The Journal of Supercomputing (2023) 79:3580–3615
https://doi.org/10.1007/s11227-022-04791-y

New network interface selection based on MADM and multi-objective whale optimization algorithm in heterogeneous wireless networks

Brahim Mefgouda[1] · **Hanen Idoudi**[1]

Accepted: 25 August 2022 / Published online: 7 September 2022

Abstract

Multi-attribute decision-making (MADM) approaches are commonly used to model and solve the network interface selection problem in heterogeneous wireless networks. Despite their importance and advantages to deal with this issue, they suffer from the rank reversal problem (RRP) and the selection of the highest-ranking score network without considering the user's/service requirements. In this paper, a novel method is introduced to solve the MADM limitations. Besides, the weights assignment technique is modelled as a multi-objective problem. Then, an extended version of the Whale Optimization Algorithm is applied to obtain the suitable weights of the decision criteria. The obtained results showed that applying the developed technique with MADM approaches reduces (sometimes avoids completely) the RRP by an average up to 94%, compared to Analytical Hierarchy Process. It also allows meeting the user's/service requirements by optimizing data rate and packet loss, for streaming services, by an average up to 14.3 (kbps) and 20×10^6(ms), respectively.

Keywords Network interface selection · Heterogeneous wireless networks · Multi-attribute decision making · Whale optimization algorithm · Rank reversal problem · Quality of service

1 Introduction

Recently, after the deployment of several radio access technologies (RATs), including 3GPP technologies (e.g., 3G, 4G, 5G, 6G) and IEEE standards (e.g., WiMAX, Wi-Fi), researchers have focused on introducing new architectures and wireless

✉ Brahim Mefgouda
brahim.mefgouda@ensi-uma.tn

Hanen Idoudi
hanen.idoudi@ensi-uma.tn

1 National School of Computer Science, University of Manouba, Manouba, Tunisia

technologies to interconnect and integrate RATs. Consequently, new type of wireless environments, called Heterogeneous Wireless networks (HWN) environments [1], has emerged.

Nowadays, a user's equipment (e.g. laptops, vehicles, smartphones, etc.) contains multiple wireless access network interfaces to ensure its connection to any available wireless network located in the HWN environment, thus realizing the Always Best-Connected (ABC) concept [2]. The latter refers to ranking, selecting and, then, connecting dynamically and seamlessly the users' equipment to the best RAT that satisfies the users' and/or service requirements. To achieve ABC, the user equipment should solve the problem of network interface selection.

Indeed, the network interface selection (NIS) problem is a key challenge for the HWN environment and the main function of vertical Handover (VHO). The latter can be divided into three main phases [3]: vertical handover initiation (also called vertical handover information gathering), vertical handover decision including the NIS procedure, and vertical handover execution. The first phase aims at recognizing and collecting all the necessary information needed to start the VHO process including static and dynamic parameters. The second phase is the most important in the VHO process. Its main purpose is to determine if the connection with current candidate network is worthy or it should change to another candidate network by using a NIS approach [1]. The last phase of VHO consists in connecting the user equipment to the target candidate network selected in the previous phase.

The major objective of NIS process is to achieve the always best-connected concept by ranking the list of candidate networks located in an HWN environment, selecting and connecting it to the best wireless network according to the user's and/or service preferences [2]. The NIS problem is considered as a decision-making problem composed of a limited number of networks (alternatives); each of which has its specific attributes (decision criteria). In NIS, the decision-maker has to rank these alternatives according to their satisfaction.

The NIS solution can be centralized (network-centric) or decentralized (user-centric) [4]. The first type is managed by the network operator that is responsible for choosing the best RAT for the user equipment. Although the centralized solution has many advantages such as achieving load-balancing and avoiding the selfish behaviour of mobile users, it is hard to be implemented if there are many network operators, and it does not meet the user's requirements. However, in the centric solution, the user's equipment makes decision based on many parameters (e.g. the received signal strength (RSS), the available bandwidth and the required energy per service). These parameters are called decision criteria.

