensate for the significant path loss experienced at millimeter wave frequencies, it becomes necessary to deploy a large number of small base stations (BSs). Given their ability to provide high capacity and data rates, the integration of various types of small-coverage BSs, such as picocells, femtocells, and drone-based BSs, is being introduced in Heterogeneous networks (HWNs). The Macrocell, picocell, and femtocell are shown in Fig. 1. The dense deployment of small coverage BS having different radio access technologies (RATs) is another challenge [3]. Dual connectivity, rapid growth in mobile connections, ultra-dense networks, carrier aggregation, network diversity, complex relationships in optimization operations, and the use of insufficient handover decision techniques are just a few of the factors that have a significant impact on mobility management in HWNs [81]. The relationship between these characteristics of HWNs and the various technologies may give rise to concerns about the handover that is associated with mobility, depending on the circumstances. The dense deployment of small BS in the HWN increases the possibility of frequent and unnecessary handovers. When dual connectivity is used in conjunction with carrier aggregation, different handover scenarios may occur. It can occur as a result of the ability to assign multiple component carrier frequency bands to a single mobile node (MN) simultaneously.

Managing handovers becomes increasingly challenging in high-speed mobility scenarios to guarantee uninterrupted connectivity, essential for supporting emerging applications like IoT, machine-to-machine, and device-to-device communications. Figs. 2 and 3 depict

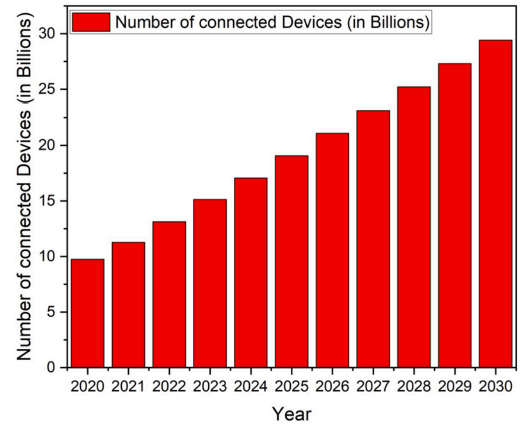

Fig. 2. Next-decade device connectivity in HWNs.

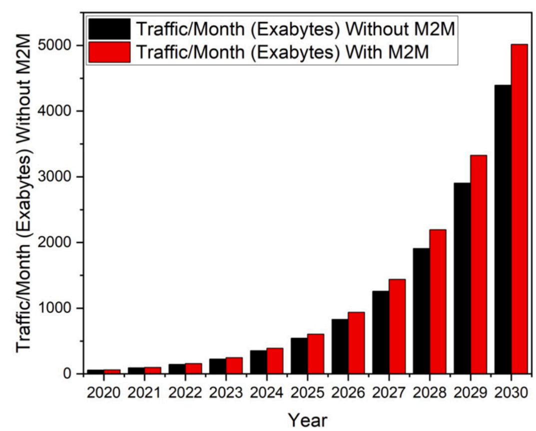

Fig. 3. Data demand expected in next decade due to HWN M2M connectivity.

the expected growth in the number of connected devices and the corresponding surge in data volume over the upcoming decade. So, the challenges of mobility and its factors must be dealt with effectively. One of the primary challenges in the practical implementation of next-generation wireless networks to support industry 5.0 scenarios is ensuring seamless connectivity alongside high speed mobility in HWNs.

This study, has examined various factors that affect the design of an efficient, robust, and reliable vertical handover management technique in HWN. This article compares and evaluates different approaches to assigning importance weights to each network criteria and utilizing vital multi-attribute decision-making (MADM) techniques to address the challenges of network selection and handover decisions in HWNs. The primary attention of this article is on algorithmic strategies, number of decision attributes employed in handover control points, and types of network utilities considered. In this article, a comprehensive and detailed mathematical implementation of several essential MADM techniques is presented. The strengths and limitations of these techniques are highlighted, along with how to normalise and assign priority weights to each criteria in a step-by-step manner. This study addresses the research gap by examining the interdependence, interaction, and influence of handover decision criteria for appropriate network selection assessments in determining a precise handover decision. Moreover, the article delves into the significance of various methods for allocating importance to each network attribute and the ongoing research trend of implementing MADM strategies to address the challenges of network selection in high-throughput networks. This study has also described some of the hybrid methods to select a suitable network in an HWN that reduces handover time and the frequency of unnecessary handovers due to the ping-pong effect and satisfy QoS as per users' requirements. The study has conducted an analysis of the priority weight distribution of handover decision criteria generated through the applications of different techniques such as the analytic hierarchy process (AHP), fuzzy analytic hierarchy process (FAHP), CRiteria Importance Through Inter-criteria Correlation (CRITIC), entropy, and a combination of these methods. In addition, this study has examined the ranking order of accessible networks obtained using techniques such as the technique for order of preference by similarity to ideal solution (TOPSIS), VIekriterijumsko KOmpromisno Rangiranje (VIKOR), grey relational analysis (GRA), and PROMETHEE. Furthermore, this work has demonstrated the consequences of these techniques on the prioritization of available access networks in highly dense HWN infrastructure, considering various network traffic scenarios. This study has the following major contribution:

- Identification of different factors that can influence the performance of MADM-based network selection approaches in terms of handover decision, ping-pong effect, ranking abnormality, and handover failure.
- Contrast, assess, and analyze various methods of assigning importance weights to each handover decision criteria and employing critical MADM techniques to tackle the challenges associated with network selection and handover decisions in heterogeneous wireless networks.
- Exploring diverse research prospects concerning various handover strategies using MADM techniques to address mobility management challenges in heterogeneous networks.

The remaining section of this work is organized as follows: Section 2 has discussed the fundamental concept of handover in HetNet and the various handover decision criteria, aspects, characteristics, and phases. Section 3 addresses the necessity of MADM techniques in modeling network selection models and outlines their general steps. In Section 4, the importance of normalization is examined, along with various methods for achieving normalization. Section 5 discusses subjective and objective criteria weight methods, requirements, determination, and characteristics of priority weights of decision criteria for alternatives, and explores their computation steps and advantages and disadvantages. Section 6 provides a comprehensive overview of essential ranking MADM techniques, including their computational steps, as well as their advantages and disadvantages when applied to the design of a suitable network selection model. Section 7 presents the study's findings in terms of requirements and performance analysis and identifies the remaining research opportunities for developing appropriate models to address mobility management challenges in HetNets using MADM techniques. Finally, in Section 8, the study is summarized, conclusions are drawn, and potential avenues for future research are discussed.

2. Background

2.1. Handover

Handover refers to the procedure of transferring the on-going connection from one BS to another while a service request is being served during the roaming of MN in a heterogeneous network [91]. A handover can be classified as a hard handover or a soft handover, depending on the current point of attachment (PoA) of the mobile node to BS. A hard handover or break before make handover occurs when MN is connected to only one PoA during the handover process, whereas a soft handover or make before break handover occurs when MN creates a connection to the target PoA prior to the release of the previous PoA during the handover period in the HWN. The research community classifies handover into three different categories: horizontal, vertical, and diagonal, based on the types of underlying network and radio access technologies [2]. The term horizontal handover refers to the process of transferring the connection between BSs that utilize the same radio technology. Horizontal handover is initiated in a homogeneous network to preserve the physical connection and load balancing wherever the connection quality falls below a specified current threshold. The mechanism for managing handover decisions is either totally contained inside the network or within MN. There are several techniques for handover control, but from a decision control perspective, handover may be classified into three categories: network control handover, mobile control handover, and network-assisted handover. A network control handover situation occurs when a network entity has complete control over the decision-making process during a handover. The term network-centric was used to describe this type of handover. This is possible because the network control handover decision point is inside a network. This allows it to use information about network conditions to make better decisions. In the mobile assistant handover approach, the network asks MNs to measure the signal strength from BSs that are adjacent to the servicing network. The network makes the handover decision based on reports received from the mobile node. The mobile node continuously monitors and analyzes the signal strength of adjacent BS and commences the handover process when specific handover conditions specified in the mobile control decision method are satisfied. Mobile-controlled handover provides total control over the handover procedure to any MN participating in the process of transfer of PoA [38]. The handover process that occurs between BSs that use different RATs is known as vertical handover. In the HetNet environment, the vertical handover decision process is triggered whenever a new available RAT offers a better quality of service (QoS) and quality of experience (QoE) than the current servicing RAT. The diagonal handover is a combination of horizontal and vertical handovers. The handover mechanism in HWN required due to

- Degrade in quality of signal, imbalance traffic load, high-speed mobility, change in user preference, lack of resource, and heterogeneity of network.
- Variations in access technology architecture, protocols, and the potential for a wide range of services across different radio access networks.
- Multi-RAT architecture with overlapping network coverage, MN has a tendency to make frequent switches among RATs.
- Mobile nodes move between networks in search of the best connection for the desired level of service quality.
- Simultaneously operating a number of different services on multi-service multimode mobile terminals.
- Ultra-densification of small cells in heterogeneous network to enable good coverage area, connectivity, capacity, support kinds of applications, high mobility, and increased available bandwidth.
- Dynamic nature of mobile users' services, network conditions, application requirements, service characteristics, mobile terminal constraints, and the dependable nature of networks.

Connection time, available bandwidth, power consumption, mandatory cost, security, user preferences, speed, dwell time, and coverage area are some of the core factors that affect handover. So, when making a handover decision, it is not appropriate to consider only one parameter to address the aforementioned issues. An inappropriate handover decision may lead to increase in ping pong handover, force termination of ongoing transaction, handover failure, blocking of new request, handover blocking, and handover delay which degrade quality of service and quality of experience.

2.2. Handover decision criteria

The features that are examined to determine whether or not a handover is required are known as handover criteria. It might aggregate various networks, terminals, users, services, and application-related data to initiate the handover process to guarantee a seamless handover. The handover decision mechanism relies on analyzing and measuring various network-related parameters, including network coverage, bandwidth, latency, connection quality, received signal strength, carrier-to-

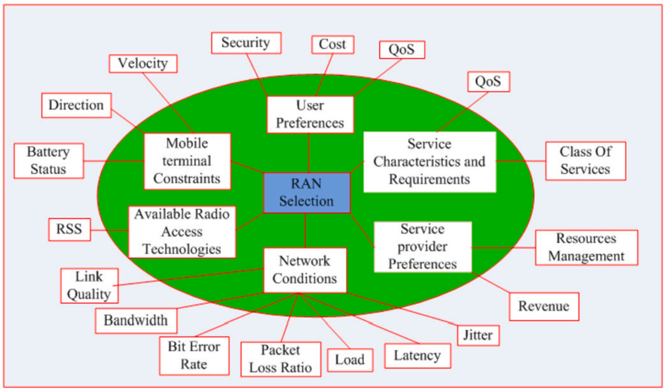

Fig. 4. Types of Handover Decision Criteria.

interference ratio, signal-to-interference ratio, bit error rate, monetary cost, and security level. Additionally, terminal-related aspects such as velocity, battery power, and location tracking may be taken into consideration. User-related parameters encompass user profiles and preferences, while service-related criteria involve service capability, QoE, and QoS. In order to achieve precise handover decisions, the HWN architecture necessitates the incorporation of various handover criteria. Some of the handover criteria might have complicated or even contradictory characteristics [75]. The Fig. 4 presents a variety of handover criteria that can be classified under several categories.

2.3. Handover decision phases

Typically, the handover procedure is divided into three stages. When a user roams and network status changes due to roaming, the handover process initiates, commencing first stage of information gathering. In second stage of handover process, mobility management systems deliberate over which new RAT will be used to fulfill the requirements of handover requests. The PoA is moved from old BS (or PoA) to new BS (or PoA) in the third and final step of handover process. Sustaining a consistent connection between MN and BS during their movement is of utmost importance for mobile service providers. In initial stage of the handover process, various factors are assessed, including operator policies, user preferences, application requirements, QoS demands, and the state of the RAT. This evaluation aims to ensure uninterrupted connectivity throughout an ongoing transaction. During the second phase, known as the decision phase, network selection algorithms are employed to determine the appropriate network. In the final phase, known as the execution phase, the user is allocated to the selected network to service ongoing requests [89]. The handover procedure is shown in Fig. 5.

3. MADM technique

MADM is an operational research mathematical optimization technique that is used to arrive at the best possible decision in situations that include a variety of complicated and contradictory criteria for complex decision problems [5]. It is an area of optimization that can be used to address and analyze issues involving decision-making processes. This is a robust and flexible decision-making method that addresses a wide range of complex decision factors and provides relevant information to help the decision-maker make the best possible decision. A decision matrix $D[m \times n]$ can be used to define a MADM problem. Let $m = \left\{a_1, a_2, \dots a_i, \dots a_m\right\}$ be a set of alternatives from which one needs to select one of the best alternatives, $k = \left\{dm_1, dm_2, dm_3, \dots dm_i, \dots dm_k\right\}$ decision makers can select, while $n = \left\{c_1, c_2, \dots c_j, \dots c_n\right\}$ a set of attributes used to calculate each alternative's performance. The $x^k_{i,j}$ represent the score of i^{th} alternative with respect to the j^{th} criteria of the decision matrix (DM), D^k decided by k^{th} decision maker. The variables

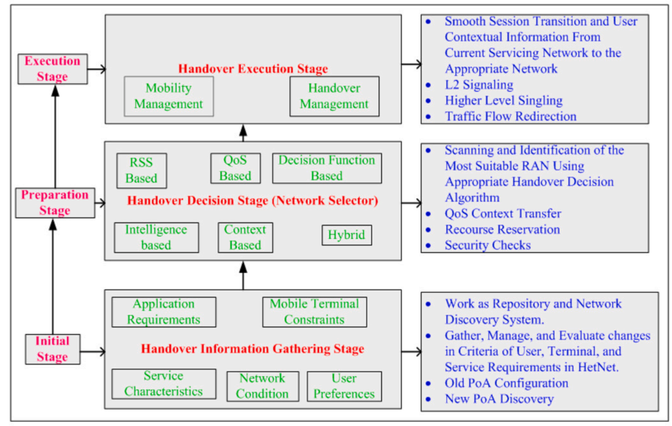

Fig. 5. Three Phases of Handover Process.

