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Network selection in heterogeneous wireless networks using multi-criteria decision-making algorithms: a review

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Abstract It is expected that next-generation wireless networks will provide a plethora of mobile wireless services to users and ubiquitous network coverage at all times. Meeting these expected goals requires that new and existing networks be seamlessly integrated together to form Heterogeneous Wireless Networks (HWNs). Thus, seamless and efficient handover mechanisms are pertinent for optimal network performance in HWNs; so that the mobile user can switch from one access network to another, in search of the best connection for the demanded services. The HWNs' performance can be reduced, if efficient network selection is not achieved. In HWNs, network-selection decisions can be evaluated by using multi-criteria, or a single criterion. However, network selection and decision-making in HWNs often involves taking into account a large number of complex and conflicting network-decision factors, or criteria. Thus multi-criteria decision-making techniques are more efficient than single-criterion techniques. Multi-Criteria Decision-Making (MCDM) techniques comprise of a developed branch of operational research for assisting in the resolution of complex decision-making problems. MCDM is an important tool that has been used to model and analyze handover-decisions and network-selection problems in HWNs. This paper reviews and classifies the most significant MCDM algorithms that have been used to address the network decision-making problems in HWNs in terms of algorithmic approach, the type of calls, the cardinality of decision criteria employed, handover-control points and the types of network utilities. Comprehensive step-wise mathematical implementations of the reviewed MCDM schemes are presented, while pointing out their strengths and limitations. This paper review fills a research gap in the investigation on network-selection criteria's interdependence and interactions, and their effects on criteria's weight of importance. It then provides an insight into the importance of network-criteria weighting and the current research trend in the application of MCDM algorithms to network-selection problems in HWNs.

Keywords Multi-criteria decision-making algorithms · Network selection · Heterogeneous wireless networks

1 Introduction

The explosive growth of wireless communication through the deployment of cellular networks and the internet has made the always-connected phenomenon a reality. To support always-best connected (ABC) at an affordable bandwidth cost, cellular networks are integrated with other non-cellular wireless networks. This integration creates heterogeneous wireless networks (HWNs), that can be more efficient and has flexible network capacities for the operators; while providing the consumers with diverse data-transmission rates and cost [1].

An heterogeneous wireless network is a wireless network, where different Radio Access Technologies (RATs) that differ in operating parameters and characteristics, such as: bandwidth, latency, security level, reliability or cost can coexist. It allows mobile nodes (MNs) to connect to different RATs supporting network services with diverse

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quality of service (QoS) requirements [2]. In HWNs, RAT selection can be network-centric or user-centric. RAT-selection decisions are based on the network criteria, the application requirements and users' preferences, which lead to multi-criteria influenced decision processes. The convergence of the different RATs, e.g., Long Term Evolution-Advance (LTE-A), Worldwide interoperability for Microwave Access (WiMAX), Universal Mobile Telecommunications System (UMTS) and Wireless Local Area Network (WLAN) in the HWNs would be based on a common IP platform [3], which enhances seamless networks co-operation and simplification.

Over its coverage area, LTE-A can offer downlink and uplink peak-data rates of 3 Gigabits per second (Gbps) and 1.5Gbps, respectively [4]; WiMAX can offer 100 Megabits per second (Mbps) for MNs and 1 Gbps for fixed node [5], while employing 8×8 Multiple-Input-Multiple-Output (MIMO) antennae architecture and a 256-Quadrature Amplitude Modulation (QAM) scheme, Wireless-Fidelity (IEEE 802.11ac and 802.11ad) can offer a data rate of up to 7Gbps [6, 7]. High-Speed Packet Access (HSPA) and UMTS can offer data rates of up to 14.4 and 3.1 Mbps, respectively. WLAN can offer higher data rates over a smaller geographical coverage area compared to HSPA and UMTS. Vertical handover in HWNs requires automatic and precise timing, in order to prevent any QoS degradation of communicating nodes in HWNs. In homogeneous networks, a handover decision is usually triggered when signal availability indicators, such as received signal strength (RSS) or signal to interference to noise ratio (SINR) falls below a preset threshold. However, in HWNs, handover can be triggered when any RAT that can offer a better QoS than the current RAT is available. In HWNs, single indicator variables such as RSSs or SINRs are inefficient for vertical handover (VHO) triggering, because of the effect of heterogeneity of network parameter standards across the HWNs [8, 9]. Hence, HWNs have multiple handover decision indicators. These wireless network indicators are sometimes conflicting. This makes handover management in HWNs a very dynamic and complex decision problem. To achieve efficient HWNs performance, the HWNs' handover mechanism requires a robust network selection algorithm that can handle complex decision-making problems and ensures transparent and seamless switch over between RATs [9]. This is a challenge for next-generation wireless networks (NGWNs) designers, since non-optimal network selection can lead to undesirable network effects, such as: high new call blocking, handoff call-dropping probabilities and poor QoE.

The VHO decision process in HWNs involves complex and often-conflicting multi-criteria, which can be modelled as multi-criteria decision-making (MCDM) problems. MCDM is an advanced tool of the optimization-research technique for resolving multiple and conflicting criteria-decision problems. MCDM methods offer HWN designers a decision-making tool that considers all the criteria of the decision problem, using a more robust, explicit, rational and efficient decision-making process for wireless access-network selection. A lot of MCDM schemes, such as Simple Additive Weighting (SAW) [10], Multiplicative Exponent Weighting (MEW) [11], Grey Relational Analysis (GRA) [12], Analytic Hierarchy Process (AHP) [13], ELimination Et Choix Traduisant la REalité (ELECTRE) [14], Technique for Order Preference by Similarity to Ideal Solutions (TOPSIS) [15], Distance to Ideal Alternatives (DIA) [16], MULTIplicative forms with Multi-Objective Optimization Ratio Analysis (MULTIMOORA) [17], VlseKriterijumska Optimizacija I Kompromisno (VIKOR) [18] and Preference-Ranking Organization Methods for Enrichment Evaluation (PROMETHEE) [19], have been utilized in HWNs. There are other types of algorithms that have been employed to resolve the problems of VHO and network selection in HWNs that can be found in the literature, such as utility functions [20], game theory [21] and genetic algorithms [22]. However, there are some major drawbacks in the application of these algorithms, with respect to the application of MCDM algorithms in VHO and access-network selection in HWNs.

The Utility theory-based algorithm requires the use of different utility functions for each mobile user, network criterion and network alternative [23]. Utility function-based algorithms could become cumbersome to apply; as the size of the HWNs and the mobile users scale up. Another drawback of the utility function-based algorithm is the very restrictive assumptions on users' preferences. These restrictive assumptions on users' preferences make the resulting utility-function-based network-selection model simple, but not adequate; while less restrictive assumptions on users' preferences make the resulting network-selection model more adequate, but also more complicated [24].

Some major limitations of the Game-theory-based decision model for network selection in HWNs are the assumptions that the players (mobile users or network operators) are rational and would act mutually for the benefit of one another [25, 26]. However, these are not always the case, as players can act selfishly, in order to increase their payoffs/utilities to the detriment of the overall HWNs' performance. Due to the iterative solutions for Game theory-based decision-making, the models for network selection-decision problems in HWNs, achieving equilibrium convergence that leads to Nash Equilibrium (NE) from different players can be computationally time-consuming. Also, the NE decision from the game theory can sometimes not be the Pareto-optimum (best optimum).

The Genetic-algorithm (GA) technique for network-selection decision making is an iterative evolutionary optimization search method. It that emulates the principles of biological natural selection and genetics [27] for the survival of the fittest. In HWNs, the GA encodes the decision variables of network selection-decision problems into a finite string of a number of elements to form a set. This finite string is referred to as the chromosome set; and its number values are referred to as alleles. Iterative optimization search is conducted by using mathematical operations that mimic natural biological operations (mutation, crossover, reproduction, and selection) to obtain a more desirable chromosome set or decision solution. GA relies on the size of the decision variables (population size) of network-selection problems. The population size is a crucial factor that affects the scalability and performance of genetic algorithms. A small population size could lead to premature convergence, and hence produce substandard network-selection decisions; while large population sizes could lead to unrequired consumption of the critical processing/computational time or resources in the HWNs. This can present a weak point the application of GA for network selection decision making in HWNs.

This review is primarily focused on MCDM algorithms and their applications to radio-access network selections in HWNs. The rest of the paper is organized as follows. Section 2 discusses the vertical handover and management process in HWNs. Section 3 reviews the MCDM methods and presents a performance evaluation of some selected MCDM-Based network-selection techniques in HWN. Section 4 presents the classifications of MCDM techniques applied in HWNs, and gives an insight into the different RAT-selection, decision criterion usage and its popularity in making network-selection decisions in HWNs. In Sect. 5, the key highlights of various MCDM methods applied in HWNs are given; Sect. 6 concludes the review.

2 Handover management in HWNs

The handover process in HWNs allows MN to change its point of attachment (PoA) in one wireless network cell to another in the same wireless network technology (horizontal handover), or different wireless network technology (vertical handover). A handover process can occur when MN senses any available networks that offer better QoS than its current network's PoA. The dynamic nature of mobile-users' service requirements necessitates the implementation of a robust vertical handover-management process in HWNs. Moreover, in order to minimize the ping-pong effect and the handover latency, handover initiation, decisions and their execution should be given serious consideration and proper management. The ping-pong handover in HWNs is when two or more subsequent handovers occur between the incumbent and target PoAs. This paper focuses on handover decisions. Figure 1 is an example of HWNs that comprise overlapping LTE-A, WLAN, and UMTS, with MNs. An MN equipped with LTE-A, WLAN and UMTS network interfaces, while located within the HWNs should be able to connect with any of the available RATs, such as: the donor-evolved node-base station (DeNodeB) of LTE-A, access point (AP) of WLAN and node-base station (NodeB) of UMTS. When the MNs are equipped with message-forwarding capabilities, MN5, for example could be engaged by the DeNodeB of the LTE-A networks, as a co-operative forwarding relay node for MN4. This could occur, if the transmission channel qualities between DeNodeB to MN5 and MN5 to MN4 are better than the direct-transmission channel quality of DeNodeB to MN4. The RATs are integrated to complement one another in the HWNs.

The European Telecommunications Standards Institute (ETSI) has specified loose and tight coupling approaches for integrating WLAN-cellular networks [28]. In the loose coupling approach, the external IP network receives the data flows from the different types of networks directly, and only signalling the information is required between cellular networks and other complementary networks. In the tight coupling approach, complementary networks communicate with the external network (internet networks) through the cellular networks gate-way access router [29]. In homogeneous networks, in order to maintain physical connection and load balancing; horizontal handover is initiated when the link quality condition falls below a certain preset threshold, unlike in HWNs, where vertical handover is initiated, based on complex network criteria and users' preferences, in order to dynamically select the network with the optimal QoS at all times. In HWNs, the single RSS or the SINR criterion of the link alone is not an adequate indicator for handover decisions; multiple criteria are required. In most cases, these criteria frequently conflict with one another. Therefore a trade-off needs to be reached. The criteria need to be combined and weighted rightfully together for optimum network-selection decision-making. The network-selection technique plays an important role in ensuring that the QoS requirements in HWNs are maintained [1]. Considering that HWNs consist of integrated networks with different range values of RAT parameters and characteristics, it would be logical to create a level playing field for comparison of the RATs' diverse parameters. This can be achieved by transforming the diverse network parameters and user preferences to the same range of values e.g., [0, 1], via a normalization process. An efficiently designed network-selection scheme can ensure optimum network connection, while balancing the trade-offs that exist among the network conditions, user preferences, and service applications; and consequently ensuring a minimal amount of network handoffs. A

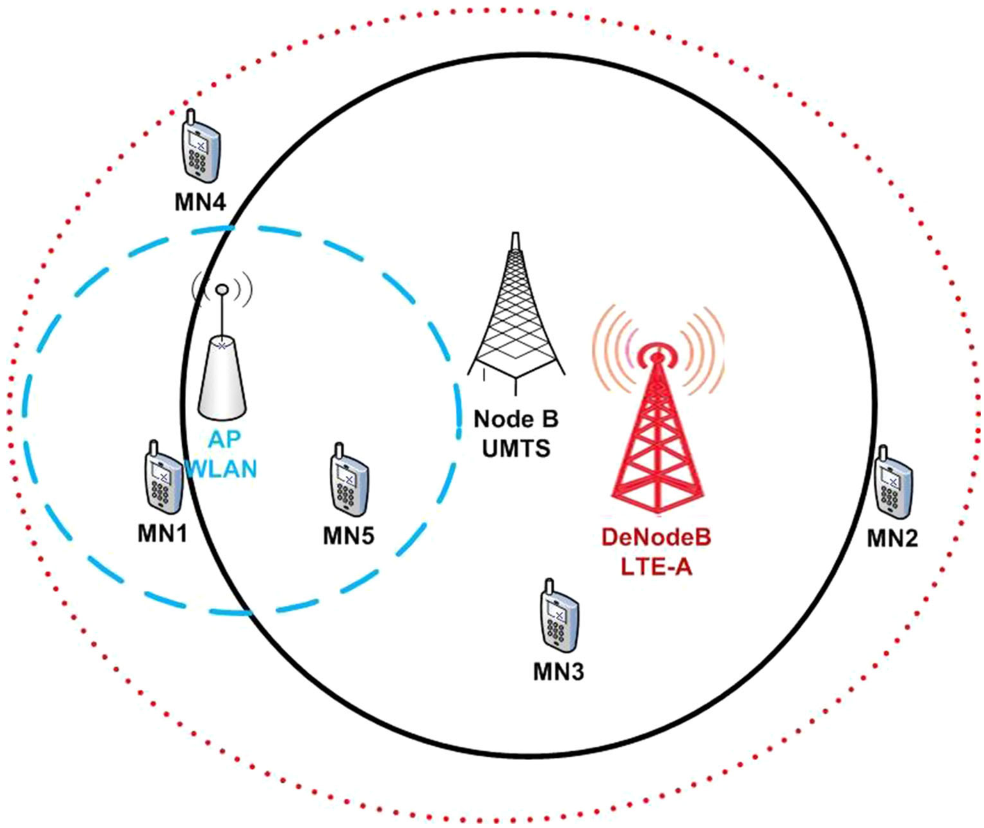

Fig. 1 An example of heterogeneous wireless networks

network-selection algorithm can be initiated, whenever a new network alternative is sensed, or when the requested service class changes. Connecting low mobile speed MNs to access network with smaller coverage area and high mobile speed MNs to access network with larger coverage area can reduce any unnecessary handoffs and handover signaling overheads [30].

In vertical handover/switching management, seamlessness and automation are two major challenges that must be tackled, in order to achieve ABC for the network users [31]. The vertical handover procedure can be categorized as a hard or a soft handover. Handover is said to be hard if the MN is connected only to one PoA at a time during the handover from one PoA to another. This is referred to as a break-before-make handover. The hard handover is fairly simple. It requires less co-ordination between the incumbent and the target PoAs and control signalling overheads from the handover management unit's point-of-view. Hence, it is fast to initiate and easy to execute by the handover-management unit. A hard handover process could make the MNs experience a noticeable glitch in their network connectivity, or yield some form of degraded quality of service, when moving from one wireless network cell to another. A ping-pong effect could also occur between the incumbent and the target PoAs, whenever MNs move transiently, around the wireless network cell-edge [32]. The handover is considered a soft handover, if the MN creates a connection to the target PoA prior to the release of the previous PoA during the handover period in the HWNs. This is referred to as make-before-break handover. The soft handover is more complex. It requires more control signalling overhead and co-ordination between the incumbent and the target PoAs. Therefore, it is relatively slower to initiate and execute compared to the hard handover process. This is usually a regular challenge for the handover-management unit in HWNs. To achieve a seamless handover connection, the handover process needs to be transparent to the MNs, without MNs perceiving any service degradation during the handover process; as the MNs transit from one wireless network to another. Hence, the handover process must be fast and smooth, with minimal handover latency and packet loss.