In literature, to solve and model this problem, many research works were conducted and several approaches were introduced such as MADM approaches-based NIS (MADM-NIS) [5–15], utility function-based NIS (UF-NIS) [16, 17], Artificial Neural Networks-based approaches for NIS (ANN-NIS) [18, 19], Markov Decision Process-based approaches for NIS (MDP-NIS) [20, 21], fuzzy logic-based NIS (FL-NIS) [22] and game theory-based NIS (GT-NIS) [23, 24].

Due to the fact that the NIS problem can be considered as a Multi-Attribute Decision-Making problem, Multi-Attribute Decision-Making approaches are the most applied to solve, model and optimize the network selection problem in HWN environments. In fact, they offer many advantages to the users' equipment during the NIS process. For instance, we can cite their easy implementation, their high precision in selecting the best candidate network and their ability to rank rapidly the available networks. Nonetheless, they suffer from two weaknesses [25, 26]. The first one is the Rank Reversal Problem (RRP), also known as Ranking Abnormality. RRP consists of re-ranking of the available networks when a network (alternative) is removed from or added to the HWN environment. This change may negatively impact the selection of the best interface. The second drawback is that MADM algorithms choose the network having the highest score irrespective of the user's and/or a specific application requirement.

The aforementioned limitations unavoidably influence the selection of the best wireless network, which prevents the realization of the always best-connected concept, deteriorates the overall performance of the user's equipment connectivity. They also result in a poor Quality of Service (QoS) offered to users' equipment, in terms of a high packet loss, packet jitter and packet delay, and increase the number of the unnecessary handovers, ping-pong effects and handover failure (i.e. ignoring the vertical handover requests caused by the saturation of resources). These problems may lead to the dissatisfaction of the mobile users and rise the energy efficiency by reducing the battery lifetime of the mobile user

One of the solutions proposed to overcome the MADM-NIS limitation is to obtain the suitable weights of networks attributes. Indeed, weights refer to the quantitative metrics reflecting the importance of the decision criteria. The weights assignment techniques are generally applied to compute the decision criteria weights. They can be subjective or objective. The first type calculates weights according to the decision maker's experience or the application requirements. Among the most popular subjective techniques, we can mention the analytical hierarchy process (AHP) [27], fuzzy analytic hierarchy process (FAHP) [28], Analytic Network Process (ANP) [29], and fuzzy analytic network process (FANP) [30]. Although these methods meet the QoS user's/service requirements (subjectivity) when combined with MADM approaches to solve the NIS problem, they rise the ratio of the rank reversal problem, increase the power consumption and delays and, consequently, lead to unnecessary handover. On the other hand, objective weighting methods (e.g. the Entropy technique, Coefficient Variation (CV) and Standard Deviation (SD)) use mathematical techniques to achieve specific purposes. Despite the fact that they can reduce (or avoid) the rank reversal problem (objectivity), they do not satisfy the user's/application QoS preferences and do not meet the users' requirements during the vertical handover process ABC.

Therefore, To deal with MADM-NIS shortcomings, the suitable networks attributes' weights should be determined. The objective of this research work is to introduce a novel weights assignment technique that can be combined with any MADM approach to improve the performance of the latter and overcome its limitations. The developed technique aims at reducing the rank reversal phenomenon while meeting the QoS requirements of the user's and/or service requirements.

The main novelty of the present study consists in modelling the weights assignment as a multi-objective problem defined by three objective functions applied to achieve the NIS objectivity and subjectivity during VHO by reducing the rank reversal problem and by meeting the user's/application QoS preferences, respectively. Besides, an extended version of the Whale Optimization algorithm, called Guided Population Archive Whale Optimization, is used to solve the introduced multi-objective problem and obtain the suitable decision criteria weights.