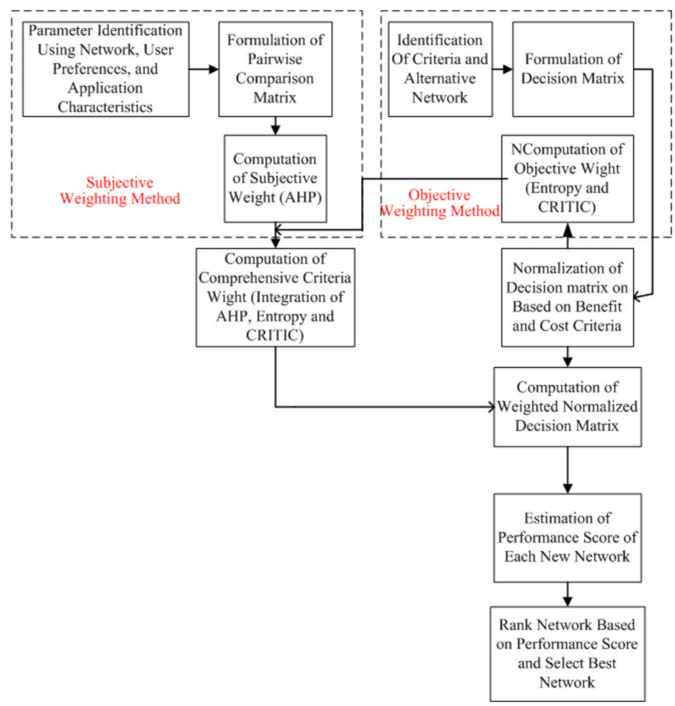

Fig. 6. In the context of Network Selection, General Steps in the MADM Technique.

m, n, and k represent the total count of alternative networks, criteria, and decision-makers, respectively. The $w^k = \left\{w^k_1,\ w^k_2, \dots w^k_j, \dots w^k_m\right\}$ is the set of weight vectors decided by decision-makers. w^k_j is the weight of j^{th} criteria for k^{th} decision-maker, which indicates how important it is to contribute to attaining the expected objective of the decision-maker in selecting the best alternative from several alternatives.

The decision matrix, as utilized in MADM, is employed to identify and choose the most suitable alternative from a set of alternatives. In the context of MADM-based network selection, these approaches can be applied to select the appropriate RAT in an HWN to ensure uninterrupted service during roaming [25].

$$D^k = \begin{bmatrix} x^k_{1,1} & \cdots & x^k_{1,n} \\ \vdots & \ddots & \vdots \\ x^k_{m,1} & \cdots & x^k_{m,n} \end{bmatrix}$$

$$w^k = \left\{w^k_1,\ w^k_2,\ w^k_3, \dots w^k_j, \dots w^k_n\right\}$$

The MADM technique is being extensively employed to tackle vertical handover decision challenges in HWN due to its ease of implementation and accurate decision-making capabilities [77]. For making optimal network selection decisions, many MADM approaches have been suggested in the literature. A general outline of MADM based network selection techniques is shown in Fig. 6. The further subsections of the article give an in-depth examination of the present MADM techniques and address optimal network selection challenges in HWNs [7].

3.1. Network decision matrix

The DM can be defined as $DM = [x_{ij}]_{m \times n}$ where x_{ij} is the preference value of the i^{th} alternative network with the j^{th} attribute. Attributes can be classified into two categories: benefit criteria and cost criteria. Benefit criteria refer to attributes where higher values are preferred for making optimal decisions. On the other hand, cost criteria, also known as non-beneficial attributes, are characterized by a preference for lower values when making the best decisions. Let's assume the set of beneficial attributes is represented as AT_1 and the set of non-beneficial attributes as AT_2. In order to effectively compare different alternatives and attributes, it can be difficult when they are measured using different dimensions. Therefore, it is necessary to normalize these variables to ensure their comparability.

3.2. Normalised decision matrix

Due to the presence of diverse units of measurement and possibility of huge variation in the range of values of different decision criteria in the decision matrix, direct comparisons among its characteristics are unfeasible. To ensure meaningful attribute comparisons, it becomes imperative to acquire normalized values for each attribute, thereby enabling accurate comparisons between the values [44][103]. In the existing body of literature, various methods for normalization have been presented. One such method, has been illustrated, which is the utilization of max-min normalization, as shown in the following equation (1), where $[r_{ij}]_{m \times n}$ and r_{ij} is normalised decision matrix (NDM) and the normalized value of the i^{th} alternative with the j^{th} attribute, respectively. Furthermore, this study will delve into other crucial and widely recognized normalization methods in a subsequent section.

$$NDM = [r_{ij}]_{m \times n} = \begin{cases} \frac{x_{ij}}{\max\{x_{ij}\}} & \forall c_j \in AT_1 \\ \frac{\min\{x_{ij}\}}{x_{ij}} & \forall c_j \in AT_2 \end{cases} \tag{1}$$

3.3. Weighted normalized decision matrix

When making decisions regarding handover, multiple handover criteria for alternative networks are evaluated, but not all criteria carry equal significance. It is crucial to assign suitable and justified priority weights to each attribute that influences the decision in order to accurately select the most suitable alternative network. This process guarantees the selection of the best network alternatives [63][64][73]. To assign weight to criteria, subjective, objective, and comprehensive methods can be used. The weighted normalized matrix is the matrix that can be obtained by the multiplication of the normalized decision matrix and the weight vector (w_j) of criteria. The estimation of the weighted normalized decision matrix is a crucial step in the decision-making process when choosing the optimal network alternative. The calculation for this can be found in equation (2).

$$WNDM = [r_{ij} \times w_j]_{m \times n} \tag{2}$$

3.4. Performance Score (PS)

MADM techniques are utilized to determine the final ranking of accessible alternatives and the selection of the best alternative network based on its performance score. In this process, the network alternative with a higher performance score is assigned a higher rank, whereas the alternative with a lower performance score is given a lower rank [95][13][31]. As an illustration, the performance score in the weighted sum model technique can be approximated using equation (3).

$$PS = \sum_{j=1}^{j=n} r_{ij} \times w_j \tag{3}$$

4. Normalization techniques

When selecting the suitable number and relevant criteria for alternatives among the available alternatives, there are several critical considerations. These challenges arise from the presence of diverse characteristics and a wide range of measurable dimensions. This disparity can create difficulties when comparing the alternatives directly, leading to incompatibility in the comparison process. This is an initial step found in nearly all MADM techniques, commonly known as standardization. It proves advantageous to convert the values of different measurable units into a standardized range from zero to one. Normalized decision matrices can be obtained using different mechanisms, including linear, max-min linear, sum linear, vector enhanced accuracy, and logarithmic normalization [30][59][48][102], which can be obtained through following equations (4)-(9):

Linear normalization: Linear normalization transforms different criteria measured on different scales into a common scale. It involves rescaling the values of the criteria so that they fall within a specific range, often between 0 and 1, or sometimes -1 to 1.

$$r_{ij} = \begin{cases} \frac{x_{ij}}{x_j^{max}} & \forall c_j \in AT_1 \\ \frac{x_j^{min}}{x_{ij}} & \forall c_j \in AT_2 \end{cases} \tag{4}$$

Max Min Liner Normalization: It is a linear transformation method to standardize diverse decision criteria measured on different scales into a common range. Which ensures the minimum value of the criterion is transformed to 0, the maximum value to 1, and the other values proportionally scaled in between.

$$r_{ij} = \begin{cases} \frac{x_{ij} - x_j^{max}}{x_j^{max} - x_j^{min}} & \forall c_j \in AT_1 \\ \frac{x_j^{max} - x_{ij}}{x_j^{max} - x_j^{min}} & \forall c_j \in AT_2 \end{cases} \tag{5}$$

Sum Linear Normalization: It involves scaling the values of each criterion so that they collectively sum up to a predetermined value, often 1 or 100, ensuring that their combined weights align with the total weight distributed to all criteria. It also ensures that the relative importance of each criterion to the overall decision is reflected accurately.

$$r_{ij} = \begin{cases} \frac{x_{ij}}{\sum_{i=1}^{i=m} x_{ij}} & \forall c_j \in AT_1 \\ \frac{\frac{1}{x_{ij}}}{\sum_{i=1}^{i=m} \frac{1}{x_{ij}}} & \forall c_j \in AT_2 \end{cases} \tag{6}$$

Vector Normalization: It transforms the original vector values so that they maintain their relative proportions but are adjusted to adhere to a certain norm, usually a magnitude of 1 for ease of comparison. Its principle is based on the Euclidean norm, which ensures that the vectors maintain their relative direction and proportionality but are adjusted to have a standardized magnitude, enabling fair comparisons and collective analysis.

$$r_{ij} = \begin{cases} \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} & \forall c_j \in AT_1 \\ 1 - \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} & \forall c_j \in AT_2 \end{cases} \tag{7}$$

Enhanced Accuracy Normalization

$$r_{ij} = \begin{cases} 1 - \frac{x_j^{max} - x_{ij}}{\sum_{i=1}^{i=n} x_j^{max} - x_{ij}} & \forall c_j \in AT_1 \\ 1 - \frac{x_{ij} - x_j^{min}}{\sum_{i=1}^{i=n} x_{ij} - x_j^{min}} & \forall c_j \in AT_2 \end{cases} \tag{8}$$

Logarithmic Normalization: The principle of this method is to apply a logarithmic function to the original values to rescale them into a comparable format. This method is more useful when the data spans a wide range and contains outliers or extremely large values, helping to manage and normalize such variations. This method is more effective in compressing a wide range of values, making extreme values more manageable while retaining the relative proportions and differences between data points.

$$r_{ij} = \begin{cases} 1 - \frac{ln\left(x_{i,j}\right)}{ln\left(\prod_{i=1}^{i=m} x_{i,j}\right)} & \forall c_j \in AT_1 \\ 1 - \frac{\frac{ln\left(x_{i,j}\right)}{ln\left(\prod_{i=1}^{i=m} x_{i,j}\right)}}{m-1} & \forall c_j \in AT_2 \end{cases} \tag{9}$$

Where $1 \le i \le$ m and $1 \le j \le n$. x_j^{max} and x_j^{min} is the maximum and minimum values of the j^{th} attribute, respectively. Which normalization technique is the most effective and could be directly determined? This is a crucial question. This determination relies on the complexity and nature of the decision problems.

5. Weighting methods

5.1. Analytic hierarchy process

Analytic Hierarchy Process (AHP) is a method to assign subjective priority weight to each decision criteria used to simplify complex problems by breaking them down into smaller, more manageable components. The technique involves comparing different alternatives in pairs to determine the best alternative, assigning appropriate importance weights to each criterion within alternative networks. The AHP was initially introduced by Saaty and has proven to be highly effective in making accurate and appropriate decisions for intricate decision-making problems. It achieves this by allocating suitable importance weights to all attributes of alternatives. The AHP approach organizes complex decision-making problems into hierarchies, with the top level (goal) being independent of all sub-levels and each attribute within a level also functioning independently. To illustrate, a hierarchical structure of the AHP process is depicted in Fig. 7. A valid question to prioritize the intermediate criteria level in relation to the top-level objective would be: "Which criterion is the most crucial in achieving the overall goal, and to what degree?" Similarly, when prioritizing the bottom level of alternatives in relation to the criteria at the middle level, the key question to consider would be: "Which alternatives are preferred in meeting the given criterion, and to what extent?"

It employs pairwise comparisons to ensure flexibility and consistency, utilizing hierarchical structuring and prioritization. However, AHP relies on the condition of criteria independence within the network, and as the number of criteria increases, the computational cost of pairwise comparisons also increases. AHP is commonly utilized for calculating the priority weights of each decision criteria. The first step in AHP is creating a hierarchical structure, as shown in Fig. 7 in which goals are kept at the top level.

The pairwise comparison matrix illustrates the relationship between different attributes by assessing the relative importance of criteria i and j in relation to the overall goal. The size of the pairwise comparison matrix is determined by the number of criteria in the decision problem being evaluated. The values within the pairwise comparison matrix are subjective and depend on the decision-maker's knowledge, expertise, and preferences for ranking the alternatives. To determine the values within the pairwise comparison matrix, the decision maker asks the question, "How significant is criteria i compared to criteria j in achieving the goal through the k^{th} alternative?" This helps in establishing the values required for constructing the pairwise comparison matrix. [61][62][60].

Table 1
Predefined Scale.