The control of handover decision-making is usually classified into: Network-Controlled Handover (NCHO), Mobile-Controlled Handover (MCHO), Network-Assisted Handover (NAHO) and Mobile-Assisted Handover (MAHO) [31]. The handover decision involves some measuring and gathering of the information necessary for the handover. The handover decision-management mechanism can either be located in the network entity or in the mobile entity. If the network entity has the total control of the handover decision-management mechanism, it is referred to as a NCHO; and the handover is said to be network-centric. The NCHO has the ability to balance the overall network load; since the decision point is located in the network within the service area; and this allows the NCHO to exploit, more accurately, the knowledge of the network's conditions [33]. It is required in an NCHO, that all the wireless networks be co-operatively involved. Additionally, the network users' co-operation is important. Some important drawbacks of the network-centric approach are the increase in overall network complexity, handover latency, signalling overhead [2], and the probability of a single point of network failure.

An alternative approach to the network-centric handover process is the user-centric handover approach [34]. If the MN entity has the total control of the handover decision-management mechanism, it is referred to as an MCHO. In a user-centric framework, the network selection algorithms are implemented at the users' MNs [35, 36]. This method offers the distributive control of the handover-management process. It has low overall network and implementation complexities, with reduced handover latency. Unlike the network-centric framework, it generates low signalling overhead, and it is scalable. The MNs can discover accessible network interfaces of several wireless networks based on the regular broadcast services of the various active networks. However, user-centric handover networks can be plagued by instability, if they are not properly implemented.

Hybrid handover management control exists HWNs. If the information measured and gathered by the network entity is shared with MN to assist the MN in making and managing/controlling its handover decision, such a handover process is referred to as an NAHO [37]. Also, when the information measured and gathered by the mobile terminals is shared with the network entity for the network's managing and controlling handover decisions, the handover process is referred to as a MAHO [38]. Having an efficient handover-management process is vital for the seamless integration of diverse radio access networks in HWNs. Figure 2 shows the integral units of the handover management process.

2.1 Handover decision-information gathering

This unit serves as a repository and a network-discovery system for newly available networks. It gathers, manages and evaluates the changes in the gathered handover information, to make decisions on whether to initiate a handover process, or not. QoS application information (required bandwidth and the minimum delay), device-terminal information (battery power level and MN's speed), network information (network security level and network load) and users' contextual information (users' locations and users' preferences) are stored and managed here. The contextual information is the user-associated information that is used to define the state of a user entity or a system in a specific situation [39]. When a handover event is triggered, the vital information required for handover decisions is consequently forwarded to the handover-decision unit. The handover event is usually triggered when the evaluation of the collected key parameters indicates a need for such a handover.

2.2 Handover decision-making

This is the heart of the handover-management process. It is also referred to as the network selector. This unit helps to decide whether the MNs should remain connected to its existing network, or should switch over to a more suitable network. In the case of switching MNs over to another network, this unit decides the most suitable network for the MNs, from the set of available network alternatives by using an MCDM algorithm, and taking into account the criteria necessary for handover decision-making. The decision output of a handover-decision unit is then passed on to the handover-execution unit.

2.3 Handover execution

The handover execution ensures smooth session transition and transfer of user-contextual information from the incumbent network to the target network-without any degradation in the QoS of the ongoing calls. The handover execution also helps to facilitate the authentication and authorization of MNs to the target network. The next

Fig. 2 The integral units of the handover management process

section presents the MCDM methods, the mathematical implementations and the applications in HWNs.

3 MCDM methods and application in HWNs

MCDM is a technique for achieving optimal decision-making in multi-criteria decision problems. MCDM analysis is a well-known field of decision-making technique and a branch of operation-research. It is a robust decision-making tool that offers a flexible technique that is able to handle a wide range of complex decision variables; and thus, offer useful insight/guidance for the decision-maker in arriving at the best decision [40]. An MCDM problem can be mathematically defined by using a decision matrix problem, $D(M \times N)$,

$$D = \begin{array}{c} \\ \\ \end{array}\begin{array}{cc} \begin{array}{cccccc} C_1 & C_2 & \cdots & C_j & \cdots & C_N \end{array} & \\ \begin{bmatrix} x_{1,1} & x_{1,2} & \dots & x_{1,j} & \dots & x_{1,N} \\ x_{2,1} & x_{2,2} & \dots & x_{2,j} & \dots & x_{2,N} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{i,1} & x_{i,2} & \cdots & x_{i,j} & \cdots & x_{i,N} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{M,1} & x_{M,2} & \cdots & x_{M,j} & \cdots & x_{M,N} \end{bmatrix} & \begin{array}{c} A_1 \\ A_2 \\ \vdots \\ A_i \\ \vdots \\ A_M \end{array} \end{array}, \tag{1}$$

$$W = \{w_1, w_2, w_3, \ldots, w_j, \ldots, w_N\}. \tag{2}$$

$\{A_1, A_2, A_3, \ldots, A_i, \ldots, A_M\}$ denotes the set of M alternatives, from which the decision-maker can choose; while $\{C_1, C_2, C_3, \ldots, C_j, \ldots, C_N\}$ denotes the set of N criteria on which each alternative performance is evaluated. The $x_{i,j}$ indicates the performance rating of the ith alternative, with respect to the jth criterion of the decision matrix, D. M and N are the total number of network alternatives and criteria, respectively. W is the weight vector of importance of the criteria; and w_j is the weight of importance of the jth criterion. The value of w_j indicates how important the contribution of criterion jth is in achieving the desired goal of selecting the best alternative, by the decision maker. The goal of the MCDM defined matrix problem is to determine and select the best alternative from the list of alternatives presented. The solution to the MCDM defined problem can be obtained by MCDM techniques.

A number of MCDM techniques have been proposed for making network-selection decisions in the literature. The following sub-sections give an extensive review of the currently proposed MCDM schemes and their application to access network-selection problems in HWNs. They can also analyze the strengths and weaknesses of each scheme.

3.1 Simple additive weighting

Simple Additive Weighting (SAW) is an MCDM technique that is based on the weighted average. It allows the determination of the score of each alternative by mathematical multiplicative operations of the normalized alternative criteria with the relative weights of importance, as indicated by the decision-makers. SAW is also sometimes referred to as the weighted-linear combination. It is one of the simplest MCDM algorithms [41]. In SAW, the ranking of each alternative is the total weight of that alternative, as determined by the weighted value of the normalized criteria of that alternative, which is also the weighted average of the network criteria. The weighted average of the ith alternative from the total number of M alternatives is determined by multiplying $r_{i,j}$ by the corresponding criterion weight of importance, w_j of the jth criterion, as assigned by the network decision-makers. The $r_{i,j}$ is defined as the normalized performance score of the ith alternative with respect to the jth criterion in the normalized decision matrix. When summation of the weighted products of all the criteria for each network alternative is performed, the network alternative with the largest weight product performance score is ranked as the best network. The computation of SAW ranking procedure comprises the following steps:

1. Given a decision matrix problem, D, as shown in (1), where $\{A_1, A_2, A_3, \ldots, A_i, \ldots, A_M\}$ is the set of M alternatives, $\{C_1, C_2, C_3, \ldots, C_j, \ldots, C_N\}$ is the set of N criteria and entry $x_{i,j}$ indicates performance score of the ith alternative with respect to the jth criterion. If the larger the value of a criterion, the better the performance of the criterion, then such criterion is referred to as benefit criterion. Calculate the normalized decision-matrix element, $r_{i,j}$ for the benefit criteria as follows:

$$r_{i,j} = \frac{x_i, j}{x_j^{max}}, \ i = 1, 2, 3, \ldots, M, \ j = 1, 2, 3, \ldots, N. \tag{3}$$

   Similarly, if the smaller the value of a criterion, the better the performance of the criterion, such criterion is referred to as cost criterion. Calculate the normalized decision-matrix element, $r_{i,j}$ for the cost criteria as follows:

$$r_{i,j} = \frac{x_j^{max}}{x_{i,j}}, \ i = 1, 2, 3, \cdots, M, \ j = 1, 2, 3, \ldots, N, \tag{4}$$

   where x_j^{max} and x_j^{min} are the maximum and minimum entries of the jth column in D , respectively.

2. Obtain the assigned weight w_j of each criterion in the network.

3. Compute each SAW rank index, A^i_{SAW} of the ith alternative using Eq. (6)

$$A^i_{SAW} = \sum_{j=1}^{N} w_j r_{i,j}. \tag{5}$$

4. Finally, obtain the highest ranked SAW ranking index, A^{i*}_{SAW} which corresponds to the best/optimum network alternative for the multi-criteria decision problem by using the formula,

$$A^{i*}_{SAW} = \arg \max_{i \in M} \sum_{j=1}^{N} w_j r_{i,j}. \tag{6}$$

SAW has been extensively applied in making network-selection decisions. For example, in [42], Singh et al. have proposed SAW algorithm for making vertical handoff decisions in 4G wireless networks, due to its simplicity. Pink et al. [43] have addressed the MCDM problem for group-decision problems under a distributed network-selection framework. The work is based on the computation of group benefits for each alternative network, using the SAW algorithm for vertical handover in HWNs. The performance of the SAW algorithm is investigated by varying the mobile user-group sizes and their requirements.

A Distributed Vertical Handoff Decision (DVHD) based on the SAW algorithm has been proposed in [10] for HWNs with overlapping cellular network and WLANs. The cellular network and WLANs are assumed to be managed by a single network operator. The MNs could be allowed to roam into, or vertically handed over to WLAN, when the MNs demand higher bandwidths, data rates and have low terminal mobility, or demand lower monetary cost for wireless-network services from the HWNs. The cellular network is referred to as the home network; while the WLANs are referred to as the visiting networks. The main aim of the proposed scheme in [10] is to reduce the processing overhead in the MNs by delegating the computation of handoff metrics for network selection from the MNs to the visiting networks (WLANs). If an MN wants a VHO to WLAN, it broadcasts its handoff information metrics (required bandwidth, data rate, power consumption, latency and network service cost) to the surrounding WLANs. The nearby WLANs compute their respective handoff-decision metrics, and broadcast their results back to the MN. The MN, in turn, sends these handoff-decision metrics from the WLANs to the cellular network. The cellular network uses these results to trigger the VHO of the MN to the best WLAN. The simulation results show that the DVHD scheme exhibited better performance in terms of processing delay, handoff blocking rate and throughput, than the centralized vertical handoff-decision scheme.

Liu et al. in [44] have employed a SINR and Analytical Hierarchy Process (AHP) based on SAW to address the handover decision-making problem in an integrated WLAN and Wideband Code Division Multiple Access (WCDMA) network. The scheme uses SINR, user-required bandwidth and network traffic cost as the network decision criteria. The weights of the decision criteria are determined by the AHP; and the SAW algorithm is used to rank the best access network.

Some of the attractive features of SAW are its simplicity, its efficiency [42, 45] and its ability to transform the raw decision data in a proportionally linear operation, which ensures that the relative order of magnitude of the standardized scores remains the same [46].

3.2 Multiplicative exponent weighting

Multiplicative Exponent Weighting (MEW) is an MCDM ranking scheme that is based on the weighted products of the criteria of the alternatives [47]. The MEW is also referred to as the Weighted Product Method (WPM). MEW is very similar to the SAW algorithm [48]. The main difference is that the mathematical addition and multiplication operations used in SAW are replaced by multiplication and exponential operations in MEW. Given an MCDM problem of decision-matrix D, as expressed in (1), the MEW ranking index, A^i_{MEW} for the ith alternative of the MCDM problem is evaluated using the equation (7),

$$A^i_{MEW} = \prod_{j=1}^{N} r_{i,j}^{w_j}. \tag{7}$$

The normalized decision-matrix element $r_{i,j}$ is defined in (4) and (5) for benefit and cost criteria, respectively. The weight (w_j) of the jth criteria is positive for the benefit criteria and the weight $(-w_j)$ is negative for the cost criteria. The highest ranked network alternative, A^{i*}_{MEW} from MEW is obtained as,

$$A^{i*}_{MEW} = \arg \max_{i \in M} \prod_{j=1}^{N} r_{i,j}^{w_j}. \tag{8}$$

A number of network-selection algorithms have been designed based on MEW. For example, in [48], a MEW algorithm has been employed to make vertical handoff decisions, based on different criteria, namely: bandwidth, delay, packet-loss-ratio (PLR) and monetary cost per byte. Simulation results for conversational, streaming, interactive, and background service traffics show that MEW has a similar performance to SAW and Technique for Order Preference by Similarity to Ideal Solutions (TOPSIS) algorithms under the four network-traffic classes.

TalebiFard et al. [11] have presented a dynamic context information-aware network selection for handover in HWNs environment, based on modified MEW. The context information is fuzzy in nature. In order to effectively deal with the fuzzy nature of the contextual information, the MEW is modified by using interval data. The results show that the network-ranking performance of the modified MEW is less computationally expensive, more robust in dynamic decision-making under sensitivity analysis, and less prone to ranking abnormality, when compared to TOPSIS. Ranking abnormality occurs, when a ranking algorithm alters its best alternative ranking; if a low-ranked alternative is removed or added to the set of alternatives.

MEW has some weak points. It penalizes the alternatives with poorer criteria scores than the other alternatives in its ranking selection. This is due to its mathematical exponential operation. unlike SAW; MEW has the non-linear transformation properties.

3.3 Analytic hierarchy process

The Analytical Hierarchy Process (AHP) can be described as a technique that divides a complex problem into a number of simpler sub-problems. The AHP utilizes pair-wise comparison to find the optimal solution [1]. The AHP was first introduced by Saaty [49]. It is a highly useful technique for decision-making. The AHP decomposes the complex decision-making problem into a linear top-to-bottom form as a hierarchy, where the upper levels are functionally independent from all the lower levels; and the elements in each level are also independent. Basically, the complex problem is hierarchically structured into a minimum of three levels, which are: top level (the goal of the problem); second level (the criteria); and the final or bottom level (the alternatives). However, in some problems, it is possible to have more levels after the second level. These extra levels are generally referred to as sub-criteria levels. In order to prioritize the middle criteria level with regard to the goal of the top level, an appropriate question to ask is: “Which criterion is most important for achieving the goal of the top level, and to what extent?” Also, to prioritize the third-bottom level of the alternatives with regard to the middle level of the criteria, the most appropriate question to ask is: “Which alternatives are preferable to meet the given criterion, and to what extent?” An important strength of the AHP analysis is the provision of a Consistency Ratio (CR) check. The *CR* allows for the measure of the degree of consistency of the comparison judgment. The comparisons are assumed to be consistent, if CR < 0.1; otherwise, it is assumed that inconsistencies have occurred in the comparison process; and hence, the comparison must be revised.