The contributions of the current study are summarized below:

1. Defining a new mathematical model to formulate the weights assignment technique as a multi-objective optimization problem (MPO). This model can be combined with any MADM approach without considering the networks' attributes and the normalization technique used to optimize the weights vector of the networks' decision criteria. In fact, subjectivity is the satisfaction of the user's/application QoS requirements; whereas objectivity refers to meeting the user's/application needs in terms of QoS parameters. In the proposed technique, we achieve subjectivity by maximizing or minimizing the benefit (cost) of the QoS parameters required by the user's/application. However, objectivity is attained by emphasizing the summation of the absolute value (SV) of the ranking values differences of the candidate networks. SV is calculated by the MADM-NIS approach.
2. Proposing a new NIS framework based on MADM approaches and multi-objective metaheuristic algorithms. The latter uses an extended version of the multi-objective whale optimization algorithm, also named multi-objective whale optimization algorithm for the NIS problem (MOWOA-NIS), to optimize the suitable decision criteria weights based on the formerly-introduced formulation. Performance of MOWOA-NIS are investigated with typical MADM techniques including Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) and Simple Additive Weighting (SAW).

This paper is organized as follows. The next section introduces the existing solutions suggested to overcome the MADM-NIS drawbacks. It also discusses their performance. In Sect. 3, we illustrate how the MADM approach is applied to model the NIS problem. Afterwards, the TOPSIS-NIS and SAW-NIS approaches are described. In the Sect. 3, the motivations and contributions of this work are highlighted. Section 5 is divided into two parts. Firstly, the introduced model employed to formulate the weighting assessment techniques as a multi-objective optimization problem is presented. Finally, the algorithm used in the suggested technique (multi-objective whale optimization algorithm for NIS technique (MOWOA-NIS)) is depicted and its complexity is studied. The simulation results are discussed in Sect. 6, some concluding remarks are presented in Sect. 7, and future work directions are presented in Sect. 8.

2 Related work

In literature, different MADM approaches (such as Technique for Order Preference by Similarity to Ideal Solution-based approaches for NIS (TOPSIS-NIS) [5–7], Simple Additive Weighting-based approaches for NIS (SAW-NIS) [8, 9], ViseKriterijumsa Optimizacija I Kompromisno Resenje-based approaches for NIS (VIKOR-NIS) [10], Analytical Hierarchy Process -based approaches for NIS (AHP-NIS) [11, 12], Gray Relational Analysis-based approaches for NIS (GRA-NIS) [13, 14], the Combined Compromise Solution for NIS (COCOSO-NIS) [15], etc.) were suggested to solve and model the NIS problem. They provide higher accuracy, can support real-time applications, offer a high decision precision during ranking, are simple to implement and perform the networks' ranking rapidly. However, they suffer from two major limitations: the Rank Reversal Phenomena (RRP) and the low satisfaction of user's and/or application requirements [25, 26].

Various solutions were proposed to remedy these limitations. They can be classified into two main categories: solutions based on replacing the normalization technique method by another mathematical techniques and solutions relying on changing the weights assignment technique applied to obtain the decision criteria weights of the used MADM approach.

In the former, it is assumed that that the normalization technique can cause rank reversal problem [31–33]. For instance, in [34], authors avoided the RRP by replacing the original normalization technique of TOPSIS by max-min normalization method. However, researchers did not focus on the user's/application preferences.

In [35], Chandavarkar et al. proposed a new algorithm, called Simplified and Improved Multiple Attributes Alternate Ranking (SI-MAAR), to overcome the RRP and make the MADM-NIS approach more reliable. The authors replaced the original weights calculation and normalization technique by a closeness index (utility) matrix obtained thought estimating networks' attributes. The simulation results approve that the introduced algorithm considered the service characteristics, but did not meet the user's preferences.

In [36], researchers removed the RRP by substituting the normalization technique of TOPSIS by a sigmoid function (diminishing marginal utility and monotonic utility functions). However, the introduced algorithm was not flexible as it required target knowledge and the base point of each network decision criteria. In addition, in the context of user's/service requirement, the authors did not evaluate its performance when used in a known application or traffic class.