Importance Weight	Attribute Importance
1	Equal Significance
3	Moderate Significance
5	Strong Significance
7	Very Strong Significance
9	Extreme Significance

The inclusion of a consistency ratio (CR) assessment in AHP enhances the analysis of each decision criteria priority weight. The concept of consistency ratio in AHP is utilized to ensure the reliability of decisions concerning the allocation of importance weights to each decision criterion. The CR serves as a measure to assess the level of consistency in pairwise comparison decisions. If the CR value is below 0.1, it indicates that the comparisons are considered consistent. However, if the CR exceeds this threshold, it implies that there may be errors in the comparisons, and corrective measures need to be taken to address them [98][29]. The AHP method meets the required computational time constraints, but it comes with the trade-off of higher memory consumption when compared to other MADM approaches.

During the construction of the pairwise comparison matrix, a predefined table is used to find the significance of criteria i over criteria j. It has been shown in Table 1. In Table 1, missing 2, 4, 6, and 8 are utilized to represent the intermediate relative significance of attributes, and $\frac{1}{3}, \frac{1}{5}, \frac{1}{7}$ and $\frac{1}{9}$ used for inverse comparison. Similarly, $\frac{1}{2}, \frac{1}{4}, \frac{1}{6}$ and $\frac{1}{6}$ and utilized to represent the intermediate relative significance of attributes for inverse comparison. The steps involved in AHP to allocate importance weights to each attribute of alternatives are as follows:

Step 1 Create a hierarchical structure with the target at the top, criteria at the second level, and alternatives at the third level, as shown in Fig. 7

Step 2 Using a Table 1 of predefined preference scales, a pairwise comparison matrix is created by determining the significance of various criteria in terms of target.

Step 3 Determine the normalized comparison matrix (NCM) through equation (10).

$$NCM = \left[r_{ij}\right]_{n\times n} = \left[\frac{x_{ij}}{\sum_{i=1}^{n} x_{ij}}\right]_{n\times n} \tag{10}$$

Step 4 Computation of significance of each criteria i.e. priority weight $(W_i^{Criteria})$

$$W_i^{Criteria} = \sum_{i=1}^{n} r_{ij} \tag{11}$$

Step 5 Computation of weight sum value WSV_i

$$WSV_i = \sum_{j=1}^{n} \frac{x_{ij} \times w_j}{w_j} \tag{12}$$

$$\lambda_{max} = \sum_{i=1}^{n} WSV_i \tag{13}$$

Step 6 Computation of consistency index (CI)

$$CI = \frac{\lambda_{max} - n}{n - 1} \tag{14}$$

Step 7 Computation of CR

$$CR = \frac{CI}{RI} \tag{15}$$

Here, RI represents the random index based on the number of criteria used in decision-making. It is detailed in the following Table 2, where n

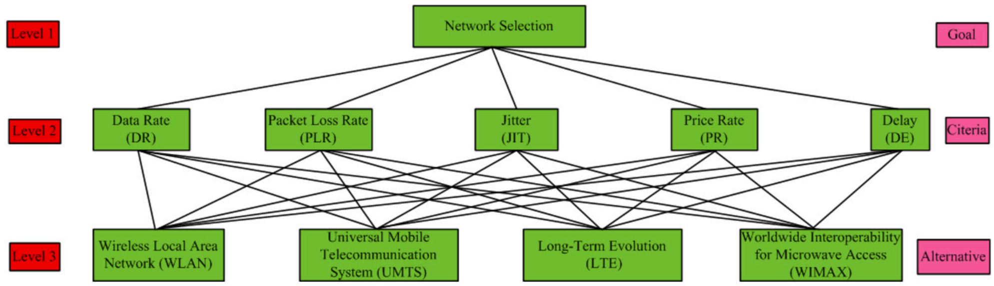

Fig. 7. AHP Hierarchical Structure.

Table 2
Random Index Scale.

n	1	2	3	4	5	6	7	8	9	10
RI	0.00	0.00	0.58	0.90	1.11	1.24	1.32	1.45	1.45	1.45

is the total number of assumed criteria in the decision-making problem [10][10][14].

In complex decision-making problems, there may be sub-criteria that influence the second level of decision-making and, consequently, the overall decision-making process. These sub-criteria are placed at the third level, while the alternatives are at the fourth level. Sometimes, there may be disagreements about why certain sub-criteria cannot be considered at the second level. Keeping the sub-criteria at the second level makes their comparison more challenging. However, comparing sub-criteria falling under a single criterion is relatively straightforward. Each alternative is assigned a value for each sub-criterion of a criterion. To calculate the weight of an attribute when sub-criteria are present, we need to create a pairwise comparison matrix between the second-level criteria in the hierarchy and determine the associated weights. Next, compare the sub-criteria falling under each criterion. For example, compare each sub-criteria 1, 2, 3, etc. under criterion 1, and so on. Finally, calculate the importance weight for each sub-criterion. This process yields both local and global importance weights for each sub-criterion and criterion. To obtain the global weights for criteria, multiply the weights of the second-level criteria by the weights of the third-level sub-criteria. In the last step, formulate a decision matrix and solve it using the global weights of the criteria, or sub-criteria [68][85][19].

5.2. Entropy method

Entropy is an objective method used to estimate and allocate the importance weight of each criterion in the decision-making process for complex decisions. This objective method is employed to calculate the priority weight of criteria in cases where decision makers hold differing perspectives on the weight values within the MADM technique decision-making criteria [71]. In the context of AHP, decision-makers are required to express their opinions regarding various criteria to construct a pairwise comparison matrix. However, with the entropy method, there is no need for such subjective opinions. The entropy weight serves as an indicator of the divergence among alternative networks based on specific criteria, enabling the comparison of multiple alternative networks. This concept drawn inspiration from transportation models where entropy is employed to measure the dispersion of trips between origins and destinations. The process of calculating weights in the entropy method follows these steps: [51][42][32].

Step 1 Normalization of the decision matrix

$$r_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \tag{16}$$

Step 2 Computation of entropy e_j, where $h = \frac{1}{\ln m}$

$$e_j = -h \sum_{i=1}^{m} r_{ij} \ln r_{ij} \tag{17}$$

Step 3 Computation of Weight Vector w_j

$$w_j = \frac{1 - e_j}{\sum_{j=1}^{n} \left(1 - e_j\right)} \tag{18}$$

$1 - e_j$ is known as the degree of diversity function.

5.3. CRITIC method

In 1995, chemical engineer D. Diakoulaki introduced the CRITIC technique as an objective method for computing priority weights of each criteria [18]. It is considered one of the most effective methods for ascertaining the objective importance weight of each criterion based on its relative importance. In this method, the priority weight of decision criteria is determined by considering both contrast intensity and conflict, which are inherent in the decision problem structure. To address such situations, objective methods for computing criteria weights, such as CRITIC, Entropy, mean, and standard deviation, are considered highly effective. This technique enables the computation of objective weights for criteria in cases where decision-makers have conflicting views and different priority weight values or it is difficult to compare different criteria [47][39]. The CRITIC process, used to compute the priority weight of criteria in alternative networks, involved the following steps:

Step 1 Normalization of decision matrix.

$$r_{ij} = \frac{x_{ij} - x_j^{worst}}{x_j^{best} - x_j^{worst}} \tag{19}$$

Step 2 Computation of standard deviation δ for each alternative criteria using normalized values.

Step 3 Construction and computation of symmetric matrix of $n \times n$ with element r_{ik}. It is calculated through the linear correlation coefficient between the vectors x_j and x_k. If the criteria are identical, the linear correlation coefficient will be one, resulting in a diagonal value of one.

Step 4 Calculation of extent to which criterion j generates a conflict within the decision-making context, as defined by the other criteria i.e., $\sum_{k=1}^{n} \left(1 - r_{jk}\right)$.

Step 5 Assessment of the quantity of information pertaining to each criterion

$$c_j = \sigma_j \times \sum_{k=1}^{n} \left(1 - r_{jk}\right) \tag{20}$$

Step 6 Computation of objective priority weight of each criteria

Table 3
Fuzzy Scale Relative Significance.

Importance Weight	Attribute Importance
(1,1,1)	Equal Significance
(2,3,4)	Moderate Significance
(4,5,6)	Strong Significance
(6,7,8)	Very Strong Significance
(9,9,9)	Extreme Significance

$$w_j = \frac{c_j}{\sum_{k=1}^{m} c_j} \tag{21}$$

Contrast strength refers to the amount of information difference between a specific criterion on two distinct alternative networks, while conflict evolution represents the information magnitude of a criterion that is common to both networks and pertains to the same alternative network. Both types of information can be used to analyze network selection problems. In order to measure the information magnitude using the CRITIC method, the standard deviation and correlation coefficient are both used in the computations to determine contrast strength and conflict evolution, respectively. The classical CRITIC weighting method faces a significant challenge in accurately assessing the contrast strength of different indicators due to variations in measurement units and magnitudes across network criteria. This issue is particularly prominent when using the standard deviation as a measure of discrimination. In the CRITIC method, conflict evolution is determined by the correlation coefficient, which can be positive or negative, reflecting the correlation between criteria i and j. However, approximating conflict using these formulas may not be suitable because both negative and positive correlation coefficients have the same absolute values.

5.4. Fuzzy AHP

To ascertain the specific numerical values reflecting the scale of relative significance, we can employ the AHP method to calculate the distribution of importance weights for decision criteria. However, it is challenging to assign a single number to each term that is universally justifiable. For example, in AHP, the term “moderate” is assigned a value of 3, but what about values like 2.5 or 3.5? How should we interpret these values, whether as “moderate” or “strong”? To address these concerns, the concept of fuzzy AHP has been developed. Fuzzy AHP converts these values into fuzzy numbers through a suitable fuzzification method. Fuzzification is a conversion procedure that transforms linguistic terms into membership functions. This allows us to replace crisp numbers like 1, 2,.., and 9 with fuzzy numbers on a scale of relative significance [16][87][46][43]. The Table 3 shows a fuzzy scale of relative significance of criteria i to criteria j in decision problem. To calculate the weights of criteria in terms of intermediate importance, we use the values (1, 2, 3), (3, 4, 5), (5, 6, 7), and (7, 8, 9). The computation of criteria weights follows a specific procedure outlined by Buckley in 1985 [11].

Step 1 Create a fuzzy pairwise comparison matrix and transform the fuzzy numbers into their reciprocals (A^{-1}) using the equation provided below. Where $(l,\ m,\ u)$ is a criteria fuzzy number with l, m, and u as lower, middle, and upper values.

$$A^{-1} = (l,m,u)^{-1} = \left(\frac{1}{u},\ \frac{1}{m},\ \frac{1}{l}\right)^{-1} \tag{22}$$

Step 2 Computation of fuzzy geometric value ($\widetilde{r_i}$) by considering $\left(l_i,\ m_i,\ u_i\right)$ and $\left(l_j,\ m_j, u_j\right)$ two fuzzy numbers of criteria.

$$\widetilde{A_i} \otimes \widetilde{A_j} = \left(l_i \times l_j, m_i \times\ m_j, u_i \times u_j\right) \tag{23}$$

$$\widetilde{r_i}\ = \left(l_1 \times l_2 \times \ldots l_n,\ m_1 \times m_2 \ldots \times m_n,\ u_1 \times u_2 \ldots \times u_n\right)^{\frac{1}{n}} \tag{24}$$

Step 3 Fuzzy geometric weight $w_i = \widetilde{r_i} \otimes \left(\widetilde{r_1} \oplus \widetilde{r_2} \ldots \oplus \widetilde{r_n}\right)^{-1}$

$$\left(r_1 \oplus r_2 \ldots \oplus n\right) = \quad \left(l_1 + ..+ l_n,\ m_1 + .. + m_n,\ u_1 + .. + u_n\right) \tag{25}$$

Step 4 To obtain crisp numerical values, utilize the centroid method for defuzzification of the fuzzy weights (w_i).

$$w_i = \left(\frac{l+m+u}{3}\right) \tag{26}$$

If total weight exceeds one, which is not desirable, it is necessary to normalize the weights. This normalization process ensures that the sum of all criteria weights becomes equal to one $\frac{w_i}{\sum w_i}$ [12].

6. Network selection strategy

In recent literature, researchers have explored numerous ranking methods to estimate accessible alternative ranks. However, this section of the paper concentrates on discussing some specific vital alternative ranking methods that hold significant importance and relevance for the advancement of network selection models in HetNets.

6.1. Weighted Sum Model (WSM)

The WSM is a fundamental and straightforward MADM technique that employs a weighted average approach. It allows decision-makers to assess a score for each alternative by multiplying normalized criteria values with suitable importance weights. In WSM, the cumulative weight of each alternative represents the weighted average of the criteria network, and this value is utilized to establish the ranking among different alternatives [24][86][28][58]. The weighted average of the i^{th} alternative is computed by multiplying r_{ij} and its corresponding criterion weight of importance w_j. The r_{ij} is normalized score of i^{th} alternative with respect to j^{th} criterion in normalized decision matrix. If the weighted products of a specific alternative network is higher than the weighted products of all other alternatives, it is considered the superior network. This is determined by adding up the weighted products of all applicable criteria for the different network alternatives available. The WSM ranking procedure requires following equation (27):

$$PS_i^{WSM} = \sum_{j=1}^{n} r_{ij} \times w_j \tag{27}$$

WSM has the potential to make optimal network selection decisions and complete quick vertical handover decisions in HWNs. The WSM technique’s performance assessment and analysis are carried out by modifying the requirements and size of mobile user groups. The simplicity and efficiency of WSM, along with its capability to convert raw decision data into a relatively linear process, make it an attractive choice for researchers. The WSM ensures that the order of ranks of the alternative network remains consistent, which eliminates the ranking abnormality problem [70][34].