The AHP method can be implemented in following steps [50], as explained below:

1. From the defined MCDM problem and its goal, construct a hierarchy model that describes the objective, the criteria and the alternatives, as shown in Fig. 3.
2. Evaluate the pair-wise comparison of the decision elements on each level in the matter of their importance to the elements in the level above, using the Saaty 1-9 fundamental scale, as defined in Table 1, then form a square comparison matrix, A of $(N \times N)$,

$$A = \begin{array}{c} \begin{array}{cccccc} C_1 & C_2 & \cdots & C_j & \cdots & C_N \end{array} \\ \left[\begin{array}{cccccc} 1 & x_{1,2} & \dots & x_{1,j} & \dots & x_{1,N} \\ x_{2,1} & 1 & \dots & x_{2,j} & \dots & x_{2,N} \\ \vdots & \vdots & 1 & \vdots & \ddots & \vdots \\ x_{i,1} & x_{i,2} & \cdots & 1 & \dots & x_{i,N} \\ \vdots & \vdots & \ddots & \vdots & 1 & \vdots \\ x_{N,1} & x_{N,2} & \cdots & x_{N,j} & \cdots & 1 \end{array} \right] \end{array} \begin{array}{c} \\ C_1 \\ C_2 \\ \vdots \\ C_i \\ \vdots \\ C_N \end{array}, \tag{9}$$

where the comparison element $x_{i,j}$ is a measure of the degree of importance of the ith criterion over the jth criterion $x_{i,j} = \frac{1}{x_{i,j}}$, $\quad x_{i,j} = x_{j,i} = 1$ and N is the number of criteria being compared.
3. Generate normalized comparison matrix, A_{Norm} using,

$$A_{Norm} = \begin{array}{c} \begin{array}{cccccc} C_1 & C_2 & \cdots & C_j & \cdots & C_N \end{array} \\ \left[\begin{array}{cccccc} 1 & y_{1,2} & \dots & y_{1,j} & \dots & y_{1,N} \\ y_{2,1} & 1 & \dots & y_{2,j} & \dots & y_{2,N} \\ \vdots & \vdots & 1 & \vdots & \ddots & \vdots \\ y_{i,1} & y_{i,2} & \cdots & 1 & \dots & y_{i,N} \\ \vdots & \vdots & \ddots & \vdots & 1 & \vdots \\ y_{N,1} & y_{N,2} & \cdots & y_{N,j} & \cdots & 1 \end{array} \right] \end{array} \begin{array}{c} \\ C_1 \\ C_2 \\ \vdots \\ C_i \\ \vdots \\ C_N \end{array}, \tag{10}$$

where

$$y_{i,j} = \frac{x_{i,j}}{\sum_{i=1}^{N} x_{i,j}}. \tag{11}$$

4. Compute the weight w_i of the ith criterion as,

$$w_i = \frac{\sum_{i=1}^{N} y_{i,j}}{N}, \tag{12}$$

with

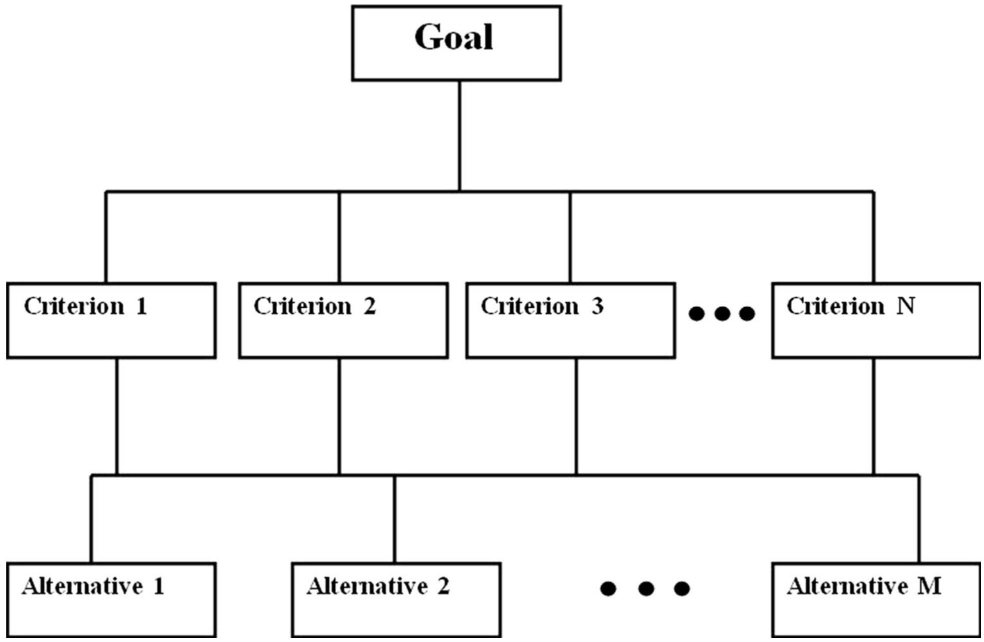

Fig. 3 An example of the AHP hierarchy structure

Table 1 The 1–9 point fundamental scale

Degree of intensity	Definition
9	Extremely important
7	Very strongly important
5	Strongly important
3	Moderately important
1	Equally important
2, 4, 6, 8	Intermediate values

Table 2 The random index

N	1	2	3	4	5	6	7	8	9	10
RI	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49

$$\sum_{i=1}^{N} w_i = 1. \tag{13}$$

5. Evaluate the consistency of the comparison, using the Consistency Ratio (CR) defined as:

$$CR = \frac{\text{Consistency Index (CI)}}{\text{Random Index (RI)}}, \tag{14}$$

where

$$\text{CI} = \frac{\lambda_{max} - N}{N - 1}. \tag{15}$$

λ_{max} is the largest eigen-value of A_{Norm}, and it is determined from the eigen-value computation of A_{Norm}. The RI value is determined, based on the matrix dimension N , see Table 2. The values for RI, as proposed by Saaty, T. L.; for up to $N = 10$ are shown in Table 2.

6. For each criterion, repeat the pair-wise comparison process with respect to the preceding hierarchical level; and then obtain the global priority weight of each hierarchy level by multiplying the normalized priority weight in the preceding hierarchical levels.
7. Make a final ranking decision on the best alternative on the basis of the highest global weight of the priorities of the alternatives with respect to all the criteria.

A number of network-selection algorithms have been developed using AHP. Li et al. [13] propose a utility-based mechanism for selecting a suitable interface network in HWNs. The application requirement of the network resource is used to derive the network utility function and to compute the network-resource status. The available access networks are ranked; and the most suitable network is selected using AHP.

In [51], Chantaksinopas et al. apply the AHP to address the problem of network selection for heterogeneous Vehicular Ad Hoc Network (VANET). In VANET, it is pertinent that a fast and seamless handoff mechanism that satisfies the stringent time constraint is developed. AHP is reported to satisfy the required computational decision-delay time by the authors; nevertheless, it requires more memory space than the rest of the MCDM algorithms.

Thus, through the major fundamental process of problem hierarchical structuring and the elicitation of priorities using pair-wise comparison, AHP is able to decompose very complex problems into simpler sub-problems and solve the sub-problems one at a time, ensuring flexibility and checking for consistency of judgment [52]. However, AHP requires independence among the network criteria; and the pair-wise comparison computational cost grows with the size of the criteria.

3.4 Analytic network process

The Analytic Network Process (ANP) is a generalized theory of AHP [53]. In ANP, the decision levels are arranged into clusters and the criteria and alternatives form elements or nodes in the clusters. The ANP deals with complex decision-making on network alternatives-without making any assumptions on the independence of the higher-level elements from the lower elements and the interactions of elements among the levels. In fact, AHP is a special case of ANP, where no dependence and interaction among the elements exist. ANP captures the measurements of influence of the elements that interact with respect to the control criteria. In most real-life problems, strong interaction and dependencies of higher-level elements on a lower-level element exist, and vice versa. Moreover, interaction and dependencies within the same level elements frequently exist. Therefore, these problems cannot be structured hierarchically using AHP; since the AHP model assumes a strict unidirectional relationship or independence among elements in its hierarchical structure; ANP does not require this strict unidirectional hierarchical-structural relationship among its elements. ANP allows for complex interactions, inter-relationships and dependence (feedback) of elements or nodes within and between the levels.

Elements within a cluster can influence any elements within the cluster, forming loops of feedback onto itself. This internal feedback is usually referred to as inner dependence. It is also possible for elements from one cluster to influence elements in another cluster. This is referred to as outer dependence. In each cluster, the elements are transformed into pair-wise square matrices, where every element is compared with every other element with respect to the higher level. This pair-wise comparison is similar to that of AHP. The largest eigen-value of each comparison matrix is used to check the consistency ratio or the acceptance of each comparison matrix. If the consistency ratio is acceptable, the eigen-vector of the eigen-value is used to build the columns of the unweighted super matrix of the ANP. The unweighted super matrix is normalized to form a weighted-super matrix, such that the sum of each column always adds up to one. A zero entry in the column represents a case where no influence or dependence or feedback exists between the given elements.

The final priority weights are computed by multiplying the weighted super-matrix with itself, until each row converges [54]. This occurs when the entries of a given row of the weighted super matrix become identical, across that given row. This matrix is widely referred to as the limit matrix in the literature. ANP being the generalized form of AHP, one of its drawbacks is its longer computational time compared to AHP. AHP uses a simple weighted sum for aggregation; whereas ANP requires the super-matrix computational convergence.

Consequently, ANP is not recommended if no dependency exists. Some other well-known MCDM techniques that can be used to analyze interactions, interdependence and feed-backs among networks criteria are Decision-Making Trial and Evaluation Laboratory (DEMATEL) and the Interpretive Structuring Method (ISM).

3.5 Technique for order preference by similarity to ideal solutions

The Technique for Order Preference by Similarity to Ideal Solutions (TOPSIS) is an MCDM technique that exploits the idea of finding the alternative that is closest to the positive ideal solution, and furthest from the negative ideal solution. The TOPSIS idea was first presented by Yoon and Hwang in [55]. TOPSIS is a very popular MCDM technique. The multi-criteria decision matrix raw-data require Euclidean normalization. The multi-criteria decision problem can be defined by the decision matrix, D of $(M \times N)$, where $A_1, A_2, A_3, \ldots, A_i, \ldots, A_M$ are the alternatives, $C_1, C_2, C_3, \ldots, C_j, \ldots, C_N$ are the criteria; and the entry $x_{i,j}$ indicates the performance score of the ith alternative, with respect to the jth criterion of the decision matrix. The TOPSIS ranking solution to the selection problem is carried out by using the following steps:

1. Construct a decision-matrix problem, D and the set of criteria weight, W, as shown below:

$$D = \begin{array}{c} \begin{array}{cccccc} C_1 & C_2 & \cdots & C_j & \cdots & C_N \end{array} \\ \begin{bmatrix} x_{1,1} & x_{1,2} & \ldots & x_{1,j} & \ldots & x_{1,N} \\ x_{2,1} & x_{2,2} & \ldots & x_{2,j} & \ldots & x_{2,N} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{i,1} & x_{i,2} & \cdots & x_{i,j} & \cdots & x_{i,N} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{M,1} & x_{M,2} & \cdots & x_{M,j} & \cdots & x_{M,N} \end{bmatrix} \end{array} \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_i \\ \vdots \\ A_M \end{array}, \tag{16}$$

$$W = \{w_1, w_2, w_3, \ldots, w_j, \ldots, w_N\}, \tag{17}$$

where $w_1, w_2, w_3, \ldots, w_j, \ldots, w_N$ is the weight of the criterion $1, 2, 3, \ldots, j, \ldots, N$, respectively.

2. Using the Euclidean normalization, the normalized element, $r_{i,j}$ of ith alternative with respect to jth criterion is given as:

$$r_{i,j} \frac{x_{i,j}}{\sqrt{\sum_{i=1}^{M} x_{i,j}^2}}. \tag{18}$$

3. Calculate the weighted normalized element, $v_{i,j}$ of ith alternative with respect to the jth criterion as follows:

$$v_{i,j} = w_j r_{i,j}, \tag{19}$$

where

$$\sum_{i=1}^{N} w_j = 1. \tag{20}$$

4. Define the Positive Ideal Solution (PIS), $V,^+$ and the Negative Ideal Solution (NIS), $V,^-$ as:

$$V^+ = \left\{ (\max_i v_{i,j} | j \in J), (\min_i v_{i,j} | j \in J') \right\} = \{v_1^+, v_2^+, v_3^+, \ldots, v_j^+, \ldots, v_N^+\}, \tag{21}$$

$$V^- = \left\{ (\min_i v_{i,j} | j \in J), (\max_i v_{i,j} | j \in J') \right\} = \left\{v_1^-, v_2^-, v_3^-, \ldots, v_j^-, \ldots, v_N^-\right\}, \tag{22}$$

respectively. J is associated with the benefit criteria and J' is associated with the cost criteria.

5. Compute the Euclidean distance separation measure from the PIS, $S,^+$ and the Euclidean distance separation measure from the NIS, $S,^-$ respectively as:

$$S_i^+ = \sqrt{\sum_{j=1}^{N} (v_j^+ - v_{i,j})^2}, \quad i = 1, 2, 3, \ldots, M, \tag{23}$$

and

$$S_i^- = \sqrt{\sum_{j=1}^{N} (v_j^- - v_{i,j})^2}, \quad i = 1, 2, 3, \ldots, M. \tag{24}$$

6. Finally, compute the closeness to the ideal solution, C_i for the ith alternative as follows:

$$C_i = \frac{S_i^-}{(S_i^+ + S_i^-)}, \quad i = 1, 2, 3, \ldots, M. \tag{25}$$

The highest value of C_i, is the closest alternative to the ideal solution; and it is subsequently ranked as the best alternative.

The TOPSIS method is widely adopted in the literature to rank and select network alternatives, however it suffers from ranking abnormality. A robust MCDM algorithm ensures that the best alternative ranking order is unaltered or unchanged, when a low-ranked alternative is removed or added to the set of available alternatives. Hence, when an algorithm suffers from the ranking abnormality problem, the ranking order is not stable. This can make the network selection-decision inefficient [56]. Tan et al. [16] have revealed that though TOPSIS suffers from the ranking abnormality problem, it provides more precision in the network rankings compared to SAW and MEW.

A hybrid approach, based on AHP and TOPSIS is utilized in [57] by Mohamed et al. for the network selection in an heterogeneous multi-access environment. Five network interfaces: UMTS, IEEE802.11b, IEEE802.11a, IEEE802.11n and Long-Term Evolution (LTE) networks are considered. The criteria are assigned weights, using AHP. The results of the hybrid approach are compared with the traditional TOPSIS and DIA techniques. The simulation results show improved performance over the traditional TOPSIS and DIA algorithms.

In [15], the authors propose a dynamic wireless-network selection technique using fuzzy linguistic variables, which comprise two modules: Vertical Hand-Off Necessity Estimation (VHONE), which uses Fuzzy Linguistic Variables (FLVs) to determine the necessity of performing vertical handoff; and the Network Access Technology (NAT) selection module, which uses TOPSIS to select the best available network from WLAN, Wireless Metropolitan Area Network (WMAN) and Wireless Wide Area Network (WWAN). The RSS, delay, jitter , PLR, throughput, network load, security , cost and MN's velocity are used for handover decision criteria.

Kaleem et al. extend their work above in [15] by developing a different design for the wireless-access network-selection scheme in an heterogeneous multimedia traffic to ensure seamless mobility and maximal end-users' satisfaction. A ranking algorithm based on the Fuzzy extension of TOPSIS (FTOPSIS) is used to prioritize all the available networks within the coverage area for MNs. For a single-service scenario, the evaluation of the numerical results shows that the FTOPSIS scheme performs better than the traditional TOPSIS-based scheme, which uses an AHP method to weight the network parameters, in terms of the percentage of network selection for prioritized security level and cost; as the MN's speed across the networks varies [58].