In [37], a NIS algorithm based on the VIKOR approach was suggested and the original normalization technique of the VIKOR approach was replaced with a vector-normalized preferred performance-based normalization technique. The proposed algorithm outperformed the traditionally MADM approaches. Specifically, it reduced the RRP and the number of handovers. Notwithstanding, the authors did not consider the user's and/or service requirements.

In [38], Alhabo and al. introduced a novel approach relying on GRA and AHP techniques. They applied an enhanced max-min method to normalize the decision matrix of the HWN environment. The simulation results show that the proposed approach reduced the rank reversal ratio and, therefore, minimized the number of handovers, compared to VIKOR and SAW approach.

Authors, in [39], developed a hybrid MADM algorithm consisting of FAHP, GRA and Standard deviation (SD) approaches. They avoided the problem of inconsistent ranking by using Max-Min technique to normalize the networks attributes for GRA and SD approaches.

In [40], Mansouri and Legris suggested a new dynamic network selection strategy, called Fuzzy Manhattan distance to the ideal alternative (FMDIA). This strategy was based on applying fuzzy logic to normalize the decision matrix of alternative and Manhattan distance to calculate the score of each alternative. The simulation results approve that the proposed strategy reduced the rank reversal problem, number of handovers and offered a good QoS, compared to Fuzzy GRA.

In [41], we avoided the RRP and met the user's/application QoS preferences by replacing the original normalization technique of Combined Compromise Solution approach (COCOSO) by a sigmoid function. However, the likelihood of the ranking abnormality remains possible.

Yongzhou Lu et al. [42] applied a utility function to normalize the networks attributes of TOPSIS approach to ensure the QoS of terrestrial satellite networks, reduce the blocking rate and enhance the network reliability.

However, solutions included the second category, based on calculating the suitable decision criteria weights to overcome the MADM shortcomings, are widely applied to overcome the MADM-NIS drawbacks in the network selection field. For instance, the authors overcame the MADM-NIS limitations by maximizing the summation of the absolute value of the ranking differences among candidate networks, such as [43, 44], to reduce the rank reversal problem affecting MADM approaches. In [43], researchers utilized a genetic algorithm to optimize decision criteria weights of TOPSIS and SAW approaches. The experimental results demonstrate that the proposed method can meet QoS service requirements and avoid rank reversal. Moreover, in [44], the PSO algorithm was applied to optimize decision criteria weights of the distance. The obtained findings reveal that the introduced technique minimized the rank reversal.

In [14], YU et al. improved the GRA algorithm by using two weights assignment techniques: Coefficient of Variation (CV) and Intuitionistic Normal Fuzzy Analytic Hierarchy Process (INFAHP). The former was employed to obtain the objective decision criteria weights. However, the latter was used to compute the subjective decision criteria weights. The experiments results show that subjectivity and objectivity were achieved by reducing the unnecessary vertical handoffs and satisfying the application requirements.

In [45], researchers improved the TOPSIS by using two weighting methods (the FAHP and Entropy) that achieved the objective and the subjective preferences and, thus, met the QoS preferences.

In [46], a novel NIS approach based on MADM approaches and fuzzy-AHP technique was developed. Furthermore, a non-linear fuzzy model was introduced to obtain the suitable weights of the networks' attributes. In addition, utility functions were applied to obtain the utility values of decision criteria parameters. The simulation results approve that the introduced algorithm considered the service characteristics, but did not satisfy the user's preferences.

Priya and Malhotra [47] enhanced the performance of TOPSIS approach by using the FAHP to calculate the suitable decision criteria weights. The proposed approach reduced the rank reversal problem and the unnecessary handover, compared to AHP-TOPSIS, PE-TOPSIS and PSD-TOPSIS proposed in [48].

In [8], researchers optimized the satisfaction of the user's QoS requirements in HWN by combining the TOPSIS method with the fuzzy logic.