6.2. Multiplicative Exponent Weighting (MEW)

The MEW method is a MADM technique used to select the best alternative by considering weighted products of criteria. It is also known as the Weighted Product Method (WPM). MEW and WSM exhibit many similar characteristics. However, the main distinction lies in the mathematical operations used. MEW employs multiplication and exponentiation instead of addition and multiplication. Numerous network selection algorithms based on MEW have been proposed. To tackle the vagueness of contextual data, adapting the MEW technique to include interval data leads to an effective network selection process for handover scenarios. Sensitivity analysis demonstrates that the modified MEW approach offers cost-effective, robust, and flexible classification performance in dynamic decision-making compared to the TOPSIS. Ranking anomalies can occur in MEW when lower-level alternatives are added or removed from a set of accessible alternatives networks. These anomalies affect the ranking of the best alternatives and the selection of appropriate networks. The exponential operation used in the MEW algorithm tends to penalize alternatives with lower criteria scores, leading to ranking anomalies [101][97]. MEW, in contrast to WSM, exhibits nonlinear transformation characteristics. The performance score of i^{th} alternative can be obtained by equation (28).

$$PS_i^{WPM} = \prod_{j=1}^{n} r_{ij}^{w_j} \tag{28}$$

6.3. Weighted Aggregated Sum Product Assessment Model (WASPAS)

The integration of the weighted sum model and the weighted product model gives rise to a hybrid model that combines the strengths of both approaches. A more specific representation of this model is WASPAS = WSM+WPM, highlighting the fusion of these two methodologies. The performance score of each alternative networks can estimate through equation (29).

$$Q_i = \lambda Q_i^1 + (1-\lambda) Q_i^2 \tag{29}$$

where $0 \le \lambda \le 1$, Q_i^1 and Q_i^2 are the performance score of i^{th} alternatives estimated by WSM, and MEW methods, respectively [96], [84].

6.4. TOPSIS

Yoon and Hwang were the first to introduce the TOPSIS ranking technique. This method determines the best alternative by measuring its proximity to the ideal solution and its distance from the worst solution, which is known as the Euclidean distance. TOPSIS is a widely used MADM technique that involves assessing the alternative that is closest to the best possible solution known as the positive ideal solution, or PIS and farthest from the worst possible solution referred to as the negative ideal solution, or NIS. Before utilizing the information obtained from the multi-criteria decision matrix, it is necessary to normalize it using the Euclidean normalization method. The decision matrix, $D(m \times n)$ can be used to define the multi-criteria decision problem where $a_1, a_2, \dots a_n$ are alternatives, and $c_1, c_2, \dots c_m$ attribute of each alternative. The entry in decision matrix x_{ij} represents score of i^{th} alternative, with respect to j^{th} attribute of decision matrix. Typically, the vector normalization method is employed in TOPSIS for ranking purposes, although it is not limited to this technique alone. The following steps outline the general process for obtaining a TOPSIS ranking solution for complex decision problem.

Step 1 Define the decision matrix by taking into account the alternatives and their associated attributes.

$$DM = \left[x_{ij}\right]_{m \times n}$$

Step 2 Normalization of decision matrix

$$NDM = \left[r_{ij}\right]_{m \times n} = \left[\frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}\right]_{m \times n} \tag{30}$$

Step 3 Computation of weighted normalized decision matrix (WNDM)

$$WNDM = \left[v_{ij}\right]_{m \times n} = \left[r_{ij} \times w_j\right]_{m \times n} \tag{31}$$

Step 4 Computation of best solution (v_j^+) and worst solution (v_j^-)

$$v_j^+ = \begin{cases} v_j^{max}, & if \forall c_j \in AT_1 \\ v_j^{min} & if \forall c_j \in AT_2 \end{cases} \tag{32}$$

$$v_j^- = \begin{cases} v_j^{min}, & if \forall c_j \in AT_1 \\ v_j^{max}, & if \forall c_j \in AT_2 \end{cases} \tag{33}$$

Step 5 Computation of Euclidean distance from best (S_j^+) and worst solution (S_j^-)

$$S_j^+ = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^+\right)^2} \tag{34}$$

$$S_j^- = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^-\right)^2} \tag{35}$$

Step 6 Closeness coefficient (CC_i) or performance score

$$CC_i = \frac{S_j^-}{S_j^- + S_j^+} \tag{36}$$

The alternative with a higher value of CC_i is considered to be closest to the best solution and therefore deemed the most preferable alternative network. The TOPSIS approach is commonly utilized in the literature for ranking and selecting network alternatives, despite its susceptibility to ranking irregularities. Ranking irregularities can occur when the ranking order changes due to the addition or removal of low-performing candidates networks. To address this issue, a flexible and robust MADM method ensures that the rankings of alternatives remain consistent even when lower-ranking alternatives are added or removed. Inconsistent rankings can lead to inadequate and unstable network selection decisions if a ranking algorithm exhibits ranking irregularities. Although TOPSIS has a higher probability of ranking irregularities compared to WSM and MEW, it provides more precise rankings for alternatives. Ranking irregularities are a significant drawback of TOPSIS [93], [23], [53].

Mohamed et al. proposed a hybrid approach that combines the principles of AHP and TOPSIS for network selection in a HWNs environment in which an mobile node may consist of multiple network interfaces. Their study focused on evaluating five different network interfaces. The authors employed AHP and TOPSIS to calculate the performance scores of the alternative networks. The AHP method was utilized to assign weights to the evaluation criteria, while TOPSIS was employed for ranking and selecting the best network alternative [41]. The results of the hybrid technique outperform the conventional TOPSIS and distance to ideal alternative (DIA) strategies in terms of consistency [82]. Mehbodnia et al. introduced a ranking mechanism called Fuzzy Extension TOPSIS (FTOPSIS) to prioritize the available networks within the service area of a MN in their proposed model. Through simulations, the results showed that the FTOPSIS method outperformed the conventional TOPSIS method in terms of security priority level and the ratio of network selection to cost, specifically in a single service scenario. Chamodrakas et al., on the other hand, utilized fuzzy set theory-based TOPSIS to identify energy-efficient radio access networks in HWNs [15]. To address the challenge of ranking order abnormalities in network selection techniques, parameterized utility functions are employed to simulate the varying QoS requirements of different applications, including energy consumption indicators for both real-time and non-real-time applications. User preferences for different applications and scenarios can be determined through linguistic assessments. Lahby et al. developed an enhanced version of TOPSIS known as ETOPSIS, which utilizes the Analytic Network Process (ANP) to assign reference weights to each network attribute in order to make vertical handover decisions in HWNs. The model takes into account the relative importance of PIS and NIS parameters when calculating the network rankings. Research indicates that ETOPSIS effectively reduces the number of handovers and instances of ranking abnormalities. It outperforms other methodologies such as WSM, MEW, and TOPSIS across various traffic scenarios, including background, conversational, interactive, and streaming traffic.

Falowo et al. [21] investigate difficulties of picking suitable available access network technology for a set of requests from a multi-mode terminal while taking preferences and user requirements into consideration. An enhanced TOPSIS group decision-making technique, which incorporates concepts of weighted criteria and priority of request aggregation, has been developed to deal with the problem of selecting the most appropriate available access network technology for groups of requests in HWNs. To assess the relevance of the network criterion, a weighting system called weighted ranking of multiple criteria is devised and applied. The TOPSIS method is then used to rank networks. In terms of handover request drop rate, latency, jitter, and average throughput, the results reveal that the system beats the typical signal handover technique [80]. TOPSIS is a widely used MADM decision-making approach, however, it might suffer from ranking irregularities. These ranking anomalies may deteriorate the effectiveness of the outcomes. As a solution to the ranking abnormality problem in TOPSIS, publication [99] proposes a multi attribute network selection mechanism using the Iterative TOPSIS technique for HWNs access in order to solve the ranking abnormality problem. But Iterative TOPSIS is computationally expensive as compared to traditional TOPSIS. TOPSIS benefits include its intuitive ease of understanding and computation, as well as its adaptability to a wide range of multi-criteria selection issues with sometimes competing criteria interests. In addition to rank reversal and anomalies, TOPSIS has a number of flaws, including a lack of weight elicitation and consistency verification of criterion weight decisions [27].

6.5. Evaluation based on Distance from Average Solution (EDAS)

The EDAS is an efficient MADM technique introduced by Keshavarz Ghorabaee. Initially used for inventory classification, it ranks alternatives by calculating their positive and negative distances from the average solution. While TOPSIS utilizes positive and negative Euclidean distances from the PIS and NIS for each alternative, EDAS determines positive and negative distances between each alternative and the average alternative. EDAS is a straightforward and effective MADM method that relies solely on decision information represented by numerical values, meaning it deals with quantitative data. It is particularly useful for problems involving conflicting criteria. The best alternative in EDAS is determined based on the distance to the average solution. The method is designed to handle problems where the performance values of alternatives for each criterion follow a normal distribution. This assumption allows for consideration of both optimistic and pessimistic scores in evaluating alternatives and effectively addresses uncertainty in decision-making data. EDAS has been refined for application in various scenarios, including MADM problems characterized by uncertainty [76]. The process of ranking accessible alternatives and selecting the optimal alternative typically involves the following steps:

Step 1 Defining the average solution matrix Av_j.

$$Av_j = \left[av_{ij}\right]_{m\times n} = \left[\frac{\sum_{i=1}^{n} x_{ij}}{n}\right]_{m\times n} \tag{37}$$

Step 2 Computation of positive distance from average (PDA) and negative distance from average (NDA).

$$PDA = \left[pda_{ij}\right]_{m\times n} = \begin{cases} \frac{max\left(0,\left(x_{ij}-av_{ij}\right)\right)}{av_{ij}}, & if\forall c_j \in AT_1 \\ \frac{max\left(0,\left(av_{ij}-x_{ij}\right)\right)}{av_{ij}}, & if\forall c_j \in AT_2 \end{cases} \tag{38}$$

$$NDA = \left[nda_{ij}\right]_{m\times n} = \begin{cases} \frac{max\left(0,\left(av_{ij}-x_{ij}\right)\right)}{av_{ij}}, & if\forall c_j \in AT_1 \\ \frac{max\left(0,\left(x_{ij}-av_{ij}\right)\right)}{av_{ij}}, & if\forall c_j \in AT_2 \end{cases} \tag{39}$$

Step 3 Computation of weighted sum of PDA (SP_i) and NDA (SN_i).

$$SP_i = \sum_{j=1}^{n} w_j \times pda_{ij} \tag{40}$$

$$SN_i = \sum_{j=1}^{n} w_j \times nda_{ij} \tag{41}$$

Step 4 Computation of normalised value of SP (NSP_i) and SN (NSN_i)

$$NSP_i = \frac{SP_i}{max_i\left(SP_i\right)} \tag{42}$$

$$NSN_i = 1 - \frac{SN_i}{max_i\left(SN_i\right)} \tag{43}$$

Step 5 Normalization of the value of NSP_i and NSN_i

$$AS_i = \frac{1}{2}\left(NSP_i + NSN_i\right) \tag{44}$$

6.6. VIKOR

Multi-criteria decision-making often requires finding a compromise solution that takes various factors into account. The VIKOR method was initially introduced as a compromise approach to calculating the preference ranking score for a single alternative based on multiple criteria. The VIKOR ranking score considers both the highest group utility among the opponents and the minimum individual regret. The VIKOR aims to find a balanced solution that satisfies multiple criteria while minimizing individual regrets [64][73][56]. The decision matrix, $D(m\times n)$ can be used to define the multi-criteria decision problem where $a_1,\ a_2,\dots a_m$ are alternatives, and $c_1,\ c_2,\dots c_n$ attribute of each alternative. The entry in the decision matrix x_{ij} represents the score of the i^{th} alternative, with respect to j^{th} attribute of decision matrix. In order to rank accessible alternatives using the VIKOR method, the general steps listed below are followed:

Step 1 Find the best (x_j^+) and worst (x_j^-) values for each attribute of all alternatives through the equations (45) and (46).

$$x_j^+ = \begin{cases} x_j^{max}, & if\forall c_j \in AT_1 \\ x_j^{min}, & if\forall c_j \in AT_2 \end{cases} \tag{45}$$

$$x_j^- = \begin{cases} x_j^{min}, & if\forall c_j \in AT_1 \\ x_j^{max}, & if\forall c_j \in AT_2 \end{cases} \tag{46}$$

Step 2 Computation of the unity measure S_i

$$S_i = \sum_{i=1}^{m}\left(w_j \times \frac{x_j^+ - x_{ij}}{x_j^+ - x_j^-}\right) \tag{47}$$

Step 3 Computation of individual regret R_i

$$R_i = \max_j\left(w_j \times \frac{x_j^+ - x_{ij}}{x_j^+ - x_j^-}\right) \tag{48}$$

Step 4 Computation of (S^+), (S^-), (R^+) and (R^+)

$$S^+ = \min_i S_i \tag{49}$$

$$S^- = \max_i S_i \tag{50}$$

$$R^+ = \min_i R_i \tag{51}$$

$$R^- = \max_i R_i \tag{52}$$

Step 5 Computation of (Q_i)

$$Q_i = \vartheta \times \frac{S_i - S^+}{S^- - S^+} + (1-\vartheta)\times\frac{R_i - R^+}{R^- - R^+} \tag{53}$$

In order to acknowledge and incentivize the strategy that maximizes group utility, a weight variable, denoted as ϑ, is introduced. Alternatives with the minimum value of ϑ are assigned a rank of one. This compromise solution takes into account the principles of accepting advantage and acceptable stability in decision-making

Case 1: Acceptable advantage

$$Q\left(A^2\right) - Q\left(A^1\right) \geq DQ \tag{54}$$

Where $DQ = \frac{1}{m-1}$ and A^1 and A^2 represent the scores or evaluations of the alternatives ranked as one and two, respectively.