Chamodrakas et al. [59] utilize Fuzzy TOPSIS based on fuzzy set theory to select energy-efficient networks in HWNs. For the elimination of the ranking abnormality problem, the network-selection method incorporates the use of parameterized utility functions to model the diverse QoS elasticity of different applications; and it adopts different energy consumption metrics for real-time and non-real-time applications. Linguistic assessments are employed to configure user preferences for different applications and situational contexts. The aggregation of multiple criteria for the determination of the overall ranking and selection of the networks is performed through the use of the fuzzy-set representation of the TOPSIS method that resolves the issue of inconsistency related to conflicting decision criteria.

In [56], an Enhanced TOPSIS (E-TOPSIS) is proposed for the selection algorithm for the vertical handover decision in a HWN using the ANP for the weighing of the criteria. The scheme takes into account the relative importance of a positive ideal solution and negative ideal solution parameters in its ranking computation. The authors have shown that the number of handoffs and ranking abnormality phenomena are reduced; and E-TOPSIS provides better results than some existing MCDM methods, such as SAW, MEW and TOPSIS for background, conversational, interactive and streaming traffic classes.

Charilas et al. [60] explore a scheme that fused MCDM network selection mechanisms with game theory; so that network access-admission control could be modelled efficiently as a non-cooperative game. In this scheme, networks are modelled as players; and they play against each other, so as to maximize their payoff and admission-control policies, which ensure maximum QoS for all service requests.

In multi-service HWNs, the mobile terminal nodes have the capability to support two or more classes of calls, such as voice, web-session, video-streaming, etc. simultaneously in any of the available RATs. In [61], Falowo et al. consider the problem of RATs selection for a group of calls from a multi-mode terminal taking into account the users' preferences. A modified TOPSIS group decision-making algorithm is employed; the weights of the criteria and the priorities of calls are aggregated in addressing the problem of optimal RAT selection for group of calls in the HWNs. In [62], a network criteria-weighting scheme, called Weighted Rating of Multiple Attributes (WRMA) is developed and used to determine the relative importance of the network criteria. The networks are then ranked, using TOPSIS. The results show that the scheme outperforms the traditional signal handoff method published by the National Institute of Standards and Technology (NIST) in all four Key Performance Indicators(drop rate; delay; jitter; and average throughput).

MCDM algorithms are popular decision-making tools; however, they can suffer from the problem of ranking abnormalities. These ranking abnormalities can potentially decrease the quality of the results. A multi-attribute network selection by Iterative TOPSIS for HWNs access is proposed in [63, 64]. The authors employ an Iterative TOPSIS process to tackle the ranking abnormality challenge in TOPSIS; however, Iterative TOPSIS has the drawback of being computation-intensive.

Some advantages of TOPSIS include being intuitively easy to understand and compute, and its flexibility for adaptation to diverse multi-criteria selection problems with often-conflicting criteria interests. As a limitation, TOPSIS does not provide for weight elicitation, and consistency checking of the judgments on criteria weights; and it also suffers from rank reversal or ranking abnormalities [65].

3.6 Distance to ideal alternative

The Distance to Ideal Alternative (DIA) is an MCDM ranking scheme that is similar to the TOPSIS algorithm. DIA uses the Manhattan distance to measure the distance of the alternatives from the PIS and the NIS of network alternative solutions, instead of the Euclidean distance measure, as proposed in TOPSIS. Compared to TOPSIS, the DIA suffers less from the ranking abnormality. The Manhattan distance between two vectors, say $\mathbf{v}(\mathbf{v_1}, \mathbf{v_2})$ and $\mathbf{a}(\mathbf{a_1}, \mathbf{a_2})$ is defined as: $D_{MN}(\mathbf{v}, \mathbf{a}) = |(\mathbf{v_1} - \mathbf{a_1})| + |(\mathbf{v_2} - \mathbf{a_2})|$, where |.| denotes the absolute value operation. The DIA is designed to mitigate the ranking abnormality problem. Unlike the Euclidean distance measure, the Manhattan distance measure allows the network-alternative solutions to change smoothly when lower-ranked network alternatives are removed from, or added to the network-alternative set [16].

In [66], a Novel Method, based on the Mahalanobis Distance (NMMD) is presented. The Mahalanobis Distance is used for criteria weight normalization,unlike the use of the Euclidean and Manhattan distances in criteria weight normalization in TOPSIS and DIA, respectively. The NMMD scheme is claimed by the authors to outperform both TOPSIS and DIA in dealing with ranking abnormality, because of the ability of the Mahalanobis distance to mitigate ranking abnormalities. The Mahalanobis distance is defined as a dissimilarity measure between two random vectors $\mathbf{v}$ and $\mathbf{a}$ of the same distribution with the covariance matrix C , of vectors $\mathbf{v}$ and $\mathbf{a}$. The Mahalanobis distance $D_{MS}(\mathbf{v}, \mathbf{a}) = \sqrt{(\mathbf{v} - \mathbf{a})^T C^{-1} (\mathbf{v} - \mathbf{a})}$, where $(.)^T$ denotes the transpose operation and $(.)^{-1}$ denotes the inverse operation [67]. When the covariance matrix is the an identity matrix, the Mahalanobis distance transforms to the Euclidean distance; and if the covariance matrix is a diagonal matirx, then the distance measure is transformed to a normalized Euclidean distance. The Mahalanobis distance scheme uses the covariance data; and hence, it requires a high volume of data to determine the covariance for its ranking to be reliable. This can present a computational drawback for any large set of alternatives. Also for very few alternatives, say two (2), there are insufficient data to compute a meaningful covariance for reliable alternative ranking; this also limits the implementation of the NMMD scheme [68]. The DIA technique is implemented by using the following steps:

1. Follow the step 1 and up to step 3, as discussed in the TOPSIS technique; then determine the PIS, a_i^+, and NIS, a_i^-, of the ith alternative as:

$$a_i^+ = \max_j v_{i,j}, \tag{26}$$

and

$$a_i^- = \min_j v_{i,j}. \tag{27}$$

2. Next, obtain the Manhattan distance from the PIS, D_j^+, and the NIS, D_j^-, for each alternative.

$$D_j^+ = \sum_{i=1}^{M} |v_{i,j} - a_i^+|, \tag{28}$$

$$D_j^- = \sum_{i=1}^{M} |v_{i,j} - a_i^-|. \tag{29}$$

3. Then, determine the maximum and minimum Manhattan distance values, D^+ and D^-, respectively.

$$D^+ = \max D_j^+, \tag{30}$$

$$D^- = \min D_j^-. \tag{31}$$

4. Finally, compute the absolute distance of the jth alternative to the Positive Ideal Alternative (PIA)

$$\mathrm{DIA}_j = \sqrt{(D_j^- - \min D_j^+)^2 + (D_j^- - \max D_j^-)^2}. \tag{32}$$

The alternative with the smallest DIA_j value has the shortest distance to the PIA, and is ranked as the best alternative.

In [16], the network selection in HWNs with network interfaces: UMTS, 802.11b, 802.11a, 802.11n, LTE and network criteria: jitter, packet delay, network utilization, PLR, and monetary cost per byte are investigated using DIA. The comparison results with SAW, MEW and TOPSIS algorithms show that the DIA outperforms TOPSIS in terms of ranking abnormality. Using the ranking-value difference as the ranking-accuracy metric, the DIA ranking accuracy is shown to be better than that of SAW and MEW.

3.7 Preference ranking organization method for enrichment evaluation

The Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE) is an MCDM technique that is based on the principle of outranking. It is flexible and easy to implement [69]. A number of PROMETHEE variants, PROMETHEE II-VI, have been proposed [69–73]. An important component of PROMETHEE is the preference function, as shown in Fig. 4 and Table 3. For each stated criterion, the preference function [74] maps the difference obtained between two alternatives into a preference degree of values between [0, 1]. Six proposed mapping-preference functions can be found in the literature [75]; and these are shown in Fig. 4 and Table 3, where the threshold parameters m, l, q, p, s, r, and σ are defined by the decision-maker; and the preference input parameter, x, represents the difference between two alternative values.

Consider a given set, $A\{a_1, a_2, a_3, \ldots, a_m\}$ of M alternatives and a set, $G\{g_1, g_2, g_3, \ldots, g_N\}$ of N criteria, the following steps illustrate how the PROMETHEE algorithm is implemented.

1. Compute the difference between alternatives a and b, according to criterion g_j based on their pair-wise comparison.

$$d_j(a,b) = g_j(a) - g_j(b), \tag{33}$$

where $d_j(a,b)$ is the difference between the evaluation of a and b on each criterion and $(a,b) \in A$.

2. Map the result of the criterion difference $d_j(a,b)$ as input to the preference function from a selected preference function.

$$P_j(a,b) = F_j(d_j(a,b)),\ j = 1, 2, 3, \ldots M, \tag{34}$$

where $P_j(a,b)$ denotes the preference of alternative a with regards to alternative b with respect to the jth criterion.

3. Compute the global or overall preference index, $\pi(a,b)$,

$$\pi(a,b) = \sum_{j=1}^{M} w_j P_j(a,b),\ \forall a, b \in A, \tag{35}$$

where $\pi(a,b)$ of a over b is defined as the weighted sum of $P(a, b)$ for jth criterion and w_j is the weight associated with the jth criterion.

4. For each alternative, determine the positive outranking flow, $\phi^+(a)$, as,

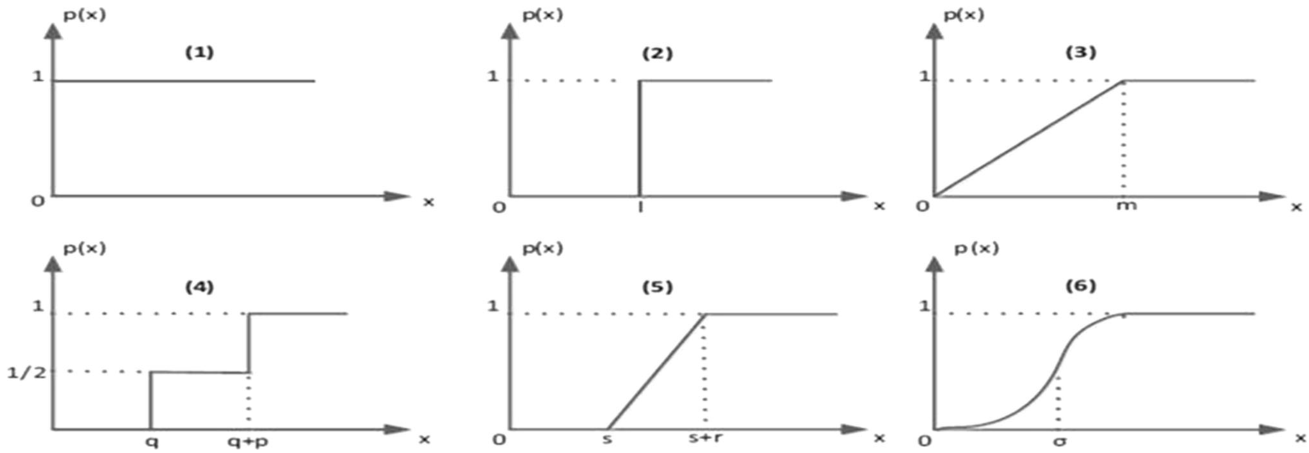

Fig. 4 Preference functions [76]

Table 3 Preference functions

S/N	Preference function	Definition
1	Usual criterion	$p(x) = \begin{cases} 0, & x \le 0, \\ 1, & x > 0. \end{cases}$
2	U-shape criterion	$p(x) = \begin{cases} 0, & x \le l, \\ 1, & x > l. \end{cases}$
3	V-shape criterion	$p(x) = \begin{cases} \frac{x}{m}, & x \le m, \\ 1, & x > m. \end{cases}$
4	Level criterion	$p(x) = \begin{cases} 0, & x \le q, \\ \frac{1}{2}, & q < x \le q + p, \\ 1, & x > q + p. \end{cases}$
5	V-shape with indifference criterion	$p(x) = \begin{cases} 0, & x \le s, \\ \frac{(x - s)}{r}, & s < x \le s + r, \\ 1, & x > s + r. \end{cases}$
6	Gaussian criterion	$p(x) = \begin{cases} 0, & x \le 0, \\ 1 - e^{-\frac{x^2}{2\sigma^2}}, & x > 0. \end{cases}$

$$\phi^+(a) = \frac{1}{N-1} \sum_{x \in A} \pi(a, x), \tag{36}$$

and negative outranking flow, $\phi^-(a)$, as,

$$\phi^-(a) = \frac{1}{N-1} \sum_{x \in A} \pi(x, a). \tag{37}$$

5. Finally, calculate the net outranking flow, $\phi(a)$, for each alternative,

$$\phi(a) = \phi(a)^+ - \phi(a)^-. \tag{38}$$

In [19], the network selection in HWNs that comprise WiMAX, Wi-Fi and two UMTS (UMTS1 and UMTS2) networks is investigated, using PROMETHEE. The UMTS2 is assumed to be the prevailing network on which users with multi-modal terminal devices are currently connected. The users make a vertical-handover decision, when other alternative target networks can provide ABC, rather than the prevailing network. Packet delay, packet jitter, PLR, monetary cost per byte, allowed bandwidth and network utilization are used as the decision factors for selecting the available alternative target network by the MNs for conversational, background, interactive and streaming network traffic. The AHP is used to determine the weights of the handover-decision factors subjectively; and the alternative networks are ranked and selected using PROMETHEE. Network selection decisions made by PROMETHEE are compared with the AHP-ranking decisions. The results show that both the PROMETHEE and the AHP network ranking order are similar to PROMETHEE having a better performance in ranking abnormality. PROMETHEE has an average abnormality ranking of 28 % compared to AHP with 47 %.

PROMETHEE is reported to be more robust for the network selection on all the network-traffic classes compared to AHP. A number of specialized software tools, such as PROMCALC [77] and DECISION LAB [78] have been specifically designed for the implementation of PROMETHEE I–VI.

3.8 ELimination et Choix Traduisant la REalit*é*

ELimination et Choix Traduisant la REalit*é* (ELECTRE) is a mathematical-ranking tool that employs the outranking technique for comparison between the multi-criteria alternatives. ELECTRE was introduced by Roy, B. in [79]; and subsequently, there have been several proposed variants, ELECTRE II, III, and IV, ELECTRE IS and ELECTRE TRI [80]. In ELECTRE III, a set $C\{c_1, c_2, c_3, \ldots, c_N\}$ of N criteria and set $A\{a_1, a_2, a_3, \ldots, a_M\}$ of M alternatives along with a set $G\{g_1, g_2, g_3, \ldots, g_k\}$ of K functions for each criterion are defined. The set G is defined on the set C, such that $g_l(a_j)$ indicates the performance of the alternative a_j with respect to the criterion c_l. Furthermore, we define the preference threshold model by introducing three pseudo-criteria: veto threshold $v_l(g_l(a_j))$, preference threshold $p_l(g_l(a_j))$ and the indifferent threshold $q_l(g_l(a_j))$ on the set of criteria C, where $v_l(g_l(a_j)) > p_l(g_l(a_j)) > q_l(g_l(a_j)) > 0$. The introduction of these thresholds produces outranking relations with allowance for data uncertainty in ELECTRE III.

For a given lth criterion, the alternative a_i is preferred to alternative a_j, if

$$g_l(a_i) > g_l(a_j + p_l(g_l(a_j))), \tag{39}$$

a_i is weakly preferred to alternative a_j, if

$$g_l(a_j) + q_l(g_l(a_j)) < g_l(a_i) \leq g_l(a_j) + p_l(g_l(a_j)), \tag{40}$$

a_i indifferent to alternative a_j, if

$$g_l(a_j) + q_l(g_l(a_j)) \geq g_l(a_i) \text{ and } g_l(a_i) + q_l(g_l(a_i)) \geq g_l(a_j). \tag{41}$$

The concordance index for each pair of alternatives measures how much the alternative a_i is better than the alternative a_j for a given lth criterion. The discordance index measures by how much the alternative a_i is worse than the alternative a_j for a given lth criterion. The credibility index measures the degree of strength of the claim that the alternative a_i is at least as good as the alternative a_j. The algorithm of ELECTRE III can be realized by using the following steps below:

1. Given a decision matrix problem; define the veto v_l, preference p_l and the indifference q_l threshold parameters and the weight w_l for the lth criterion.
2. Compute the concordance index for the lth criterion $c_l(a_i, a_j)$ as:

$$c_l(a_i, a_j) = \begin{cases} 1, & g_l(a_i) + q_l(g_l(a_i)) \geq g_l(a_j), \\ 0, & g_l(a_i) + p_l(g_l(a_i)) \leq g_l(a_j), \\ \dfrac{g_l(a_i) + p_l(g_l(a_i)) - g_l(a_j)}{p_l(g_l(a_i)) - q_l(g_l(a_i))}, & \text{otherwise.} \end{cases} \tag{42}$$

3. Obtain the overall concordance matrix $C(a_i, a_j)$

$$C(a_i, a_j) = \frac{\sum_{l=1}^{M} w_l c_l(a_i, a_l)}{\sum_{l=1}^{M} w_l}, \tag{43}$$

where $w_l(l = 1, 2, 3, \ldots, M)$ is the weight of the lth criterion.

4. Obtain the discordance index $d_l(a_i, a_j)$ of the paired alternatives for each criterion as:

$$d_l(a_i, a_j) = \begin{cases} 1, & g_l(a_i) + v_l(g_l(a_i)) \leq g_l(a_j), \\ 0, & g_l(a_i) + p_l(g_l(a_i)) \geq g_l(a_j), \\ \dfrac{g_l(a_i) - p_l(g_l(a_i)) - g_l(a_j)}{v_l(g_l(a_i)) - p_l(g_l(a_i))}, & \text{otherwise.} \end{cases} \tag{44}$$

5. Calculate the credibility index $S(a_i, a_j)$ for all alternative pairs for each criterion,

$$S(a_i,a_j)=\begin{cases} C(a_i,a_j), & d_l(a_i,a_j)\le C(a_i,a_j),\forall l,\\ C(a_i,a_j)\prod\limits_{l\in J(a_i,a_j)}\dfrac{1-d_l(a_i,a_j)}{1-C(a_i,a_j)}, & d_l(a_i,a_j)>C(a_i,a_j), \end{cases} \tag{45}$$

where $J(a_i, a_j)$ is the set of criteria for which the discordance (a_i, a_j) is greater than the concordance (a_i, a_j). The outranking credibility degree matrix becomes,

$$S=\begin{bmatrix} S(a_1,a_1) & S(a_1,a_2) & \dots & S(a_1,a_j) & \dots & S(a_1,a_N)\\ S(a_2,a_1) & S(a_2,a_2) & \dots & S(a_2,a_j) & \dots & S(a_2,a_N)\\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots\\ S(a_i,a_1) & S(a_i,a_2) & \dots & S(a_i,a_j) & \dots & S(a_i,a_N)\\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots\\ S(a_N,a_1) & S(a_N,a_2) & \dots & S(a_N,a_j) & \dots & (a_N,a_N) \end{bmatrix}. \tag{46}$$

The outranking credibility index takes the concordance and discordance indices into account, to show how much a_i outranks a_j.

The final ranking of the alternatives is performed on the outranking-credibility matrix by using either the ascending-distillation process or the descending-distillation process. In the ascending-distillation process, the alternative with the lowest qualification score is removed from the procedure; and the distillation process is repeated for all the remaining alternatives. In the descending-distillation process, the alternative with the highest qualification score is assigned and removed from the procedure; and the distillation process is repeated for all the remaining alternatives. (Interested readers can see [80–82], for more resource information on ELECTRE and its variants.)

MCDM schemes such as: SAW, MEW, TOPSIS, AHP and ANP can be considered as complete aggregation of the additive type. The complete aggregation of the additive type can lead to the situation where the trade-offs between good and bad scores on some criteria scores over other criteria can occur. Hence, such aggregation can lead to the loss of detailed and important information. However, ELECTRE is a non-compensatory MCDM method; and it avoids such trade-offs. ELECTRE III's ability to deal with inaccuracy, the imprecision of information and the uncertainty in data gives it an edge as a ranking technique over other MCDM methods.

Machine to Machine (M2M) communication is a growing area of interest in HWNs. In [83] Ahmad et al. have investigated the performance of vertical handover for M2M in an heterogeneous mobile Ad hoc Networks (HetMANET) using ELECTRE. The network selection process of the M2M device is carried out by considering five criteria: Network load, delay, jitter, velocity, network load, and power consumption. The average stay time of the MN in the network, number of handovers, and energy consumption are used as the performance metrics. The ELECTRE based MCDM handover decision technique is found to outperform a-two state Markov decision process model.

In HWNs, the network selection is influenced by the requested service indicated by the user. The application of ELECTRE in network selection in HWNs' environment is studied in [14], while considering three services, namely: VoIP (low bit rate, real-time), streaming (high bit rate, soft real-time), and web browsing (varying bit rate, bursty, non-real-time). The ELECTRE algorithm is adapted to be able to provide complete ranking for an HWN that comprises UMTS, IEEE802.11a, IEEE802.11b, IEEE802.11n and LTE-Advance networks, even in scenarios where the utilities of some of the network criteria are non-monotonic. The authors, however, fail to address the drawbacks that can result from the complicated ranking process, and the incomplete ranking result that occurs with the use of ELECTRE in their scheme. A drawback of the ELECTRE III method is that it suffers from the complicated ranking process and the incomplete ranking result; and these are often difficult to interpret [82, 84].

3.9 Grey relational analysis

Grey Relational Analysis (GRA) is an MCDM technique that explores the grey system theory for analyzing the relationship between a reference and a comparative series. GRA was first proposed in [85]. The comparative series is generated from all the performance values of each alternative. The comparative series process is analogous to the normalization process. This process helps to eliminate errors of scale in decision-making that can occur as a result of comparing criteria of relatively different dimensional units or scales and diverse ranges. The comparative series of all the alternatives are compared with the defined reference series to produce grey relational grade coefficients for the compared alternatives. The alternative with the highest grey relational grade coefficient from the comparison between itself and the reference series is ranked as the best alternative.

Given M alternative N criteria, $y_{i,j}$ can be defined as the performance score of the ith alternative with respect to the jth criterion. Hence, $Y_i = \{y_{i,1}, y_{i,2}, y_{i,3}, \ldots, y_{i,j}, \ldots, y_{i,N}\}$ are the performance scores of the ith alternative with respect to all the criteria. GRA can be used to select the best alternative from the set of alternatives with multiple criteria, by executing the following steps below:

1. Generate the comparative series $X_i = \{x_{i,1}, x_{i,2}, x_{i,3}, \ldots, x_{i,j}, \ldots, x_{i,N}\}$ from the original raw data performance score Y_i of ith alternative with $x_{i,j}$ the comparative performance score of the ith alternative with respect to jth criterion, and similarly for all the alternatives. If the criterion is a benefit criterion, then the comparative sequence elements are defined as;

$$x_{i,j} = \frac{y_{i,j} - \min\{y_{i,j}\}}{\max\{y_{i,j}\} - \min\{y_{i,j}\}}, \quad \text{for } i = 1,2,3,\ldots,M, \quad j = 1,2,3,\ldots,N.$$

If the criterion is a cost criterion, the comparative sequence elements are defined as;

$$x_{i,j} = \frac{\min\{y_{i,j}\} - y_{i,j}}{\max\{y_{i,j}\} - \min\{y_{i,j}\}}, \quad \text{for } i = 1,2,3,\ldots,M, \quad j = 1,2,3,\ldots,N, \tag{48}$$

while if the criterion is the closer to the nominal value y_j^*, the better then the comparative sequence element are defined as;

$$x_{i,j} = 1 - \frac{|y_{i,j} - y_j^*|}{\max\{\max\{y_{i,j}\} - y_j^*, y_j^* - \min\{y_{i,j}\}\}}, \quad \text{for } i = 1,2,3,\ldots,M, \ j = 1,2,3,\ldots,N. \tag{49}$$

2. The range of the comparative sequence obtained from step 1 is [0, 1]. The closer alternative value of the comparative sequence is equal to 1, or equal for the all criteria; the more the alternative is desired. In fact, the ideal alternative has its comparative sequence as;

$$X_0 = \{x_{0,1}, x_{0,2}, x_{0,3}, \ldots, x_{0,j}, \ldots, x_{0,N}\} = \{1, 1, 1, \ldots, 1\}, \tag{50}$$

unfortunately, such ideal alternative may not exist in the problem being analyzed. The ideal alternative is defined as the reference alternative against which the performances of the comparative sequences are measured and ranked.

3. Compute the grey relational coefficient, to determine how close is a given comparative score $x_{i,j}$ of a given ith alternative to the reference score $x_{0,j}$ for the jth criterion using;

$$\eta(x_{0,j}, x_{i,j}) = \frac{\Delta_{min} + \Phi\Delta_{max}}{\Delta_{i,j} + \Phi\Delta_{max}}, \quad \text{for} \quad i = 1,2,3,\ldots,M, \ j = 1,2,3,\ldots,N. \tag{51}$$

where $\Delta_{i,j} = |x_{0,j} - x_{i,j}|$, $\Delta_{min} = \min\{\Delta_{i,j}\}$, $\Delta_{max} = \max\{\Delta_{i,j}\}$ and Φ is the distinguishing coefficient with $\Phi \in [0, 1]$. The range of grey relational coefficient $\eta(x_{0,j}, x_{i,j})$ can be varied for the values of distinguishing coefficient Φ, as in (52); but, the ranking order of the alternatives for a given problem is unaltered with any variations in Φ. For most decision problems, Φ is usually assigned a value of 0.5.

4. Finally, compute the aggregate grey relational coefficient $\Psi(X_0, X_i)$ of ith alternative as;

$$\Psi(X_0, X_i) = \sum_{j=1}^{N} \eta(x_{0,j}, x_{i,j}) w_j, \quad \text{for} \quad i = 1,2,3,\ldots,M. \tag{52}$$

The $\Psi(X_0, X_i)$ represents the correlation between the reference sequence and the comparative sequence of the ith alternative, w_j is the weight of the jth criterion and

$$\sum_{j=1}^{N} w_j = 1. \tag{53}$$

The GRA measures the degree of closeness of the comparative sequence to the reference sequence; hence, the best alternative is the closest alternative to the reference sequence.

Joe et al. [12] present a network-selection algorithm, considering power consumption in a HWN, which consists of CDMA, Wireless Broadband (WiBro) and WLAN for the case of the vertical handover. A proposed power consumption-prediction algorithm estimates the expected lifetime of the MN, based on its current battery level, traffic class and power consumption for each network access of the MN. The target candidate network is excluded from the target network list, to prevent any unnecessary handovers in the pre-processing procedure; if the expected lifetime of the mobile station in that target candidate network is not satisfactory. AHP and GRA are employed for the final network selection, using QoS, cost and lifetime as the decision criteria. The simulation results show that the proposed algorithm ensures lengthier lifetime in the hybrid CDMA, WiBro and WLAN environments.

Song et al. in [1] propose a network-selection scheme for an integrated WLAN and UMTS using the integrated AHP and GRA technique. The scheme considers and defines the main QoS components in the HWNs as throughput (a), timeliness (b), reliability (c), security level (d), and cost (e). Secondary hierarchy level QoS parameters, delay (b (i)), response time (b (ii)), and jitter (b (iii)) are defined as sub-factors for the main QoS parameter of timeliness, and also the bit-error rate(c (i)), burst error (c (ii)), and the average number of retransmissions per packet (c (iii)) QoS parameters are defined for the main QoS factors of timeliness and reliability. AHP is used to assign weights to the main factors and sub-factors QoS in two steps. The AHP step does a pair-wise comparison on the main QoS factor and the QoS sub-factors, individually. The next step assigns a global priority to the main QoS factors and priority to the sub-factors QoS. Finally, the global priorities of sub-factors are achieved through multiplying the priorities of the sub-factors by the global priorities of the corresponding main QoS factor. The consistency of the weight criteria is always checked by using the CR. The GRA evaluates user preference and service class quantitatively; and it ranks the network alternatives efficiently, to ensure that users enjoy the best available services without any unnecessary handoff of QoS-deciding factors as possible.

In their simulation, it is observed that users are able to enjoy either real-time or non-real-time service during movement within the integrated WLAN and UMTS. Their scheme selects delay-sensitive network alternatives for real-time applications, and a high-throughput high-reliability network alternative for non-real-time applications. The simulation results show that the proposed network selection scheme can efficiently decide the trade-off among user preferences, service applications, and network conditions.

Markaki et al. [86] study the problem of network selection between General Packet Radio Service (GPRS) and WLAN. A subsequent network selection scheme that uses AHP and GRA is proposed. To enhance the quality of experience of the users within the HWNs, the main QoS parameters: delay, jitter, loss probability and throughput are identified and used as decision criteria for the network-selection algorithm. The weights of the network QoS are assigned by using AHP; while the GPRS and WLAN are ranked using GRA for best quality of experience provisioning.

Load balancing and call blocking probability are important parameters that must be controlled in HWNs, in order to achieve an acceptable users' quality of experience (QoE). Zhang et al. [87] propose the combined use of Fuzzy AHP and Entropy (FAHPE). Fuzzy AHP and Entropy are subjective and objective weighting techniques, respectively. The FAHPE is used to assign the weight of important to network criteria in an integrated network that consists of WiMAX, Time Division-LTE (TD-LTE) and LTE-Frequency Division Duplex (LTE-FDD). In addition, the least square and the Lagrange optimization techniques are applied to the evaluated weights from FAHPE to obtain the optimal network criteria weights. Finally, GRA is utilized to rank and select the networks, in order to achieve network-load balancing and reduced call-blocking probability in the integrated networks. The FAHPE-GRA scheme is more objective-due to the entropy-weighting technique employed. This, however, introduces more complexity, because of the introduction of the least square and Lagrange function optimization.

In MCDM algorithms, the importance of expert information affects the weight assigned to the network criteria. To take advantage of this fact, a Multiple AHP (M-AHP) weight scheme is proposed by Lahby et al. [88] for UMTS, WLAN and WMAN HWNs. The scheme takes into account the multiple experiences of five experts that influence the evaluation of the decision matrix and the weights of the criteria. The weights from M-AHP are aggregated using the geometric mean; and finally, the network ranking and the selection are achieved by using GRA. This scheme could, however, fail to become scalable, as the number of network users increases.

Zhang et al. [89] introduce a different approach to network selection in integrated WLAN and UMTS by modifying the traditional GRA to achieve the Always-most Suitable Connection (ASC) access network. They define a new series called the worst-case series, in addition to the ideal reference and comparative series in the traditional GRA algorithm. AHP is used to evaluate the weights of the network criteria. However, their technique has the drawbacks of increasing the computational time and cost for practical implementation.