Case 2: In the context of acceptable stability in decision-making, if any of the fundamental requirements are not met, a list of compromise solutions is offered, which includes the following alternatives:

- Alternative a^1 and a^2 if only condition C_2 is not satisfied, or.
- Alternative $a^1, a^2, \ldots a^{(m)}$ if condition C_1 is not satisfied and $a^{(m)}$ is computed by the relation

$$Q\left(a^m\right) - Q\left(a^1\right) < DQ \tag{55}$$

The alternative compromise group can be identified using this approach. In the context of HWNs, factors influencing network decision-making, including voice and data traffic, are taken into account. The evaluation of HWNs considers criteria such as bandwidth availability, total bandwidth, packet latency, packet jitter, packet loss rate, and monetary cost per byte. VIKOR outperforms other methods such as GRA, ELECTRE, and MEW in voice connection applications, while GRA and MEW perform better in data connection applications. However, the study does not investigate the impact of different criterion weights on the algorithmic vertical handover decisions [55], [67], [57], [22].

In HWNs, there can be scenarios where handover decision criteria, application requirements, and user preferences are ambiguous, imprecise, or uncertain. Fuzzy logic is a suitable approach for addressing ambiguity and uncertainty in such cases. Sasirekha et al. utilize a combination of FAHP and VIKOR methods to select an appropriate network from a set of five available network interfaces. They consider ten handover decision criteria in their research. By incorporating fuzzy logic, they aim to handle the uncertainties and imprecisions associated with HWNs and make more informed network selection decisions [20]. In their research papers, Mehbodniya et al. introduce a method called fuzzy VIKOR (FVIKO) for optimal network selection in HWNs. When comparing the outcomes of FAHP and VIKOR with TOPSIS techniques, it becomes evident that the results obtained from FAHP TOPSIS exhibit greater consistency. Additionally, both FAHP and VIKOR demonstrate lower computational costs compared to FAHP TOPSIS, which further adds to their advantages [50], [69]. All network criteria and user preferences are weighted using a fuzzy linguistic variable-based weighting scheme and the FVIKOR ranking procedure to select the appropriate network. Baghla et al. [6] investigate the impact of criterion weight normalization approaches on the VIKOR method for HWN network selection. Based on the observations, the choice of normalization technique employed has an impact on the occurrence of ranking abnormalities and the ping-pong effect during handover procedures in MADM. The findings indicate that the max-min normalization method yielded superior results for background and streaming traffic, whereas the Euclidean normalization method proved more effective for interactive traffic classes. However, it is important to note that the authors did not consider the weight-sensitive behavior associated with weight normalization procedures in their study [26][66][17].

6.7. PROMETHEE

This particular MADM approach is widely recognized for its flexibility, simplicity, and straightforward implementation, as it incorporates the outranking concept [83]. PROMETHEE, being a versatile MADM approach, offers multiple versions to cater to different needs. An integral component of PROMETHEE is the preference function, which plays a crucial role. By utilizing the preference function, it becomes feasible to transform the disparity between two alternatives into a preference degree, ranging from 0 to 1, for each criterion. In an article [9], six mapping preference functions were presented, where the decision maker and preference input reflect difference between two alternative values. The decision matrix, $D(m \times n)$ can be used to define the multi-criteria decision problem where $a_1,\ a_2, \ldots a_m$ are alternatives, and $c_1,\ c_2, \ldots c_n$ attribute of each alternative. The entry in the decision matrix x_{ij} represents the score of the i^{th} alternative, with respect to j^{th} attribute of decision matrix. Within this section, our focus has solely been on PROMETHEE-I and PROMETHEE-II. To implement the PROMETHEE algorithm, the following steps are involved:

Step 1 Normalization of decision matrix

$$R_{ij} = \begin{cases} \frac{\left[x_{ij} - min\left(x_{ij}\right)\right]}{\left[max\left(x_{ij}\right) - min\left(x_{ij}\right)\right]}, & if \forall c_j \in AT_1 \\ \frac{\left[max\left(x_{ij}\right) - x_{ij}\right]}{\left[max\left(x_{ij}\right) - min\left(x_{ij}\right)\right]}, & if \forall c_j \in AT_2 \end{cases} \tag{56}$$

Step 2 Computation of the evaluative difference of i^{th} alternative with respect to all other available alternatives. Step 3 Computation of Preference function ($P_j(a,b)$)

$$P_j(a,b) = \begin{cases} 0, & if\, R_{aj} < R_{bj} \Longrightarrow D\left(M_a - M_b \le 0\right) \\ R_{aj} - R_{b,j}, & if\, R_{a,j} > R_{b,j} \Longrightarrow D\left(M_a - M_b > 0\right) \end{cases} \tag{57}$$

Step 4 Computation of aggregated preference value using aggregate preference function ($\prod(a,b)$)

$$\prod(a,b) = \frac{\left[\sum_{j=1}^{n} w_j \times P_j(a,b)\right]}{\sum_{j=1}^{n} w_j} \tag{58}$$

Step 5 Computation of leaving (positive) flow (φ^+) for a^{th} alternative and entering (negative) flow φ^- while $a \neq b$

$$\varphi^+ = \frac{1}{m-1} \sum_{b=1}^{m} \prod(a,b) \tag{59}$$

$$\varphi^- = \frac{1}{m-1} \sum_{b=1}^{m} \prod(b,a) \tag{60}$$

Step 6 Determination of the net outranking flow ($\varphi(a)$) for each alternative.

$$\varphi(a) = \varphi^+(a) - \varphi^-(a)$$

Step 7 Computation of the ranking of all accessible alternatives based on the value of the net outranking flow $\varphi(a)$. High values of $\varphi(a)$ rank highest, and lowest values of $\varphi(a)$ rank lowest. In PROMETHEE I, instead of taking the total value of leaving (φ^+) and entering (φ^-) it considers the average of leaving and entering flow while $a \neq b$

$$\varphi^+ = \sum_{b=1}^{m} \prod(a,b) \tag{61}$$

$$\varphi^- = \sum_{b=1}^{m} \prod(b,a) \tag{62}$$

PROMETHEE I takes a different approach compared to defining ranks. Instead, it calculates preferences and makes decisions based on them. For example, if an alternative has a higher leaving flow value, it is considered better, whereas if an alternative has a lower entering flow value, it is considered better. There could be the following three preference indicators:

- Alternative a is preferred over alternative b, i.e., P_a^b if
  $\varphi^+(a) > \varphi^+(b)\ and\ \varphi^-(a) - \varphi^-(b)\ Or$
  $\varphi^+(a) > \varphi^+(b)\ and\ \varphi^-(a) = \varphi^-(b)\ Or$
  $\varphi^+(a) = \varphi^+(b)\ and\ \varphi^-(a) < \varphi^-(b)$
- Indifference situation, I_a^b if
  $\varphi^+(a) = \varphi^+(a)\ and\ \varphi^-(a) = \varphi^-(a)$
- Incomparable situation, R_a^b if
  $\varphi^+(a) > \varphi^+(b)\ and\ \varphi^-(a) > \varphi^-(b)\ Or$
  $\varphi^+(a) < \varphi^+(b)\ and\ \varphi^-(a) < \varphi^-(b)$

The selection of a network in HWNs, involving four networks, is analyzed using the PROMETHEE method [40]. In this study, MN assesses and selects a suitable destination network among four accessible networks for different types of network traffic in HWNs. The selection process takes into consideration factors such as packet latency, jitter, packet loss ratio, monetary cost, acceptable bandwidth, and network utilization. To rank and select the most appropriate alternative network from the available networks, PROMETHEE is utilized. Additionally, the AHP method is employed to subjectively assign weights to the criteria for making handover decisions. The research findings indicate that the ranking orders obtained from the PROMETHEE and AHP networks are comparable. However, PROMETHEE outperforms AHP in terms of abnormality ranking, with an average abnormality rating of 28% for PROMETHEE compared to 47% for AHP. PROMETHEE techniques demonstrate greater stability in network selection compared to the AHP method. This is primarily due to the capability of PROMETHEE techniques to handle various types of traffic, unlike the AHP method, which is more limited in this regard. PROMCALC [1] and DECISION LAB [49] are two specialized software tools that have been particularly built for the implementation of PROMETHEE I to PROMETHEE VI. PROMETHEE-I provides a partial ranking, while PROMETHEE II provides a full ranking.

6.8. Fuzzy TOPSIS

Fuzzy TOPSIS is a method utilized when dealing with decision matrices that involve performance values expressed in linguistic terms rather than precise numerical values. In such scenarios, decision-makers provide these linguistic terms without assigning any specific numerical values, which makes determining the rank of alternatives challenging. To address this challenge, fuzzy TOPSIS is employed. Instead of directly assigning linguistic terms to weights, decision-makers utilize fuzzy AHP to derive fuzzy numbers representing the weights for each criterion. This approach allows decision-makers to handle the uncertainty and imprecision inherent in the decision-making process. Additionally, the concept of group decision-making plays a crucial role in this context, involving the participation of two or more decision-makers [52][79][65]. These decision-makers involved in group decision-making may possess varying degrees of importance or have equal importance. The process typically includes the following steps:

Step 1 The process of transforming a single decision matrix derived from multiple decision matrices obtained from different decision-makers.

$$\bar{x}_{ij} = \left(\min_k \left\{ a_{ij}^k \right\},\ \frac{1}{k} \sum_{k=1}^{k} b_{ij}^k,\ \max_k \left\{ c_{ij}^k \right\} \right) \tag{63}$$

If a decision-maker assigns different fuzzy weights to the criteria, the combined fuzzy weight for the combined decision matrix can be calculated using the following group decision-making (GDM) technique:

$$\bar{w}_{ij} = \left(\min_k \left\{ w_{ij}^k \right\},\ \frac{1}{k} \sum_{k=1}^{k} w_{ij}^k,\ \max_k \left\{ w_{ij}^k \right\} \right) \tag{64}$$

Step 2 Computation of normalized fuzzy decision matrix

$$\bar{r}_{ij} = \begin{cases} \frac{a_{ij}}{c_j^*}, \frac{b_{ij}}{c_j^*}, \frac{c_{ij}}{c_j^*}, c_j^* = \max_i \left\{ c_{ij} \right\}, & if \forall c_j \in AT_1 \\ \frac{a_j^-}{c_{ij}}, \frac{a_j^-}{c_{ij}}, \frac{a_j^-}{c_{ij}} and\ a_j^- = \min_i \left\{ a_{ij} \right\}, & if \forall c_j \in AT_2 \end{cases} \tag{65}$$

Step 3 Computation of weighted normalized fuzzy decision matrix.

$$\bar{v}_{ij} = \bar{r}_{ij} \times w_j \tag{66}$$

Step 4 Computation of fuzzy $PIS(A^*)$ and fuzzy $NIS(A^-)$, where $\bar{v}_n'^{\,*} = \max_i \left\{ v_{ij} \right\}$ and $\bar{v}_n'^{\,-} = \max_i \left\{ v_{ij} \right\}$

$$A^* = \left(\bar{v}_1'^{\,*}, \bar{v}_2'^{\,*}, \bar{v}_3'^{\,*} \ldots \bar{v}_n'^{\,*} \right) \tag{67}$$

$$A^- = \left(\bar{v}_1', \bar{v}_2', \bar{v}_3' \ldots \bar{v}_n' \right) \tag{68}$$

Step 5 Computation of distance from each alternative to the fuzzy PIS (FPIS) and fuzzy NIS (FNIS)

$$(\bar{x}, \bar{y}) = \sqrt{\frac{1}{3} \left[\left(a_1 - a_2\right)^2 + \left(b_1 - b_2\right)^2 + \left(c_1 - c_2\right)^2 \right]} \tag{69}$$

Step 6 Computation of distance from each alternative to the FPIS (d_i^*) and to FNIS (d_i^-)

$$d_i^* = \sum_{j=1}^{n} d\left(\overline{v_{ij}}, \bar{v}_j'^{\,*} \right) \tag{70}$$

$$d_i^- = \sum_{j=1}^{n} d\left(\overline{v_{i,j}}, \bar{v}_j'^{\,-} \right) \tag{71}$$

Step 7 Computation of the closeness coefficient CC_i for each candidate alternative.

$$CC_i = \frac{d_i^-}{d_i^- + d_i^*} \tag{72}$$

6.9. Grey Relational Analysis (GRA)

In 1989, Deng Julong introduced the GRA, also known as grey system theory, which encompasses concepts from system sciences and uncertainty system theory. GRA consists of three main components: grey relational coefficient, data processing, and grey relational grade. One common application of GRA is to transform a multi-objective optimization problem into a single-objective optimization problem [37][45]. The grey system theory is applied in the MADM approach to examine the relationship between a reference series and its comparison series. The comparison series is formed by considering the performance scores for each alternative. This comparison series helps to mitigate scale errors in decision-making that may occur when comparing criteria with different dimensions, units, scales, or ranges. By comparing the comparison series of each alternative to a given reference series, the grey coefficient of the relative estimate for the compared alternatives is obtained. The decision matrix, $D(n \times m)$ can be used to define the multi-criteria decision problem where $a_1,\ a_2, \ldots a_m$ are the alternatives, and $c_1,\ c_2, \ldots c_n$ attribute of each alternative. The entry in decision matrix x_{ij} represents the score of the i^{th} alternative, with respect to the j^{th} attribute of the decision matrix. GRA may be used to choose the best alternative from a variety of possibilities based on many factors by following the procedures below.