Jiang et al. in [90] propose a network-selection method for the integration of UMTS and WiMAX to provide QoS guarantee per application through selecting the most suitable network, while avoiding unnecessary handoffs. Their proposed scheme uses the Variance-Coefficient Weighting (VCW), an objective weighting technique for assigning weights to the user preferences and network criteria. A modified GRA (MGRA) is used for ranking the network alternatives. In UMTS, four different services, namely: conversational, streaming, interactive and background services are defined. In the WiMAX, four different services, namely: Unsolicited Grant Service (UGS), real-time Polling Service (rt-PS), non-real-time Polling Service (nrt-PS) and Best Effort (BE) are defined [91]. The scheme is application-oriented; and it uses the QoS parameters of the different services as the decision criteria. The weights of the criteria are made to reflect the dynamic characteristics of the network by not only basing these on the networks' current conditions.

Although fuzzy theory can also be used to deal with uncertainty, GRA's capability of handling incomplete information is more realistic and more effective in some poor data environments. The ability to achieve satisfactory outcomes when using a rather limited amount of data, or with a large amount of variability in the decision factors, is another major advantage of GRA [65].

Khan et al. [92] study the performance of GRA for vertical handover against the IEEE 802.21; Media Independent Handover (MIH) standard. HWNs with Wireless-Fidelity (Wi-Fi), WiMAX and LTE are considered, using delay, network communication cost, bandwidth, throughput and jitter as the decision criteria. The vertical handover decisions are investigated under three different applications: elastic, Voice over IP (VoIP) and streaming applications. The schemes are implemented using Network Simulator (NS) 2.29. The simulation results show that the GRA technique consumes less energy, significantly reduces the handover delay and frequent handovers compared to MIH.

3.10 VlseKriterijumska Optimizacija I Kompromisno

VlseKriterijumska Optimizacija I Kompromisno (VIKOR) is developed based on the concept of a compromise solution. VIKOR determines the preference-ranking index of the individual alternative, with multiple confliction criteria. VIKOR was first proposed in [93]. The ranking index of VIKOR is derived from considering both the maximum-group utility and the minimum individual regret of the opponent. Given the decision-data matrix of entry $x_{i,j}$, where $x_{i,j}$ is the performance score of the ith alternative with respect to the jth criterion and $f_{i,j}$ is the normalized score of the ith alternative with respect to the jth criterion, with $i = 1, 2, 3, \ldots, M$ alternatives and $j = 1, 2, 3, \ldots, N$ criteria, the P-norm, L_p, can be defined [94] as;

$$L_{p,i} = \left\{ \sum_{j=1}^{N} \left[w_j \frac{(f_j^* - f_{i,j})}{(f_j^* - f_j^-)} \right]^p \right\}^{\frac{1}{p}}, \; 1 \le p \le \infty, \; i = 1, 2, 3, \ldots, M. \tag{54}$$

However, in the VIKOR scheme, the 1-norm $L_{1,i}$ is used to formulate its ranking measure. The VIKOR can be implemented in the following steps:

1. The decision matrix is normalized using the Euclidean norm,

$$f_{i,j} = \frac{x_{i,j}}{\sum_{i=1}^{M}}, \; i = 1, 2, 3, \ldots, M, \; j = 1, 2, 3, \ldots, N. \tag{55}$$

2. Compute the best, f_j^*, and the worst, f_j^-, values of all the criteria, ith $= 1, 2, 3, \ldots, N$,

$$f_j^* = \begin{cases} \max_i f_{i,j}, & i = 1, 2, 3, \ldots, M, \text{ for benefit criteria}, \\ \min_i f_{i,j}, & i = 1, 2, 3, \ldots, M, \text{ for cost criteria}, \end{cases} \tag{56}$$

$$f_j^- = \begin{cases} \min_i f_{i,j}, & i = 1, 2, 3, \ldots, M, \text{ for benefit criteria}, \\ \max_i f_{i,j}, & i = 1, 2, 3, \ldots, M, \text{ for cost criteria}. \end{cases} \tag{57}$$

3. Compute the utility, S_i, for alternative $i = 1, 2, 3, \ldots, M$ as;

$$S_i = \sum_{j=1}^{N} \left[\frac{(f_j^* - f_{i,j}) w_j}{(f_j^* - f_j^-)} \right], \tag{58}$$

and the regret measure, R_i, for alternative $i = 1, 2, 3, \ldots, M$ as;

$$R_i = \max_j \left[\frac{(f_j^* - f_{i,j}) w_j}{(f_j^* - f_j^-)} \right], \tag{59}$$

where w_j is the weight of the jth criterion.

4. Calculate the ranking index value, Q_i, for the ith alternative,

$$Q_i = \lambda \frac{(S_i - S^*)}{S^- - S^*} + (1 - \lambda) \frac{(R_i - R^*)}{R^- - R^*}, \tag{60}$$

where $S^- = \max_i S_i$, $S^* = \min_i S_i$, $R^- = \max_i R_i$ and $R^* = \min_i R_i$. S^* is the maximum majority rule index, R^* is the minimum individual regret of the opponent index and, λ is the weight for the strategy of maximum group utility; and it is usually assigned a value of 0.5 ; and $(1 - \lambda)$ is the weight of the individual regret.

5. For alternative ranking, sort Q_i, S_i and R_i in descending order, a proposed solution of the compromised alternative $Q^{[1]}$ is ranked the best as the minimum Q_i, if condition 1 and condition 2 are satisfied:****

   (a) Condition 1: Acceptable advantage; $Q^{[2]} - Q^{[1]} \ge \frac{1}{N-1}$, where $Q^{[2]}$ is the second-best ranked position of the ranking order of Q_i and N is the number of criteria considered.

   (b) Condition 2: Acceptable stability in decision-making:a The alternative $Q^{[1]}$ is the best ranked by S_i or / and if one of the conditions is not satisfied, then a set of compromised solutions is proposed, which is made up of:

(i) Alternative $Q^{[1]}$ and $Q^{[2]}$, if only condition 2 is not satisfied or,
(ii) Alternative $Q^{[1]}, Q^{[2]}, Q^{[3]}, \ldots, Q^{[K]}$, if condition 1 is not satisfied; $Q^{[K]}$ is determined by $Q^{[K]} - Q^{[1]} < \frac{1}{N-1}$, for maximum K.

In [18], a study of vertical handoff using the VIKOR algorithm in HWNs is presented. The HWNs consist of UMTS, WLAN and WiMAX. The available bandwidth, total bandwidth, packet delay, packet jitter, PLR, and the monetary cost per byte of the HWNs are employed as the network-decision criteria. Voice and data connections are considered. Under voice connection application, VIKOR is found to have the best performance among: GRA, ELECTRE and MEW; while GRA and MEW are found to have the best performance for data connection application. However, the study fails to investigate the effect of criteria weight variations on the vertical handoff decisions on algorithms.

Some handover criteria and users' preferences in HWNs can be imprecise. The Fuzzy logic technique can be applied to deal with the imprecise information [3]. In [95], Sasirekha et al. apply an MCDM technique by using Fuzzy AHP (FAHP) and VIKOR to select the optimal network from five network alternatives: WLAN, GPRS, UMTS, WIMAX and CDMA with ten decision criteria: bandwidth, latency, jitter, bit error rate, retransmission rate, PLR, monetary cost, throughput, preference and security level. The results from the FAHP and VIKOR are compared with TOPSIS and found to be consistent with the results obtained when using FAHP TOPSIS. Furthermore, the authors report the low computation cost of FAHP and VIKOR compared to FAHP TOPSIS.

Mehbodniya et al. in [96] present a fuzzy extension of VIKOR (FVIKO) for target network selection in HWNs. A prediction mechanism based on the Grey prediction theory is used to predict the future RSS values of all the networks in the range. Fuzzy linguistic variable-based weighting is used to weigh all the criteria of the networks and the users' preferences. The target network is selected, using the FVIKO ranking algorithm to determine the best candidate network for future connection for two different network scenarios: single-user and multiple-users.

Baghla et al. [97] investigate the effect of normalization techniques of criteria weights on VIKOR Method for network selection in HWNs. Euclidean, min-max and max methods are some popular criteria weight normalization techniques used in literature. VIKOR method uses the min-max method for criteria weight normalization. The type of normalization technique employed can influence the ranking abnormality of the MCDM and ping-pong effect in handover management process. The authors considered UMTS, WiMAX and WLAN integrated networks, having six network decision criteria: cost, delay, jitter, packet loss, security and bandwidth. Three criteria weight normalization techniques: Euclidean, min-max and max methods are used to normalize the criteria weights obtained from two different criteria weighting methods: AHP and ANP. These criteria weights are further used by VIKOR for network selection decisions. Background, interactive, conversational and streaming traffic classes are considered. The simulation results show that max-min normalization technique produced the best performance for streaming and background traffic classes, while the Euclidean normalization produced the best performance for conversational and interactive traffic classes. However, the authors fail to consider weight sensitivity behavior of the weight normalization techniques.

3.11 MULTIplicative form with multi-objective optimization ratio analysis

The MULTIplicative form with Multi-Objective Optimization Ratio Analysis (MULTIMOORA) is a new MCDM technique that incorporates three ranking approaches, namely: ratio system, reference point system and multiplicative form. The outputs of the three ranking systems are transformed into a single ranking output by the application of the theory of dominance. The MULTIMOORA is very robust and accurate, when compared to other MCDM techniques for ranking alternatives. MULTIMOORA was first proposed in 2010 by Brauers et al. [98]. The first known paper on the application of MULTIMOORA technique to wireless communication networks was presented in [17].

The MULTIMOORA can be realized by using the following steps:

1. Define the decision matrix problem, D, and criteria weight, W.
2. Compute the weighted Euclidean normalized normalized score, $x^*_{i,j}$, for the ith alternative jth criterion as:

$$x^*_{i,j} = \frac{w_j x_{i,j}}{\sqrt{\sum_{i=1}^{M} x^2_{i,j}}}. \tag{61}$$

3. Compute the ratio-rank index, y_i, for the ith alternative as;

$$y_i = \sum_{j=1}^{k} x^*_{i,j} - \sum_{j=k+1}^{N} x^*_{i,j}, \tag{62}$$

where k is the cardinal value of the benefit criteria and $(N-k)$ is the cardinal value of the cost criteria. The higher the value of y_i the higher is the ratio-system ranking of the ith alternative.

4. Compute the reference-point ranking index, y_i^*, for the ith alternative using the Tchebycheff min-max metric as;

$$y_i^* = \min_i(\max_j(r_j - x_{i,j}^*)). \tag{63}$$

The lower the value of y_i^* , the higher is the reference point ranking for the ith alternative. In the reference point system, the reference point $r_j = \min_i(x_{i,j}^*)$ and $r_j = \max_i(x_{i,j}^*)$ are defined for benefit and cost, respectively.

5. Evaluate the multiplicative form ranking index, U_i, for ith alternative as;

$$U_i = \frac{A_i}{B_i}, \tag{64}$$

where $A_i = \prod_{j=1}^{k} x_{i,j}^{w_j}$ for the ith alternative with benefit criteria, $j = 1, 2, 3, \ldots, k$ and $B_i = \prod_{j=k+1}^{N} x_{i,j}^{w_j}$ for the ith alternative with cost criteria, $j = k+1, k+2, k+3, \ldots, N$.

The higher the value of U_i, the higher is the multiplicative form ranking for the ith alternative. The MULTIMOORA ranking for the ith alternative is based on the dominance in the ratio, the reference point and the multiplicative form system.

Three kinds of dominance rules exist: *absolute dominance*; *general dominance*; and *overall dominance*. The MULTIMOORA-ranking technique gives a ranking score of absolute dominance, (1, 1, 1), for the ith alternative on a given ranked position, if the ratio system, the reference point system and the multiplicative form system all ranked the ith alternative as 1, respectively, for that given ranked position. Given that $(w < x < y < z)$, the ith alternative with MULTIMOORA score (z, w, w) has general dominance over the mth alternative with MULTIMOORA score (y, x, x); consequently, (w, z, w) is generally dominating (x, y, x), and (w, w, z) is generally dominating (x, x, y). The ith alternative with (y, y, y) has overall dominance over the mth alternative with (z, z, z). The ranking systems of MULTIMOORA are dimensionless. (For more interesting reading on the application of dominance theory in MULTIMOORA ranking technique, readers can see [99–101].)

3.12 Performance evaluation of MCDM-based network-selection techniques in HWNs

Based on the relative simplicity and efficiency, the SAW, GRA, TOPSIS [42] and VIKOR [102] algorithms are studied and compared with the MULTIMOORA algorithm for network-selection decision problems in HWNs via MATLAB simulation. The HWNs consist of WLAN, UMTS and WIMAX. Three traffic classes, namely: voice; file-download; and video-streaming are considered. To enhance the QoE of the users within the HWNs, data rate (Mbps), packet delays (ms), jitter (ms), PLR (%), network monetary cost per byte (unit/B) and network security level (fuzzy crisp value) are considered as the network decision criteria. The network security level is measured in literature using fuzzy membership functions (e.g., High, Medium, Low, Very low, etc.). The fuzzy membership functions are converted to their corresponding crisp (numerical) values to allow for subsequent numerical computations. The decision matrix contains the performance scores of the three different networks with respect to network decision criteria and it is given in Table 4.

One important issue in network selection is the assignment of suitable weights to different criteria in accordance with the ongoing traffic class of the user. Voice traffic is very sensitive to delay and jitter. File-download traffic is very sensitive to PLR and data rate; while video-streaming traffic is very sensitive to data rate, delay and jitter.

To ensure consistency of weight determination of criteria; the AHP method is applied to assign weights to the criteria. The criteria weights for voice, file-down load and video-streaming are presented in Table 5. The AHP consistency ratio (CR) for voice, file-download and video-streaming traffic classes are: $CR_{voice} = 0.038$, $CR_{file-download} = 0.057048$ and $CR_{video-streaming} = 0.044027$, respectively. The CRs all satisfied the $CR < 0.1$ threshold for good and consistent judgments.The comparison results of MULTIMOORA with SAW, GRA, VIKOR and TOPSIS for optimal network selection for voice, file-download and video-streaming traffic VHO are shown in Figs. 5, 6 and 7, respectively.

In Fig. 5, the implemented MCDM algorithms produced the same ranking results and selected UMTS as the optimal network for voice traffic. Selection of UMTS as the optimal network is reasonable, given that from the decision matrix, UMTS has the relative best rating on delay and jitter; also, the weights for delay and jitter are higher than other criteria in the voice-weight distribution for voice traffic. The WiMAX is ranked higher than WLAN for voice traffic because of its better delay-score rating than WLAN.