Step 1 Normalization of the given decision matrix using linear min-max normalization method

$$x_i^* = \begin{cases} \frac{x_i^0(k) - min\left(x_i^0\right)}{max\left(x_i^0\right) - min\left(x_i^0\right)}, & if\ \forall c_j \in AT_1 \\ \frac{min\left(x_i^0\right) - x_i^0(k)}{max\left(x_i^0\right) - min\left(x_i^0\right)}, & if\ \forall c_j \in AT_1 \end{cases} \tag{73}$$

Step 2 Computation of grey relational coefficient ($\zeta_i(k)$) and deviation sequence (Δ_{oi})

$$\zeta_i(k) = \frac{\Delta_{min} + \xi \Delta_{max}}{\Delta_{oi}(k)^c + \xi \Delta_{max}} \tag{74}$$

$$\Delta_{oi} = \| x_0^*(k) - x_i^*(k) \| \tag{75}$$

$$\Delta_{min} = \max_{\forall i} \min_{\forall k} \| x_o^*(k) - x_i^*(k) \| \tag{76}$$

$$\Delta_{max} = \min_{\forall i} \max_{\forall k} \| x_o^*(k) - x_i^*(k) \| \tag{77}$$

A value of ξ is smaller and distinguished ability longer, $\xi = 0.5$ is generally used. ξ is the distinguished coefficient.

Step 3 Grey relation grade (γ_i)

$$\gamma_i = \frac{1}{n} \sum_{k=1}^{n} w_k(k) \xi_k(k) \tag{78}$$

The GRA technique is utilized to assess the level of similarity between comparative sequence and a reference sequence. Consequently, the most favorable alternative is one that exhibits the highest similarity to the reference sequence [36]. Joe and colleagues have introduced a network selection strategy that addresses vertical handover in high-density networks while considering power consumption. Their proposed model estimates the MN energy usage by calculating the MN dwell time based on factors such as the current battery level, ongoing traffic class, and power consumption for each network connection. In the pre-processing step, target candidate networks are eliminated from the target network list if the predicted lifespan of the MN in that network is insufficient, thus avoiding unnecessary handovers. The final selection of a suitable network is determined by integrating the AHP and GRA, where independent aspects including QoS, cost, and lifetime are considered. Simulations demonstrate that the proposed technique offers a longer service life compared to existing methods in hybrid CDMA and WLAN scenarios.

Furthermore, Song et al. have proposed a network selection scheme that incorporates AHP and GRA methodologies to assess and determine QoS components, such as throughput, timeliness, dependability, security level, and cost, in HWNs [74]. At the second level of the hierarchy, the QoS criteria are further specified into sub-factors such as delay, reaction time, and jitter. The AHP methodology is employed in two phases to assign weights to both the QoS criteria and the sub-criteria. The subsequent step involves assigning global priorities to the main QoS criteria and the sub-criteria within QoS. Finally, the global sub-criteria priorities are calculated by multiplying the sub-criteria priorities with the global priorities of the QoS factors. Consistency ratios are utilized to ensure the consistency of weight criteria. During roaming within the HWNs environment, this model aims to provide an improved user experience for both real-time and non-real-time services. For real-time applications, the model selects a network alternative that prioritizes low latency, while for non-real-time applications, it selects a network alternative that offers high throughput and reliability. The research findings demonstrate that the proposed network selection model effectively balances service quality, network conditions, and user preferences to determine an optimal trade-off.

New service request blocking probability and load balancing are critical characteristics of high-speed networks that must be regulated in order to provide consumers with an acceptable level of service. In the paper [54], the authors propose a combined approach of fuzzy AHP and entropy, serving as subjective and objective weighting procedures, respectively, to enhance performance. In order to obtain the optimal network criterion weights, the weights determined by fuzzy AHP are further refined using least squares and Lagrange optimization techniques. The GRA is then employed in the context of HWNs to rank and select suitable networks, aiming to achieve network load balancing and minimize issues like new incoming service request blockage. The fuzzy AHP, entropy GRA (FAHPE-GRA) system is considered more objective due to the implementation of the entropy weighting approach. However, the utilization of least squares and Lagrange function optimization introduces increased computational complexity to the system [94]. The weight assigned to network criteria in MADM algorithms is influenced by the expertise and knowledge of decision-makers, as well as the number of decision-makers involved. The authors of the paper [88] propose the utilization of a Multiple AHP (M-AHP) weight system in the context of HWNs to account for the diversity of experiences among multiple specialists, which influences the evaluation and weighting of criteria by decision-makers. The weights obtained from M-AHP are aggregated using the geometric mean, and GRA is employed for network ranking and selection. However, it should be noted that as the number of network users increases, this approach may face scalability challenges.

The authors of the paper [100] introduced a novel approach to network selection by modifying the traditional GRA method. In addition to the conventional ideal reference and comparative series, they introduced a new series called the worst-case series. By considering the worst-case scenario, the modified GRA method enables the identification of the most appropriate network for selection. The network criteria weights are determined through the application of AHP. However, it should be noted that this approach has the drawback of increasing processing time and implementation costs. In the paper [35], the authors have proposed a network selection approach in HWNs that prioritizes QoS based on the specific application requirements. This approach involves selecting the most suitable network and minimizing unnecessary handovers. The model utilizes the variance coefficient weighting approach to assign weights to network criteria and user preferences. The ranking of network alternatives is achieved through a modified GRA technique. One advantage of modified GRA is that it not only considers the current conditions of the networks but also incorporates the dynamic features of the networks into the criteria weights. While fuzzy theories can handle uncertainty, GRA has the advantage of effectively handling missing information in unfavourable data situations. Additionally, GRA can produce satisfactory results even with limited data or high levels of unpredictability in the decision criteria. Furthermore, GRA can be applied to optimize multi-objective problems.

7. Discussion and findings

In this section, the study's findings are analyzed, and various research gaps related to mobility management in heterogeneous wireless communication networks are explored.

7.1. MADM and criteria cardinality

The number of handover decision criteria, also termed criterion cardinality. The identification of appropriate cardinality and types of decision criteria is a crucial aspect to consider when designing and implementing handover management. By choosing a minimal number of handover decision criteria, the computational burden at the handover control point can be reduced. However, this approach may lead to the exclusion of certain crucial decision criteria during handover. On the other hand, selecting a larger number of handover decision criteria ensures that all significant factors are taken into account when evaluating handover decisions. Nevertheless, this can slow down the decision-making process of the network selection algorithm because of heavy computing and other network burdens. The required number of handover decision criteria can range from three to ten or more, but it is important to make a balance to maintain efficiency and avoid unnecessary complexity. It is one of the important aspects of research to determine the suitable cardinality of decision criteria for low-complexity and fast handover decisions [90]

The cardinality and types of handover decision criteria used to make handover decisions in HWNs are extremely important. The handover decision criteria for selecting appropriate networks for efficient and smooth handover in HWNs and how frequently they have been referenced are the two most preferred aspects for influencing handover decisions in HWNs. In HWNs, the most frequently used criteria for handover decisions are throughput, bandwidth, monetary cost, security level, packet loss ratio, delay, and jitter, whereas the least frequently used criteria are BER, SINR, request dropping probability, and MN velocity.

7.2. MADM and handover control point

The network-centric handover strategy involves a network entity that manages and ensures seamless handover for MNs in a transparent manner. This entity is responsible for gathering important data from HWNs and may request additional information and network metrics from MNs to facilitate smooth handovers. However, as the number of MNs increases, the control signaling overhead and processing load on the network entity also increase, potentially affecting the efficiency of

HWNs. Such handover systems that rely on a single point of failure are challenging to scale and susceptible to failure.

To address these issues, one approach is to distribute the handover decision-making and control to the MNs themselves. This user-centric vertical handover mechanism allows MNs to autonomously make handover decisions and select appropriate technologies. For this purpose, MNs need to gather crucial information and measurements about the HWN environment to ensure a seamless vertical handover process. However, user-centric strategies may encounter synchronization problems because MNs might not possess comprehensive global insights into network load and other critical network statistics.

To overcome this limitation, a network resource control entity can gather information about the global network load and important network statistics. With this information, the network resource control entity can make more informed handover decisions. The network resource control can then broadcast these measurements and information to the MNs through the network resource control network, improving the effectiveness of handover decisions in HWNs. Various vertical handover mechanisms have been developed, including both network-centric and user-centric implementations, to address different vertical handover scenarios.

7.3. MADM and handover decision criteria analysis

The MADM optimization research tool has been successfully applied for many years to tackle complex decision-making challenges in real-time applications across various research fields, including science, engineering, and economics. Recently, there has been considerable interest in utilizing MADM techniques to address intricate decision-making problems in the context of the HWNs framework. The implementation of the MADM approach in HWNs can be classified in several ways, taking into account factors such as the algorithms employed, types of service requests received, assessment criteria, handover control points, user preferences, mobile terminal requirements and characteristics, application characteristics and requirements, and network utility types. Depending on how MADM techniques are applied in HWNs, the implementation can be divided into three main categories: single algorithms, integrated algorithms, and modified algorithms. These categories cater to handover decisions and network selection using mathematical applications. In the single MADM technique described in [8], a stand-alone MADM technique is used to rank and select networks in HWNs. The effectiveness of network selection can be compromised if the relative importance of decision criteria is not accurately expressed. The AHP and analytic network process (ANP) have commonly used MADM methods that subjectively allocate consistent weights to similar decision criteria. However, assessments of network preferences and criteria can be inaccurate or ambiguous. To address this, fuzzy logic theory, which handles imprecise and insufficient information scenarios, is employed to represent and analyze practical preference decisions. Researchers utilize AHP or ANP with fuzzy logic in an integrated MADM algorithm approach to process fuzzy data and determine appropriate weights for decision criteria.

Different MADM approaches have their own strengths and limitations. Techniques like SAW and MEW are relatively simpler to implement, while more robust techniques like TOPSIS and EDAS require significant computational capabilities. TOPSIS and GRA are more affected by ranking abnormalities compared to PROMETHEE and DIA. No single MADM method outperforms all others across all performance criteria. To enhance the overall objective of modified MADM computation, independent or integrated techniques can be adapted by incorporating concepts and features from other MADM methodologies. Modified MADM techniques are often used to address handover challenges. The importance of algorithmic approaches to the MADM mechanism in dealing with handover decisions in HWNs is expected to increase in future research. It is evident from Fig. 8 that, among MADM methodologies, single and integrated approaches are used 25% of the time, while modified methodologies are used 31% and 44% of the time, respectively. HWNs support multiple simultaneous services like voice, video streaming, and web browsing, whereas MNs can only access one service at a time. MNs have the flexibility to switch between independent services, such as transitioning from a voice call to a video stream. This mode of operation avoids degrading call quality by activating new calls while the previous ones are still active, utilizing group service request facilities. Given the large number of service requests, implementing group decision-making and assigning priority weights to various services are necessary MADM techniques to handle the multitude of calls effectively [92]

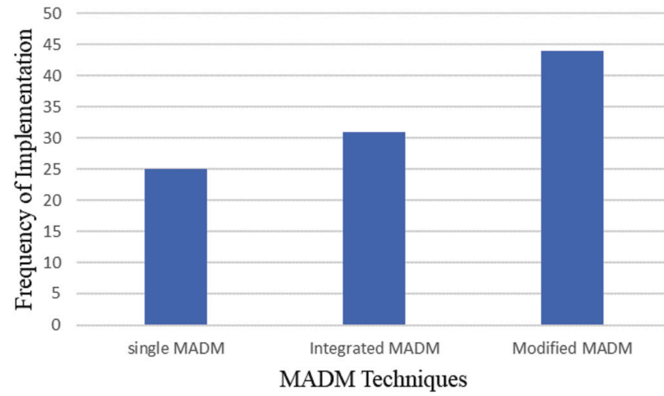

Fig. 8. Implementation of MADM Techniques in Handover in HWNs.