In Fig. 6, though the performances of the UMTS and WiMAX are almost identical in terms of PLR; however, WiMAX outperforms UMTS in the data rate, which is given a considerable weight by the file-download traffic weight. This produces WiMAX as the best network selection for file-download. MULTIMOORA, TOPSIS and VIKOR give the best network selection for the file-

Table 4 Decision matrix

Network ⇓ \ Criterion ⇒	Data rate	Delay	Jitter	PLR	Cost	Security
WLAN	54	80	15	0.03	20	0.283
UMTS	7.5	30	10	0.006	45	0.909
WiMAX	25	50	15	0.009	35	0.717

Table 5 Decision criteria weights for voice, file-download and video-streaming

Application ⇓ \ criterion ⇒	Data rate	Delay	Jitter	PLR	Cost	Security
Voice	0.065234	0.31124	0.25908	0.03723	0.0959	0.23132
File-download	0.250873	0.04618	0.05914	0.45589	0.075	0.11225
Video-streaming	0.34373	0.21864	0.20208	0.0562	0.0466	0.13273

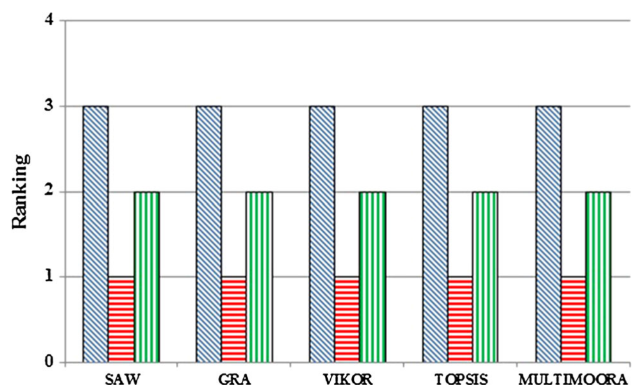

Fig. 5 Network selection for voice traffic

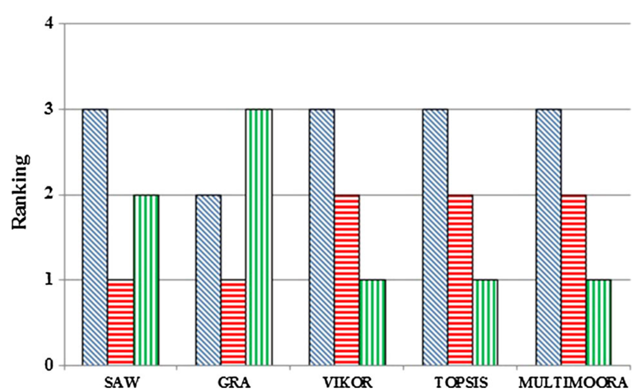

Fig. 6 Network selection for file-download traffic

downloaded traffic. Unfortunately, SAW and GRA select UMTS networks for the file-downloaded traffic; and thus, they fail to take advantage of the improved data rate offered by WiMAX network for file-downloading.

In Fig. 7, SAW and GRA provide the same UMTS network for video-streaming and the same for all other traffics. However, this leads to poor performances for

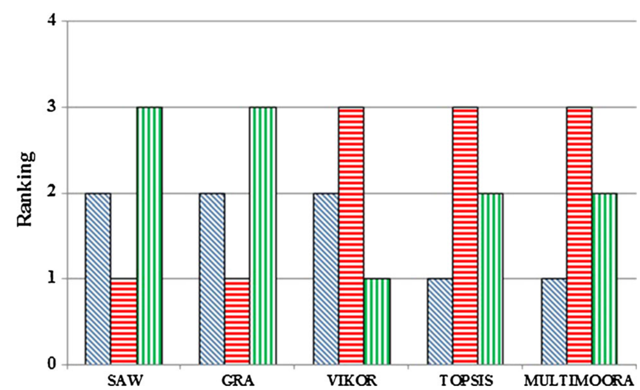

Fig. 7 Network selection for video-streaming traffic

video-streaming; unlike WLAN that is selected by TOPSIS and MULTIMOORA. VIKOR provides WiMAX for video-streaming, which gives a better performance on the data rate, delay and jitter than UMTS, but not WLAN, for video-streaming traffic. In the next section, a comprehensive categorization of reviewed MCDM applications to handover decision-making problems in HWNs is presented.

4 Categorization of MCDM application and analysis of criteria

The MCDM technique is an operational research-optimization tool that has been applied in solving complex practical decision-making problems in various practical fields, like science, engineering economics, etc. The application of MCDM algorithms to resolve complex decision-making has attracted a lot of attention in wireless communication networks, where multiple competing and conflicting decision criteria are ever present. This section takes on the task of categorizing the application of various reviewed MCDM techniques in handover schemes of HWNs, as proposed by wireless communication researchers. The categorization of the application of MCDM techniques in HWNs is based on algorithms, the types of calls, the cardinality of decision criteria, handover control point and the types of network utilities, as presented through Sects. 4.1–4.5.

4.1 MCDM application based on algorithm approach

The MCDM application in HWNs for handover decision and network-access selection under algorithmic application can be grouped into three sub-divisions, based on the way the MCDM algorithms are applied in HWNs. These are: single, integrated and modified algorithm approaches.

4.1.1 Single algorithm

In the single-algorithm approach, an independent MCDM algorithm is employed as a stand-alone MCDM algorithm for the access-network ranking and the selection process in the HWNs. The single-algorithm approach can be found in [10, 14, 43, 103]. The right determination and consistency of the weighting of importance of the decision criteria are very important in selecting the access networks. The criteria weights reflect the true relative importance of the decision criteria for network selection.

4.1.2 Integrated algorithm

When the true relative importance weighting of the decision criteria is not correctly captured, the access network selection performance becomes inefficient. This is therefore an undesirable situation. Some of the popular MCDM techniques that assign weights to decision criteria in a consistent manner are the AHP and ANP. The mobile users' evaluation of their network preferences and criteria are usually imprecise and inherently uncertain or fuzzy. To capture this true practical preferential evaluation and assessment, fuzzy logic theory is best at handling such in imprecise and incomplete information scenario. In the Integrated MCDM algorithm approach, researchers combine two or more independent methods to determine the appropriate decision-criteria weighting, using AHP or ANP and fuzzy logic to account for the fuzzy information environment. Finally, a different independent MCDM algorithm is chosen to rank the wireless-access network. The integrated algorithm approach is utilized in [12, 15, 19, 44].

4.1.3 Modified algorithm

Most of the MCDM algorithms developed have their strengths and weaknesses. Some of the algorithms (e.g., SAW and MEW) are easier to implement than others; while some are more robust (e.g., MULTIMOORA, TOPSIS and DIA); but they can be more computationally demanding than others. Some (e.g., TOPSIS and GRA) are more affected by ranking abnormality; while others (e.g., PROMETHEE and DIA) are less affected by ranking abnormality. There is no single MCDM that absolutely outperforms all the other MCDM algorithms on all the performance metrics, or measurements. Intuitively, independent or integrated algorithms can be modified to reduce their weaknesses or to enhance their strengths, using various ideas, or by infusing from other independent MCDM algorithms their attractive features to improve the desired goal for the modified MCDM algorithm. The Modified MCDM algorithm approach is exploited in [11, 60, 63, 64].

Figure 8 quantifies the noticeable growing future research trend in the nature of algorithmic application approaches of MCDM techniques in tackling the handover-decision problems of HWNs. The usage of a modified MCDM algorithm is seen to be 25 %; while the usage of single and integrated MCDM algorithms are 31 and 44 %, respectively.

4.2 MCDM application based on types of calls

HWNs support a plethora of independent services or calls, such as video-streaming, voice, or file-downloading, email, web-browsing. These services can be engaged one service at a time by the mobile users. The mobile users can also choose to engage multiple-independent services simultaneously, at any given time in the HWNs. This mode of call operation is referred to as a group call. For an independent call scenario, a mobile user might activate an independent voice call as its first call; and when the first call terminates; and then it activates, say, a video-streaming call as its second independent call. No two or more independent calls can be activated simultaneously by the mobile users. This mode of operation is sometimes implemented when limited network resources prevail, such that degradation of the QoS of the ongoing call or new calls can be avoided. Group calls allow the MN to activate its first call; and while the first call is still ongoing, a second, and a third, and more calls can be activated without perceived degradation to the quality of the calls. Multiple calls require the introduction of group decision-making and the assignment of priority weights to the multiple applications in the MCDM algorithms.

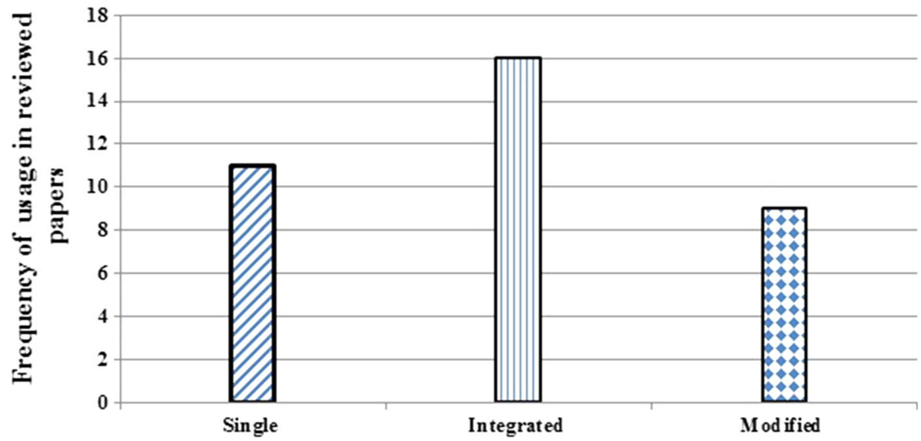

Fig. 8 Future trend in MCDM algorithmic approach for network selection in HWNs

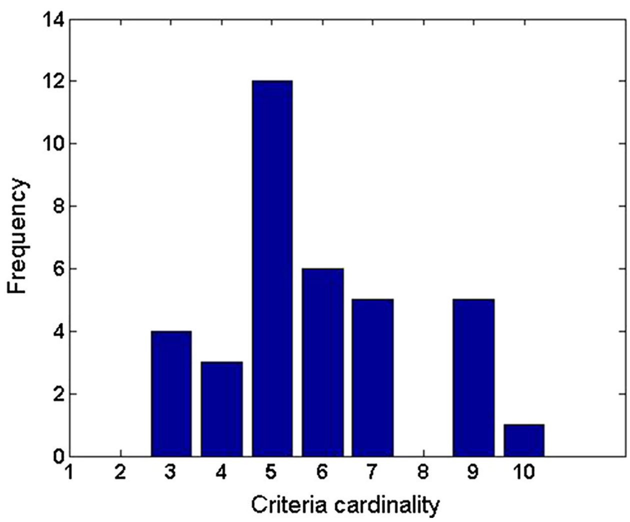

Fig. 9 Frequency of criteria cardinality in reviewed papers

The authors in [57, 58, 86, 87, 95] applied MCDM algorithms to independent call scenarios. In [43, 61] and [104] MCDMs are proposed for a group decision, for simultaneous multiple calls, or services.

4.3 MCDM application based on the cardinaltiy of decisions criteria

The cardinality of the criteria selected for handover decision-making is a hugely important issue in the handover process, its design and implementation. Selecting a very small number of criteria reduces the computational load at the handover-control point; however, this can lead to the possible exclusion of some important decision criteria or factors in the decision-making process during handover. On the other hand, choosing a large magnitude of criteria allows for the possible inclusion of every necessary and important decision factor for the handover decision-evaluation and the decision-making process for access network selection before the execution of the handover. However, this can reduce the decision-making speed of the network-selection algorithm. As shown in Fig. 9, the cardinal criteria range from three [10, 43, 44] to ten [95]. From the analysis of the criteria reviewed in the literature, Fig. 9 shows that a criteria-cardinal value of five [13, 86, 87] is the most frequently chosen magnitude.

4.4 MCDM application based on handover control point

In a network-centric handover scheme, handover is controlled and made transparent to the MNs by the network entity. The network entity measures and gathers the vital information within the HWNs. The network control entity can also request from the MNs, their MN information and network measurements, as well, in order to enhance a seamless handover. However, in a network-centric vertical handover scheme, the control signalling overhead and processing load can dramatically increase; and this, therefore, reduces the HWNs efficiency performance, as the number of MNs increases. A network-centric handover scheme is not easily scalable; and it is prone to single-point failure. One way to reduce the processing load and the signalling overhead on the network entity is to distribute the handover decision and control to the MNs.

In the user-centric or distributive vertical-handover scheme, the MNs can execute and implement their respective handover decision, and select their access technology independently in a manner that is transparent to the network entity. The MNs gather their crucial information and measurement about the HWNs environment to assist in the smooth vertical-handover process at the MNs. However, the MNs might not have a complete global knowledge of the overall network load conditions, and other vital-network statistical information; hence, the user-centric approach might suffer from user synchronization, which can lead to performance degradation in a user-centric handover scheme.

To improve the handover decision, the MNs can acquire global network-load conditions and other vital network statistical information from the network resource control (NRC) entity. The NRC entity can broadcast these measurements and information to the MNs, for more effective handover decision-making within the HWNs. Many vertical-handover schemes, such as: [1, 43, 56, 62, 86, 105] are proposed for network-centric implementation; while [10, 13, 42, 60] are proposed for user-centric vertical-handover scenarios.

4.5 MCDM application based on types of network utilities

HWNs utilities can be classified as monotonic and non-monotonic [106]. Decision criteria can be monotonically increasing or decreasing utilities; as also can non-monotonic

Table 6 Categorization of MCDM algorithm applications for network selection in HWNs

Authors ⇓ \ Categorization ⇒	Algorithm apporach	Independent \ Group calls	Criteria Cardinality	Hanover control point	Network utilities
Singh et al. [42]	Integrated	Independent	4	Distributed	Monotonic
Pink et al. [43]	Single	Group	3	Centralized	Monotonic
Tawil et al. [10]	Single	Independent	3	Distributed	Monotonic
Stevens-Navarro et al. [48]	Integrated	Independent	4	Centralized	Monotonic
TalebiFard et al. [11]	Modified	Independent	7	Centralized	Monotonic
Li et al. [13]	Single	Independent	5	Distributed	Monotonic
Chantaksinopas et al. [51]	Single	Independent	4	Distributed	Monotonic
Lahby et al. [56]	Modified	Independent	6	Centralized	Monotonic
Tan et al. [105]	Single	Independent	5	Centralized	Monotonic
Tan et al. [16]	Single	Independent	5	Centralized	Monotonic
Bari et al. [107]	Single	Independent	7	Centralized	Non-monotonic
Bari et al. [14]	Single	Independent	7	Centralized	Non-monotonic
Martinez-Morales et al. [18]	Single	Independent	6	Centralized	Monotonic
Liu et al. [44]	Integrated	Independent	3	Centralized	Monotonic
Joe et al. [12]	Integrated	Independent	6	Centralized	Monotonic
Anupama et al. [19]	Integrated	Independent	6	Centralized	Monotonic
Kaleem et al. [15]	Integrated	Independent	9	Centralized	Monotonic
Mehbodniya et al. [96]	Integrated	Independent	9	Centralized	Monotonic
Chamodrakas et al. [108]	Modified	Independent	3	Distributed	Monotonic
Zhang et al. [89]	Modified	Independent	9	Centralized	Monotonic
Falowo et al. [61]	Modified	Group	5	Distributed	Monotonic
Yang et al. [62]	Modified	Independent	5	Centralized	Monotonic
Song et al. [1]	Integrated	Independent	9	Centralized	Monotonic
Markaki et al. [86]	Integrated	Independent	5	Centralized	Monotonic
Zhang et al. [87]	Integrated	Independent	5	Centralized	Monotonic
Mohamed et al. [57]	Integrated	Independent	7	Centralized	Monotonic
Mehbodniya et al. [58]	Integrated	Independent	9	Centralized	Monotonic
Sasirekha et al. [95]	Integrated	Independent	10	Centralized	Monotonic
Charilas et al. [60]	Modified	Independent	5	Distributed	Monotonic
Bari et al. [63]	Modified	Independent	7	Centralized	Monotonic
Dhar et al. [64]	Modified	Independent	5	Centralized	Monotonic
Obayiuwana et al. [17]	Integrated	Independent	6	Centralized	Monotonic
Ahmad et al. [83]	Single	Independent	5	Distributed	Monotonic
Baghla et al. [97]	Integrated	Independent	6	Centralized	Monotonic
Khan et al. [92]	Single	Independent	5	Centralized	Monotonic
Manisha et al. [102]	Integrated	Independent	5	Centralized	Monotonic

utilities. For monotonic utilities, like throughput, that can be regarded as beneficial, the maximal value is usually the target goal; while monotonic utilities, like power consumption that can be regarded as costs, where the minimal value is usually the target goal. Non-monotonic utilities do not exist in these ways. Non-monotonic utilities result, when for some applications, the user-select access network that offers the closest QoS for the applications; and not necessarily the access network that provides the highest QoS that far exceeds its application or QoS requirements. Not all MCDM algorithms perform optimally in HWNs with non-monotonic utilities. Therefore, MCDM algorithms specially need to enhance to handle non-monotonic utilities. Bari et al. [107] propose the use of non-monotonic criteria for multi-attribute network selection. GRA is reported to have superior performance over other MCDM algorithms, such as: SAW, MEW, TOPSIS, DIA and ELECTRE in non-monotonic network criteria in HWNs with non-monotonic utilities. Unfortunately, very little consideration has been given to HWNs with non-monotonic utilities in the literature. Of the papers reviewed in this work, only [14, 107] address the issue of access-network selection in HWNS with non-monotonic utilities. Table 6 shows the summary analysis of the categorization of MCDM applications for handoff decisions and network-sections in HWNs.