7.4. Prospects in mobility management research

The fast, robust, and efficient handover mechanism in HWNs is necessary due to various factors. The factors may include a decline in signal quality, an imbalanced traffic load, high-speed mobility, changes in user preferences, resource limitations, and network heterogeneity. Furthermore, the architecture, protocols, and potential services offered by different radio access networks exhibit variations. As a result, mobile nodes frequently switch among different RATs in a multi-RAT architecture with overlapping networks coverage. Mobile node points of attachment may also frequently switch among networks to identify the best connection for their desired level of service quality. Additionally, multimode multiservice mobile nodes operates multiple services simultaneously. Ultra-densification of small BSs within HWNS is employed to ensure extensive coverage, connectivity, capacity, support for various applications, high mobility, and increased available bandwidth. The dynamic nature of mobile users' services, network conditions, application requirements, service characteristics, mobile terminal constraints, and the reliability of networks further contribute to the need for handover mechanisms.

During the course of this study, several research gaps in the field of mobility management in heterogeneous wireless mobile communication have been identified. These gaps that need to be addressed include:

- The inadequacy of a single-handover decision-criteria approach in meeting the evolving user and application requirements and service characteristics.
- Inadequate attention to the varieties, cardinality, types, and priority weighting of handover decision criteria during the formulation of handover decision schemes.
- Network-centric RAT selection approaches in handover decision mechanisms that lack the involvement of terminal, application, and user-specific features, resulting in increased complexity, delays, signaling overhead, and the potential for single-point failures. Therefore, there is a need to shift towards application- and user-centric decision schemes.

- Challenges faced by most handover decision mechanisms in network selection algorithms, particularly in addressing complex and dynamic decision difficulties and providing transparent and seamless handover among candidate access networks.
- The potential consequences of inappropriate network selection, such as an undecidable and unstable network, which can lead to issues like the ping-pong effect, frequent handovers, handover drops, and new call blocking.
- The requirement for an enhanced RAT selection mechanism to handle the tendency of frequent switching among candidate networks due to the multi-RAT architecture with overlapping network coverage and multi-interface enabled terminals. This is necessary to ensure a defined QoS for various types of service traffic.
- The necessity for an improved energy-efficient and robust handover mechanism to prevent forced termination of ongoing handover procedures and blocking of newly initiated requests.
- Ongoing research is still needed to identify the most appropriate and relevant factors and aspects in handover decision-making. The limitations of using fixed thresholds for decision-making, as they may result in frequent handover failures due to factors like high mobility of mobile nodes, shadowing, attenuations, and network imbalances.
- Mitigation of ranking abnormalities in MADM-based best RAT selection approaches to achieve a stable network with minimal handover overhead.
- Load balancing is one of the crucial aspects of a handover decision.
- The handover decision function only considers current status (intelligent and prediction techniques)
- Static adjustment coefficient factors that involve subjectivity and objectivity in the computation of comprehensive weights of considered handover decision criteria

In summary, these research gaps highlight the need for comprehensive, user-centric, and efficient handover decision mechanisms that consider various criteria, adapt to changing network conditions, and ensure a seamless transition between HWNs.

8. Conclusion and future aspects

The coexistence of cellular and non-cellular networks within next-generation wireless networks aims to deliver a wide range of services, ensure smooth services, and maintain QoS and QoE for various services for users and operators. The presence of heterogeneity, high mobility, utilization of millimeter waves, and the dense deployment of small base stations in the implementation of 5G and beyond 5G heterogeneous networks have drastically increased the probability of high-frequency of handovers. To achieve reliable and seamless handover in these networks, existing handover techniques based on a single criterion are insufficient. Homogeneous network handover techniques may not work optimally in HetNets due to the heterogeneity of handover decision criteria. MADM techniques are commonly used in research for handover and network selection in these networks due to their ability to handle complex decisions involving multiple conflicting and complex decision-making criteria. Integrated MADM techniques, although more complex and computationally intensive than single-criterion-based techniques, are preferred by researchers for HWNst. However, it is important to consider how group-decision procedures impact request aggregation when selecting multiple access networks. The selection of handover decision criteria and their combinations in HWNs is crucial for effective handover procedures. Selecting a limited number of criteria reduces computational work but may omit important criteria while considering a sufficient number of criteria increases computational burden and handover delay. Less computationally intensive network selection methods should be employed to save time and reduce computational and memory complexity for fast and seamless handover in HWNs. MADM techniques, ranging from WSM and MEW to ELECTRE and VIKOR, vary in complexity and are susceptible to criterion weight differences and ranking anomalies. To address this, researchers have used subjective weighing techniques like AHP, FAHP, and ANP, as well as objective weighting mechanisms like Entropy and CRITIC. The integration of subjective and objective weights, known as the comprehensive weighing mechanism, has also been explored. Another area of research involves determining appropriate weights for each network criterion to select the best network. The dynamic dependencies and relationships among criteria substantially influence their relative weights in HWN handover decisions. Understanding these interactions and dependencies is crucial for accurately weighting the criteria.

This paper investigates and identifies some of the vital and relevant MADM techniques for addressing handover challenges in HWNs, considering algorithmic strategies, priority weight allocation, network traffic classes, decision criteria cardinality, handover-control points, and network utilities. The study evaluates the mathematical implementations, merits, and limitations of the reviewed MADM techniques, as well as different normalizing and criterion weighting approaches. This study examines the latest research trends in mobility management within ultra-dense HetNets and identifies the remaining research gaps that need to be addressed. The findings of this study will assist researchers in addressing the current research gaps within future-generation wireless communication networks. In our future work, we aim to incorporate an effective multiple-attribute decision-making approach alongside a robust weighting method to develop a rapid and efficient network selection model. Additionally, we plan to explore the application of MADM techniques in developing frameworks for selecting appropriate consensus mechanisms for specific blockchain applications.

CRediT authorship contribution statement

Ashok Kumar Yadav: Conceptualization, Data curation, Formal analysis, Methodology. **Karan Singh:** Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. **Noreen Izza Arshad:** Project administration, Resources, Software, Writing – review & editing. **Massimiliano Ferrara:** Funding acquisition, Project administration, Supervision, Visualization, Writing – review & editing. **Ali Ahmadian:** Project administration, Supervision, Validation, Writing – review & editing. **Yehya I. Mesalam:** Formal analysis, Funding acquisition, Visualization, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

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References

[1] J. Abonyi, T. Czvetkó, Z.T. Kosztyán, K. Héberger, Factor analysis, sparse pca, and sum of ranking differences-based improvements of the promethee-gaia multicriteria decision support technique, PLoS ONE 17 (2022) e0264277.

[2] A. Ahmed, L.M. Boulahia, D. Gaiti, Enabling vertical handover decisions in heterogeneous wireless networks: a state-of-the-art and a classification, IEEE Commun. Surv. Tutor. 16 (2013) 776–811.

[3] A.T. Al-Heety, M.T. Islam, A.H. Rashid, H. Ali, A.M. Fadil, F. Arabian, Performance evaluation of wireless data traffic in mm wave massive mimo communication, Indones. J. Electr. Eng. Comput. Sci. 20 (2020).
[4] H.F. Alhashimi, M.N. Hindia, K. Dimyati, E.B. Hanafi, N. Safie, F. Qamar, K. Azrin, Q.N. Nguyen, A survey on resource management for 6g heterogeneous networks: current research, future trends, and challenges, Electronics 12 (2023) 647.
[5] A. Alinezhad, J. Khalili, et al., New Methods and Applications in Multiple Attribute Decision Making (MADM), vol. 277, Springer, 2019.
[6] S. Baghla, S. Bansal, Effect of normalization techniques in vikor method for network selection in heterogeneous networks, in: 2014 IEEE International Conference on Computational Intelligence and Computing Research, IEEE, 2014, pp. 1–6.
[7] V.D. Baloyi, L. Meyer, The development of a mining method selection model through a detailed assessment of multi-criteria decision methods, Results Eng. 8 (2020) 100172.
[8] F. Bari, V. Leung, Application of electre to network selection in a hetereogeneous wireless network environment, in: 2007 IEEE Wireless Communications and Networking Conference, IEEE, 2007, pp. 3810–3815.
[9] J.P. Brans, P. Vincke, Note—a preference ranking organisation method: (the promethee method for multiple criteria decision-making), Manag. Sci. 31 (1985) 647–656.
[10] M. Brunelli, L. Canal, M. Fedrizzi, Inconsistency indices for pairwise comparison matrices: a numerical study, Ann. Oper. Res. 211 (2013) 493–509.
[11] J. Buckley, The multiple judge, multiple criteria ranking problem: a fuzzy set approach, Fuzzy Sets Syst. 13 (1984) 25–37.
[12] J.J. Buckley, Ranking alternatives using fuzzy numbers, Fuzzy Sets Syst. 15 (1985) 21–31.
[13] H. Byun, K. Lee, A decision support system for the selection of a rapid prototyping process using the modified topsis method, Int. J. Adv. Manuf. Technol. 26 (2005) 1338–1347.
[14] B. Cavallo, Computing random consistency indices and assessing priority vectors reliability, Inf. Sci. 420 (2017) 532–542.
[15] I. Chamodrakas, D. Martakos, A utility-based fuzzy topsis method for energy efficient network selection in heterogeneous wireless networks, Appl. Soft Comput. 11 (2011) 3734–3743.
[16] D.Y. Chang, Applications of the extent analysis method on fuzzy ahp, Eur. J. Oper. Res. 95 (1996) 649–655.
[17] I. Cinemre, T. Mahmoodi, Learning-based multi attribute network selection in heterogeneous wireless access, Wirel. Pers. Commun. 125 (2022) 351–366.
[18] D. Diakoulaki, G. Mavrotas, L. Papayannakis, Determining objective weights in multiple criteria problems: the critic method, Comput. Oper. Res. 22 (1995) 763–770.
[19] M. Drissi, M. Oumsis, D. Aboutajdine, A multi-criteria decision framework for network selection over lte and wlan, Eng. Appl. Artif. Intell. 66 (2017) 113–127.
[20] C.S. Evangeline, V.B. Kumaravelu, A two-phase fuzzy based access network selection scheme for vehicular ad hoc networks, Peer-to-Peer Netw. Appl. 15 (2022) 107–133.
[21] O.E. Falowo, H.A. Chan, Rat selection for multiple calls in heterogeneous wireless networks using modified topsis group decision making technique, in: 2011 IEEE 22nd International Symposium on Personal, Indoor and Mobile Radio Communications, IEEE, 2011, pp. 1371–1375.
[22] B. Fayssal, A. Marwen, D. Fedoua, A madm method for network selection in heterogeneous wireless networks, preprint, arXiv:2201.12011, 2022.
[23] B. Fayssal, A. Marwen, D. Fedoua, Network selection schemes in heterogeneous wireless networks, preprint, arXiv:2201.12021, 2022.
[24] P.C. Fishburn, Methods of estimating additive utilities, Manag. Sci. 13 (1967) 435–453.
[25] N. Gadde, B. Jakkali, R.B.H. Siddamallaih, G. Gowrishankar, Quality of experience aware network selection model for service provisioning in heterogeneous network, Int. J. Comput. Electr. Eng. 12 (1839) 1839.
[26] M.S. Gupta, K. Kumar, Group mobility assisted network selection framework in 5g vehicular cognitive radio networks, Phys. Commun. 51 (2022) 101578.
[27] S.H. Hashemi, A. Karimi, M. Tavana, An integrated green supplier selection approach with analytic network process and improved grey relational analysis, Int. J. Prod. Econ. 159 (2015) 178–191.
[28] F. Helff, L. Gruenwald, L. d'Orazio, Weighted sum model for multi-objective query optimization for mobile-cloud database environments, in: EDBT/ICDT Workshops, Citeseer, 2016.
[29] A. Ishizaka, A. Labib, Review of the main developments in the analytic hierarchy process, Expert Syst. Appl. 38 (2011) 14336–14345.
[30] A. Jahan, K.L. Edwards, A state-of-the-art survey on the influence of normalization techniques in ranking: improving the materials selection process in engineering design, Mater. Des. 1980–2015 (65) (2015) 335–342.
[31] P. Jankowski, Integrating geographical information systems and multiple criteria decision-making methods, Int. J. Geogr. Inf. Syst. 9 (1995) 251–273.
[32] H. Jati, D.D. Dominic, A new approach of Indonesian university webometrics ranking using entropy and prométhée ii, Proc. Comput. Sci. 124 (2017) 444–451.
[33] Y. Jia, P. Xu, X. Guo, Mimo system capacity based on different numbers of antennas, Results Eng. 15 (2022) 100577.
[34] F. Jiang, C. Feng, H. Zhang, A heterogenous network selection algorithm for Internet of vehicles based on comprehensive weight, Alex. Eng. J. 60 (2021) 4677–4688.
[35] W.w. Jiang, H.y. Cui, Q.j. Yan, X.j. Wang, J.Y. Chen, A novel application-oriented dynamic network selection in an integrated umts and wimax environment, in: 2008 Third International Conference on Communications and Networking in China, IEEE, 2008, pp. 158–161.
[36] I. Joe, W.T. Kim, S. Hong, A network selection algorithm considering power consumption in hybrid wireless networks, IEICE Trans. Commun. 91 (2008) 314–317.
[37] D. Julong, et al., Introduction to grey system theory, J. Grey Syst. 1 (1989) 1–24.
[38] M. Kassar, B. Kervella, G. Pujolle, An overview of vertical handover decision strategies in heterogeneous wireless networks, Comput. Commun. 31 (2008) 2607–2620.
[39] M. Keshavarz Ghorabaee, M. Amiri, E. Kazimieras Zavadskas, J. Antuchevičienė, Assessment of third-party logistics providers using a critic–waspas approach with interval type-2 fuzzy sets, Transport 32 (2017) 66–78.
[40] M. Khalily-Dermany, Multi-criteria itinerary planning for the mobile sink in heterogeneous wireless sensor networks, J. Ambient Intell. Humaniz. Comput. (2022) 1–20.
[41] E. Khanmohammadi, B. Barekatain, A.A. Quintana, An enhanced ahp-topsis-based clustering algorithm for high-quality live video streaming in flying ad hoc networks, J. Supercomput. 77 (2021) 10664–10698.
[42] R. Kumar, S. Singh, P.S. Bilga, J. Singh, S. Singh, M.L. Scutaru, C.I. Pruncu, et al., Revealing the benefits of entropy weights method for multi-objective optimization in machining operations: a critical review, J. Mater. Res. Technol. 10 (2021) 1471–1492.
[43] L.C. Leung, D. Cao, On consistency and ranking of alternatives in fuzzy ahp, Eur. J. Oper. Res. 124 (2000) 102–113.
[44] M.C. Lin, C.C. Wang, M.S. Chen, C.A. Chang, Using ahp and topsis approaches in customer-driven product design process, Comput. Ind. 59 (2008) 17–31.
[45] S. Liu, J. Forrest, Y. Yang, A brief introduction to grey systems theory, in: Proceedings of 2011 IEEE International Conference on Grey Systems and Intelligent Services, IEEE, 2011, pp. 1–9.
[46] Y. Liu, C.M. Eckert, C. Earl, A review of fuzzy ahp methods for decision-making with subjective judgements, Expert Syst. Appl. 161 (2020) 113738.
[47] H. Lu, Y. Zhao, X. Zhou, Z. Wei, Selection of agricultural machinery based on improved critic-entropy weight and gra-topsis method, Processes 10 (2022) 266.
[48] G. Ma, R. Parthiban, N. Karmakar, An adaptive handover scheme for hybrid lifi and wifi networks, IEEE Access 10 (2022) 18955–18965.
[49] A. Makan, M. Gouraizim, A. Fadili, Sustainability assessment of wastewater treatment systems using cardinal weights and promethee method: case study of Morocco, Environ. Sci. Pollut. Res. Int. (2022) 1–13.
[50] A. Mehbodniya, F. Kaleem, K.K. Yen, F. Adachi, A fuzzy extension of vikor for target network selection in heterogeneous wireless environments, Phys. Commun. 7 (2013) 145–155.
[51] I. Mukhametzyanov, Specific character of objective methods for determining weights of criteria in mcdm problems: entropy, critic and sd, Decis. Mak. Appl. Manag. Eng. 4 (2021) 76–105.
[52] S. Nădăban, S. Dzitac, I. Dzitac, Fuzzy topsis: a general view, Proc. Comput. Sci. 91 (2016) 823–831.
[53] L. Nie, B. Liu, P. Li, H. He, L. Wu, An improved multi-attribute decision-making based network selection algorithm for heterogeneous vehicular network, Front. Comput. Sci. 16 (2022) 1–3.
[54] E. Obayiuwana, O.E. Falowo, Network selection in heterogeneous wireless networks using multi-criteria decision-making algorithms: a review, Wirel. Netw. 23 (2017) 2617–2649.
[55] S. Opricovic, G.H. Tzeng, Multicriteria planning of post-earthquake sustainable reconstruction, Comput.-Aided Civ. Infrastruct. Eng. 17 (2002) 211–220.
[56] S. Opricovic, G.H. Tzeng, Compromise solution by mcdm methods: a comparative analysis of vikor and topsis, Eur. J. Oper. Res. 156 (2004) 445–455.
[57] S. Opricovic, G.H. Tzeng, Extended vikor method in comparison with outranking methods, Eur. J. Oper. Res. 178 (2007) 514–529.
[58] J. Patel, S. Rana, A selection of the best location for a small hydro power project using the ahp-weighted sum and promethee method, Pertanika J. Sci. Technol. 26 (2018) 1591–1603.
[59] D. Pavličić, Normalization affects the results of madm methods, Yugosl. J. Oper. Res. 11 (2001) 251–265.
[60] V.S. Prasad, P. Kousalya, Role of consistency in analytic hierarchy process–consistency improvement methods, Indian J. Sci. Technol. 10 (2017) 1–5.
[61] R.W. Saaty, The analytic hierarchy process—what it is and how it is used, Math. Model. 9 (1987) 161–176.
[62] T.L. Saaty, What is the Analytic Hierarchy Process?, Springer, 1988.
[63] T.L. Saaty, Fundamentals of Decision Making and Priority Theory with the Analytic Hierarchy Process, RWS Publications, 1994.
[64] T.L. Saaty, Decision making with the analytic hierarchy process, Int. J. Serv. Sci. 1 (2008) 83–98.
[65] M.M. Salih, B. Zaidan, A. Zaidan, M.A. Ahmed, Survey on fuzzy topsis state-of-the-art between 2007 and 2017, Comput. Oper. Res. 104 (2019) 207–227.
[66] S. Salimian, S.M. Mousavi, J. Antucheviciene, An interval-valued intuitionistic fuzzy model based on extended vikor and marcos for sustainable supplier selection in organ transplantation networks for healthcare devices, Sustainability 14 (2022) 3795.
[67] A. Sanayei, S.F. Mousavi, A. Yazdankhah, Group decision making process for supplier selection with vikor under fuzzy environment, Expert Syst. Appl. 37 (2010) 24–30.

[68] V. Sasirekha, M. Ilangkumaran, G. Sakthivel, A comparative analysis of fuzzy-based ahp derived mcdm methods to select the apt heterogeneous wireless network, Int. J. Inf. Dec. Sci. 8 (2016) 227–253.
[69] P. Satapathy, J. Mahapatro, An efficient multicriteria-based vertical handover decision-making algorithm for heterogeneous networks, Trans. Emerg. Telecommun. Technol. 33 (2022) e4409.
[70] K. Savitha, C. Chandrasekar, Vertical handover decision schemes using saw and wpm for network selection in heterogeneous wireless networks, preprint, arXiv:1109.4490, 2011.
[71] C.E. Shannon, A mathematical theory of communication, ACM SIGMOBILE Mob. Comput. Commun. Rev. 5 (2001) 3–55.
[72] I. Shayea, M. Ergen, M.H. Azmi, S.A. Çolak, R. Nordin, Y.I. Daradkeh, Key challenges, drivers and solutions for mobility management in 5g networks: a survey, IEEE Access 8 (2020) 172534–172552.
[73] Y.B. Shin, S. Lee, S.G. Chun, D. Chung, A critical review of popular multi-criteria decision making methodologies, Issues Inf. Syst. 14 (2013) 358–365.
[74] Q. Song, A. Jamalipour, Network selection in an integrated wireless lan and umts environment using mathematical modeling and computing techniques, IEEE Wirel. Commun. 12 (2005) 42–48.
[75] A. Stamou, N. Dimitriou, K. Kontovasilis, S. Papavassiliou, Autonomic handover management for heterogeneous networks in a future Internet context: a survey, IEEE Commun. Surv. Tutor. 21 (2019) 3274–3297.
[76] D. Stanujkic, E.K. Zavadskas, M.K. Ghorabaee, Z. Turskis, An extension of the edas method based on the use of interval grey numbers, Stud. Inform. Control 26 (2017) 5–12.
[77] E. Stevens-Navarro, Y. Lin, V.W. Wong, An mdp-based vertical handoff decision algorithm for heterogeneous wireless networks, IEEE Trans. Veh. Technol. 57 (2008) 1243–1254.
[78] A. Stöhr, S. Babiel, P.J. Cannard, B. Charbonnier, F. van Dijk, S. Fedderwitz, D. Moodie, L. Pavlovic, L. Ponnampalam, C.C. Renaud, et al., Millimeter-wave photonic components for broadband wireless systems, IEEE Trans. Microw. Theory Tech. 58 (2010) 3071–3082.
[79] C.C. Sun, A performance evaluation model by integrating fuzzy ahp and fuzzy topsis methods, Expert Syst. Appl. 37 (2010) 7745–7754.
[80] X. Tan, G. Chen, H. Sun, Vertical handover algorithm based on multi-attribute and neural network in heterogeneous integrated network, EURASIP J. Wirel. Commun. Netw. 2020 (2020) 1–21.
[81] Y. Teng, M. Liu, F.R. Yu, V.C. Leung, M. Song, Y. Zhang, Resource allocation for ultra-dense networks: a survey, some research issues and challenges, IEEE Commun. Surv. Tutor. 21 (2018) 2134–2168.
[82] G.H. Tzeng, J.J. Huang, Multiple Attribute Decision Making: Methods and Applications, CRC Press, 2011.
[83] B. Uzun, A. Almasri, D. Uzun Ozsahin, Preference ranking organization method for enrichment evaluation (promethee), in: Application of Multi-Criteria Decision Analysis in Environmental and Civil Engineering, 2021, pp. 37–41.
[84] S.K. Vaid, G. Vaid, S. Kaur, R. Kumar, M.S. Sidhu, Application of multi-criteria decision-making theory with vikor-waspas-entropy methods: a case study of silent genset, Mater. Today Proc. 50 (2022) 2416–2423.
[85] R. Verma, N.P. Singh, Gra based network selection in heterogeneous wireless networks, Wirel. Pers. Commun. 72 (2013) 1437–1452.
[86] J. Wallenius, J.S. Dyer, P.C. Fishburn, R.E. Steuer, S. Zionts, K. Deb, Multiple criteria decision making, multiattribute utility theory: recent accomplishments and what lies ahead, Manag. Sci. 54 (2008) 1336–1349.
[87] Y.M. Wang, Y. Luo, Z. Hua, On the extent analysis method for fuzzy ahp and its applications, Eur. J. Oper. Res. 186 (2008) 735–747.
[88] K. Xiao, C. Li, Vertical handoff decision algorithm for heterogeneous wireless networks based on entropy and improved topsis, in: 2018 IEEE 18th International Conference on Communication Technology (ICCT), IEEE, 2018, pp. 706–710.
[89] A.K. Yadav, K. Singh, Enhanced mobility management model for mobile communications, in: Smart Innovations in Communication and Computational Sciences: Proceedings of ICSICCS 2020, Springer, 2021, pp. 55–67.
[90] A.K. Yadav, K. Singh, The influence of different weighting methods on madm ranking techniques and its impact on network selection for handover in hetnet, in: 2023 International Conference on Artificial Intelligence and Smart Communication (AISC), IEEE, 2023, pp. 959–963.
[91] A.K. Yadav, K. Singh, A. Ahmadian, S. Mohan, S.B.H. Shah, W.S. Alnumay, Emmm: energy-efficient mobility management model for context-aware transactions over mobile communication, Sustain. Comput. Inf. Syst. 30 (2021) 100499.
[92] A.K. Yadav, K. Singh, P.K. Srivastava, P.S. Pandey, I-merec-t: improved merec-topsis scheme for optimal network selection in 5g heterogeneous network for iot, Int. Things 22 (2023) 100748.
[93] K.P. Yoon, W.K. Kim, The behavioral topsis, Expert Syst. Appl. 89 (2017) 266–272.
[94] H.W. Yu, B. Zhang, A heterogeneous network selection algorithm based on network attribute and user preference, Ad Hoc Netw. 72 (2018) 68–80.
[95] S.H. Zanakis, A. Solomon, N. Wishart, S. Dublish, Multi-attribute decision making: a simulation comparison of select methods, Eur. J. Oper. Res. 107 (1998) 507–529.
[96] E.K. Zavadskas, Z. Turskis, J. Antucheviciene, Selecting a contractor by using a novel method for multiple attribute analysis: weighted aggregated sum product assessment with grey values (waspas-g), Stud. Inform. Control 24 (2015) 141–150.
[97] E.K. Zavadskas, Z. Turskis, J. Antucheviciene, A. Zakarevicius, Optimization of weighted aggregated sum product assessment, Elektron. Elektrotech. 122 (2012) 3–6.
[98] X. Zeshui, W. Cuiping, A consistency improving method in the analytic hierarchy process, Eur. J. Oper. Res. 116 (1999) 443–449.
[99] L. Zhang, S. Wu, X. Lv, J. Jiao, A two-step handover strategy for geo/leo heterogeneous satellite networks based on multi-attribute decision making, Electronics 11 (2022) 795.
[100] P. Zhang, W. Zhou, B. Xie, J. Song, A novel network selection mechanism in an integrated wlan and umts environment using ahp and modified gra, in: 2010 2nd IEEE International Conference on Network Infrastructure and Digital Content, IEEE, 2010, pp. 104–109.
[101] A. Zhu, M. Ma, S. Guo, Y. Yang, Adaptive access selection algorithm for multi-service in 5g heterogeneous Internet of things, IEEE Trans. Netw. Sci. Eng. 9 (2022) 1630–1644.
[102] S. Zolfani, M. Yazdani, D. Pamucar, P. Zarate, A vikor and topsis focused reanalysis of the madm methods based on logarithmic normalization, preprint, arXiv:2006.08150, 2020.
[103] R. Zulqarnain, M. Saeed, N. Ahmad, F. Dayan, B. Ahmad, Application of topsis method for decision making, Int. J. Scient. Res. Math. Stat. Sci. 7 (2020).