4.6 Analysis of criteria used for making vertical handover decisions in HWNs

The number and combination of criteria employed in making handover decisions in HWNs is of significant importance. Figure 10 and Table 7 give insight into the most preferred criteria for making handover decisions in HWNs. In Fig. 10 and Table 7, the following abbreviations denote the criteria, T ⇒ Throughput, AB ⇒ Allowed bandwidth, R ⇒ RSS, C ⇒ Cost, SL ⇒ Security level, PC ⇒ Power consumption, D ⇒ Delay, RT ⇒ Response time, BER ⇒ Bit error rate, J ⇒ Jitter, BE ⇒ Burst error, PLR ⇒ Packet loss rate, DP ⇒ Dropping probability, MNV ⇒ MN velocity, DMS ⇒ Device memory size, NU ⇒ Network utilization, TB ⇒ Total bandwidth and S ⇒ SINR. The symbol "x" in Table 7 indicates the criterion used by the given authors.

Figure 10 shows the criteria used for making handover network-selection decisions in HWNs, and the frequency of usage in the reviewed literature. As observed in Fig. 10, throughput, allowed bandwidth, monetary cost per byte, security level, delay, jitter and PLR are among the most-favoured criteria employed for making handover decisions; while bit error rate, signal to interference to noise ratio, call-dropping probability and MN velocity are the least-frequently considered criteria employed for making handover decisions in heterogeneous wireless networks. Table 7 shows the different combinations of criteria used for making handover decisions in heterogeneous wireless networks by research.

5 Key highlights of the MCDM methods applied in HWNs

As stated in the previous sections, a sizeable amount of work has been reported in the literature on the application of MCDM algorithms for making handover network-selection decisions. However, only a very few studies have so far been reported on comparative analyses of MCDM algorithms for making handover network-decisions. Sharna et al. attempt to fill this gap by conducting a comprehensive performance study for SAW, TOPSIS, and the Markov-Decision Process (MDP) in network-access selection decision-making problems, considering UMTS and WLAN networks. Network Simulator (NS) 2.29 tools are used to

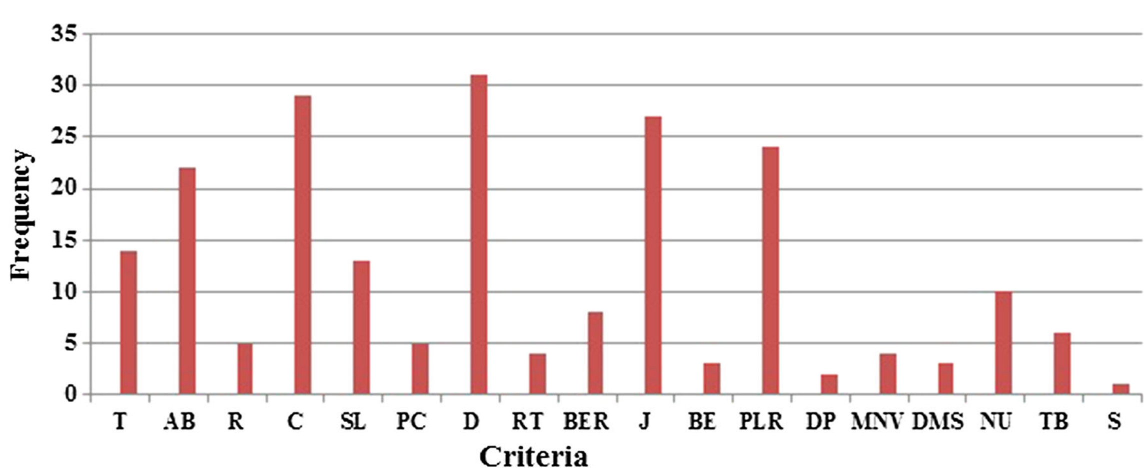

Fig. 10 Frequency of criteria in reviewed papers

Table 7 Range of criteria used for handover decision making in HWNs

Authors ⇓ \ criteria ⇒	T	AB	R	C	S	PC	D	RT	BER	J	BE	PLR	DP	MNV	DMS	NU	TB	S
Singh et al. [42]	x	x		x		x												
Pink et al. [43]	x			x			x											
Tawil et al. [10]		x		x									x					
Stevens-Navarro et al. [48]		x					x		x	x								
TalebiFard et al. [11]		x		x	x	x	x			x			x					
Li et al. [13]		x		x	x									x	x			
Chantaksinopas et al. [51]			x	x			x					x						
Lahby et al. [56]		x		x	x		x			x		x						
Tan et al. [105]				x			x			x		x			x			
Tan et al. [16]				x			x			x		x			x			
Bari et al. [107]		x		x			x			x		x				x	x	
Bari et al. [14]		x		x			x			x		x				x	x	
Martinez-Morales et al. [18]		x		x			x			x		x					x	
Liu et al. [44]		x		x														x
Joe et al. [12]		x		x		x	x		x	x								
Anupama et al. [19]		x		x			x			x		x				x		
Kaleem et al. [15]	x		x	x	x		x			x		x		x		x		
Mehbodniya et al. [96]	x		x	x	x		x			x		x		x		x		
Chamodrakas et al. [108]		x				x	x											
Zhang et al. [89]	x			x	x		x	x	x	x	x	x						
Falowo et al. [61]	x			x	x	x		x										
Yanget al. [62]		x		x			x		x	x								
Songet al. [1]	x			x	x		x	x	x	x	x	x						
Markaki et al. [86]	x						x		x	x		x						
Zhang et al. [87]		x	x		x		x					x						
Mohamed et al. [57]		x					x			x		x				x	x	
Mehbodniya et al. [58]	x		x	x	x		x			x		x		x		x		
Sasirekha et al. [95]	x	x		x	x		x	x	x	x	x	x						
Charilas et al. [60]	x			x			x		x	x		x						
Bari et al. [63]		x					x			x		x				x	x	
Dhar et al. [64]		x		x			x			x		x				x	x	
Obayiuwana et al. [17]	x			x	x		x			x		x						
Ahmad et al. [83]	x					x	x			x		x				x		
Baghla et al. [97]		x		x	x		x			x		x						
Khan et al. [92]	x	x		x			x			x								
Manisha et al. [102]		x		x			x			x		x						

evaluate and compare the expected total QoS offerings in the mean duration of a service, under different state transition probability distributions, user-perception models on the importance of QoS parameters, and network-switching costs. They utilize model users' perceptions based on the importance of QoS parameters to users, and network-switching costs [109]. The analytical and empirical results of comparative performance analyses show that TOPSIS achieves the best performance in terms of the highest expected total QoS offerings in the mean duration of a service and better ability to user perception on the importance of QoS parameters for the service.

In [3], alternative networks selection in a HWN has been studied, with the goal of always providing the ABC for the network users utilizing price, bandwidth, signal-to-noise-ratio (SNR), sojourning time, seamlessness and battery consumption, as the network selection criteria for handover. The fuzzy information from the user preference and network information are dealt with by using fuzzy logic. The fuzzy logic helps to convert the fuzzy membership function into a crisp number. The weight of the individual network criteria is determined by using the AHP, a type of subjective-weighting technique. To rank and select the best network for handover, two different classic MCDM techniques, the SAW and TOPSIS, are used and compared. The numerical results showed that the TOPSIS method has more sensitivity to changes in the weights of the criteria and users' preferences when compared with the SAW method. Thus, SAW gives a relatively conservative ranking. The Yager-ranking method has also been used; and it has been shown to be inconsistent in its ranking.

In [110], the problems of weight assignment, frequent VHO, VHO trade-off and network load-balancing associated with handover decision-making in HWNs are highlighted. A four-step integrated strategy to address these problems has been proposed. The combination of subjective and objective weighting techniques is presented to address the weighting problem. A two-step permutation-based network selection scheme (Besnet and Besper) is proposed to address the problem of frequent VHO. The authors defined a trade-off metric, called predicative residential time, to quantify the VHO trade-off performance of networks' ranking and selection. A sigmoid utility function is proposed for adjusting the weight of the network traffic load criteria. Four MCDM methods: SAW, MEW, TOPSIS and GRA have been implemented in the study; and their results are compared. SAW and MEW are observed to select the best networks under a low-weight monetary-cost criterion; while TOPSIS and GRA select the best networks under a high-weight monetary cost criterion.

Manisha et al. [102] investigate the optimal network selection using MCDM algorithms: SAW, MEW, VIKOR and TOPSIS for vertical handover decision in HWNs. SAW, MEW, VIKOR and TOPIS are selected for the comparative study based on simplicity. The WLAN, UMTS and WiMAX are integrated to form HWNs. AHP is used to determine the network criteria weights. Five network decision criteria: bandwidth, delay, jitter, network service cost and packet loss are considered. The background, conversational and streaming traffic classes are used. The simulation results showed that the four MCDM algorithms showed similar performance for the considered traffic classes. The result reveals that UMTS is the most preferred network for conversational traffic; WLAN is the most preferred network for background traffic, while WiMAX is the most preferred network for streaming traffic.

A comparative analysis of seven MCDM algorithms: SAW, MEW, TOPSIS, ELECTRE, VIKOR and GRA for networks selection under voice and data applications has been presented for an integrated WMAN, WLAN, and UMTS networks in [18]. Six criteria namely: packet delay, packet jitter, available bandwidth, total bandwidth, packet loss, and cost per byte are chosen as the decision factors. VIKOR, TOPSIS and SAW provide the best network for voice application with the lowest delay and jitter; while MEW and GRA provide the best network selection for data application with the best available bandwidth.

Considering the increasing use of MCDM techniques in making network-selection decisions for handoff calls and their associated problems, a search for new and powerful MCDM algorithms is required. Further studies are required to investigate the performance of these algorithms in terms of sensitivity-analysis and ranking abnormality, when considering elaborate services, such as: real-time video-streaming and interactive services.

6 Conclusion

For next generation wireless networks to provide connectivity at all times, they need to be heterogeneous wireless networks. For HWNs to ensure that users are always best connected, this would require robust and seamless handover algorithms. Traditional handover schemes are based on a single-criterion parameter; and they are inefficient for handovers in HWNs, because of the effect of the heterogeneity of network parameter standards across the HWNs. Consequently, the handover process cannot be efficiently and optimally determined by a single criterion. Thus, the existing handover algorithms developed for homogeneous networks cannot perform optimally in the NGWNs. Multi-criteria decision-making algorithms have been widely used in the literature to address the handover and network selection in NGWNs, because of their ability to resolve complex decision-making with multiple decision factors.

This paper has reviewed and classified the most significant MCDM algorithms that have been used to address the handover-decision problems in HWNs in terms of algorithmic approach, types of calls, the cardinality of the decision criteria employed, handover-control point, and the type of network utilities. It has presented a review of the step-wise mathematical implementations of the reviewed MCDM schemes; and it has highlighted their strengths and weaknesses.

The current trend from the literature shows that most authors prefer the use of integrated MCDM algorithms for making selection decisions in HWNs. However, integrated MCDM algorithms are generally more complex and computationally expensive than single and modified MCDM schemes.

MCDM algorithms, such as TOPSIS have been extended to support group decisions for multiple simultaneous calls. However, it is important to examine the impact of group-decision mechanisms on the aggregation of the multiple calls in the selection of the optimal access networks for multiple calls. Thus, this area of research needs further investigation.

The choice of the cardinality of handover-decision criteria and criteria combination in HWNs are very crucial for the design and implementation of an effective handover process. Choosing a relatively small number of criteria reduces the computational load at the handover control point. However, this can lead to the possible exclusion of some important decision criteria in the handover decision-making process. On the other hand, choosing a large number of criteria allows for the possible inclusion of every criterion necessary for making handover decisions. However, this can increase the computational load and the hand-over latency of network selection algorithms. For these reasons, the criteria cardinality of five is mostly used for making network selection decisions in the literature.

As the number and diversity of MNs in wireless networks increase, a handoff decision-control point would need to be more distributive than centralized. A distributive handover control point allows for network scalability and prevents a single point of failure, unlike network centralized-handle control point. Moreover, it is imperative to exploit less computationally intense algorithms for network selections in HWNs which can easily be implemented in distributive handover-control points.

This review also shows that HWN utilities can be monotonic as well as non-monotonic. The performances of MCDM algorithms such as: SAW, MEW, TOPSIS, DIA, and ELECTRE degrade in a non-monotonic HWN; whereas GRA is found to have a relatively superior performance in a non-monotonic network utility environment. Further research is needed to investigate the performance of MCDM algorithms in HWNs with non-monotonic utilities, and to develop new MCDM algorithms that have superlative performance in HWNs with monotonic and non-monotonic utilities.

It is difficult to single out any given MCDM algorithm that absolutely outperforms all the other existing MCDM algorithms in the literature in terms of the various network-selection performance metrics. MCDM algorithms are diverse in range from being very simple algorithms, such as SAW and MEW to very complex algorithms, such as ELECTRE and VIKOR. Most MCDM algorithms are sensitive to criteria-weight variations and ranking abnormality. Hence, it is imperative to develop robust MCDM algorithms that have good sensitivity analysis and ranking abnormality performance.

Another important issue in MCDM algorithms is how to determine the true weights of the various network criteria. Most network-selection algorithms explore some sort of weighting mechanism for determining the appropriate weights for the system's criteria. Although subjective weighting methods, such as: AHP and ANP; and objective weighting methods, such as Entropy technique, have been used to resolve this challenge in the literature; nevertheless, a precise weighting of the decision criteria is an essential factor and must be done properly, in order to improve the accuracy of the handoff/network-selection procedure [48, 111]. On closer examination, the decision criteria are interdependent. For example, RSS as a criterion can influence the throughput, bit-error rate, and battery-power consumption. Moreover, the allocated bandwidth can affect the throughput and delay. This dynamic interdependence and interactions inadvertently dynamically affect the relative weights of the decision criteria for handover in HWNs [112] This is an important research issue that has scarcely been given any attention in the existing literature on network selection in HWNs. It is important to investigate the interaction and inter-dependence among the criteria, which affect the true weights of the criteria.

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