Authors, in [49], suggested a network interface selection approach based on Entropy, Fuzzy Analytic Hierarchy Process (FAHP) and TOPSIS algorithm to calculate the objective weights, the service characteristics weights and the score of each candidate network located in HWNs, respectively. The obtained findings demonstrate the effectiveness of the proposed method that considered both the service and user QoS requirements.

In [50], Yu et al. combined Chi-square distance algorithm with entropy method, criteria importance through intercriteria correlation (CRITIC) and AHP methods to meet the service requirements. The Chi-square distance algorithm was employed to rank the candidate networks. However, AHP method was applied to calculate the objective and subjective weights.

In [9], authors combined TOPSIS with fuzzy logic approaches to meet the user's/application preferences and avoid the RRP. The experimental results affirm the effectiveness of the introduced algorithm. However, the user's/application requirements were not always satisfied.

Guo and al. [51] designed a framework to select the most suitable candidate network that can satisfy the user equipment needs. The proposed framework is composed of integrating utility theory, FAHP, fuzzy logic theory and MADM methods to consider the candidate network performances, service characteristics and user equipment preferences. To evaluate its performance, the author compared the latter with that of TFAHP and SAW algorithms; AHP and TOPSIS algorithms; Utility, FAHP, Entropy and MEW algorithms; and Utility and Fuzzy Logic algorithms. The simulation results show that the user's preferences and the average number of handovers offered by the designed approach is better than those provided by the other algorithms.

Radouche and Leghris [52] reduced the rank reversal problem and the average number of handovers of Cosine Similarity algorithm by combining both the subjective and objective decision criteria weights. Moreover, Cosine Similarity was utilized to compute the score of each candidate network, while the fuzzy ANP and Entropy methods was employed to assign the subjective and objective weighs, respectively. The simulation results demonstrate that the proposed algorithm is the most efficient in minimizing the number of handovers and rank reversal problem and outperformed the traditional MADM approaches such as TOPSIS, VIKOR and GRA.

In [53], the cosine similarity distance algorithm was combined with Fuzzy ANP and PSO algorithms to minimize the number of handovers and avoid the rank reversal problem in the MADM approaches, compared to the traditional VIKOR, GRA and TOPSIS. The Fuzzy ANP was applied to calculate the subjective weights; whereas the PSO algorithm was used to compute the objective weights.

Based on the above-mentioned solutions proposed to overcome the shortcomings of MADM-NIS approaches, we conclude that choosing the right MADM normalization technique can reduce the rank reversal problem. Despite their importance and excellent performance, these solutions do not always satisfy the user's and/or service preferences. Improving the MADM-NIS approach by targeting the decision criteria weights is a good solution to remedy the MADM-NIS weaknesses. Thus, a new weighting method that can achieve subjectivity, by meeting the service and/or user's requirements, and objectivity by reducing the rank reversal is defined in this work.

3 Multiple-attribute decision making methods for network interface selection

In this section, the modelling of NIS problem by the MADM approaches is first illustrated. Afterwards, the main steps of TOPSIS and SAW algorithms are described.

3.1 MADM-NIS basics

Multiple-Attribute Decision Making (MADM) is an analytic decision theory approach applied to solve multi-attribute decision problems. The MADM approaches are generally used to choose the best alternative (candidate) from a set of existing ones; each of which has its specific decision criteria. In NIS, the available networks (covered by an end-user) and their attributes represent the candidates of MADM approaches and the decision criteria, respectively. The MADM in NIS is formulated as follows [1]:

- Alternatives: It is a finite list of the candidate networks of HWN ranked by a MADM approach . The alternatives are represented as follows:

$$A = \left\{A_i, i = 1, 2, ...n\right\} \tag{1}$$

  where n is the number of the available networks (alternatives).
- Criteria or attributes: They are represented by a finite set of metrics. Each network (alternative) has its criteria values (e.g. network characteristics, application characteristics, terminal characteristics, and user's preferences) that make it individually distinct from others. They are represented as follow:

$$C = \{C_i, j, i = 1, 2, ...n, j = 1, 2, ...m\} \tag{2}$$

  where n is the number of the available networks (alternatives) and m denotes the number of network criteria.
- Weights: are represented by a vector showing the importance of networks' decision criteria. It is defined as follows:

$$W = \{W_i, i = 1, 2, ...m\} \tag{3}$$

- Decision matrix: The multiple attribute decision making for network interface selection is represented by a matrix [N, M], where N is the number of networks (alternatives) and M corresponds to the number of attributes, to facilitate solving the MADM in NIS problems.

3.2 Technique for order preference by similarity to ideal solution (TOPSIS)

TOPSIS is a multiple-attribute decision-making approach applied to rank the candidate networks. It consists in selecting the candidate network having the shortest geometric distance from the positive ideal solution and the longest geometric distance from the negative ideal solution. The TOPSIS approach is based on the following steps [54]:

- Building a decision matrix $X_{[M,N]}$ containing M candidate networks and N attributes. The format of the matrix is obtained as follows:

$$X_{ij} = \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1M} \\ x_{21} & x_{22} & \dots & x_{2M} \\ x_{31} & x_{32} & \dots & x_{3M} \\ \vdots & \vdots & \ddots & \vdots \\ x_{N1} & x_{N2} & \dots & x_{NM} \end{bmatrix} \tag{4}$$

  where x_{ij} represents the measure of the ith network for the jth criteria
- Applying a weight assignment technique to obtain the attributes' weights vector W_j, where $\sum_{i=1}^{m} w_j = 1$.
- Constructing the normalized decision matrix $D_{[NM]}$ by applying the following equation:

$$D_{i_j} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{n} x_{ij}^2}} \tag{5}$$

- Assigning each attribute of the matrix $(d_{ij})_{N\times M}$ to get a weighted normalized decision matrix D, where $(d_{ij})_{N\times M}$:

$$d_{ij} = w_j d_{ij} \tag{6}$$

- Defining the best and the worst values of each attribute by determining the positive ideal solutions (A^+) and the negative ideal solutions (A^-), where:

$$A^+ = [d_1^+ ... d_N^+] \quad \text{and} \quad A^- = [v_1^- ... v_N^-] \tag{7}$$

  – For benefit criteria:

$$V_i^+ = \max\{d_{ij}, j = 1, ..., n\} \tag{8}$$

$$V_i^- = \min\{d_{ij}, j = 1, ..., n\} \tag{9}$$

  – For cost criteria:

$$V_i^+ = \min\{d_{ij}, j = 1, ..., n\} \tag{10}$$

$$V_i^- = \max\{d_{ij}, j = 1, \ldots, n\} \tag{11}$$

- Computing the Euclidean distances between each alternative and the ideal and negative solutions. The Euclidean distance between candidate i and the ideal solution is calculated as follows:

$$S_i^+ = \sqrt{\sum_{j=1}^{m} (v_j^+ - d_{ij})^2} \tag{12}$$

While the Euclidean distance between candidate i and the non-ideal solution is obtained as follows:

$$S_i^- = \sqrt{\sum_{j=1}^{m} (v_j^- - d_{ij})^2} \tag{13}$$

- Calculating the coefficient of each candidate network and selecting the network having the highest score. The coefficient of alternatives is computed as shown below:

$$C_{\mathrm{TOPSIS}} = \frac{S_i^-}{S_i^- + S_i^+} \tag{14}$$

3.3 Simple additive weighting (SAW)

SAW is a multi-attribute decision-making approach based on computing the overall score of each candidate network (alternative) and, then, selecting the candidate network (alternative) having the highest score. The SAW process is carried out as follows [1, 55]:

- Building a decision-making matrix $X_{[M,N]}$ like the matrix presented in (4) where M and N represent the candidate networks (alternatives) and the decision criteria (attributes), respectively.
- Normalizing the decision matrix $R_{[M,N]}$:
  - For benefit criteria:

$$r_{ij} = \frac{x_{ij}}{\sum_{i=1}^{n} x_{ij}} \tag{15}$$

  - For cost criteria:

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

- Obtaining the weight vector representing the importance of attributes. The weight vector is formed as follows:

$$W_j = [w_1, ..., w_n] \quad \text{, where} \quad \sum_{i=1}^{m} w_j = 1 \tag{17}$$

- Evaluating the score of each network and selecting the network having the highest score calculated by the following equation:

$$S_{\text{SAW}} = \sum_{j=1}^{m} r_{ij} W_j \tag{18}$$

4 Motivations and objectives

As stated previously, the network interface selection process is applied to select the best available candidate network among the available ones located in a HWN environment to achieve the ABC. This process is considered as a multiple attribute decision making problem where the candidate radio access technologies (wireless networks) represent the alternatives, while the networks attributes are the decision criteria. For this reason, The MADM are the most widely used algorithms to model and solve the NIS problem. However, they suffer from two drawbacks [25, 26]:

- The first limitation is the rank reversal problem caused by the MADM approaches when ranking the HWN environments' networks. It appears when a wireless network (alternative) is removed from or added to the first decision matrix, which changes the ranking of the networks. The considered HWN environment is composed of three different wireless networks ($Network_1$, $Network_2$, and $Network_3$) ranking score after using a traditional MADM-NIS approach is as follows: $Network_1 > Network_2 > Network_3$. After removing the worst wireless network ($Network_3$), this ranking score becomes as follows: $Network_2 < Network_3$, which results in rank reversal and makes $Netwok_3$ the best one. The rank reversal problem can be remarked if a new network is added to the HWN environment.
- The second limitation is the low efficiency in meeting the user's/service requirements due to the fact that the MADM-NIS approaches always select the wireless network with the highest-ranking score without considering these needs. For example, we take into account a HWN environment composed of two different types of wireless networks ($Network_1$ and $Network_2$); each of which is defined by six network attributes (Cost, Data-Rate, Security, Packet Delay, Packet Jitter and Packet Loss). $Network_1$ has a data rate and packet loss better than $Network_2$. However, the second network is better than the first in term of cost, security, packet jitter and packet delay. When the user equipment runs a streaming service during the vertical handover (PS: The streaming applications require high data ratio and low packet loss), the MADM-NIS approaches always select the network having the highest score even if it does not have a good QoS (high data rate and a low packet loss).

The disadvantages mentioned above can negatively affect the selection of the best wireless network and the user equipment will be chosen and connected to the wrong wireless network during the vertical handover. Therefore, the increase in the number of vertical handovers and that of unnecessary handovers (ping-pong effect) prevents meeting the user and/or service requirements, which minimizes the battery life, maximizes the conception energy of the user terminal, the dissatisfaction of the services' users and the delay of decision-making and enhances the interrupt services, etc.

To avoid all these problems and remedy the limitations of the MADM-NIS approaches. A new weight-assignment technique, called Multi-Objective Whale Optimization Algorithm for NIS (MOWOA-NIS) based on a multi-attribute whale optimization problem, is introduced in this paper. Then, an extended version of the multi-objective whale optimization algorithm, named Guided Population Archive Whale Optimization Algorithm (GPAWOA) [56], is applied to solve the suggested model and overcome the drawbacks of MADM-NIS approaches. The developed technique is named Multi-Objective Whale Optimization Algorithm for NIS (MOWOA-NIS).

The novelty of the current work consists in formulating weights assignment technique as a multi-objective problem composed of three objective functions and applying an extended version of multi-objective whale optimization problem algorithm to solve the formulated problem to obtain the suitable decision criteria weights during the NIS process. Our ultimate objective is to overcome the MADM-NIS drawbacks according to type of ran service, the HWN environments and the chosen MADM approach applied to select the best network interface.

5 Our contribution

In this section,firstly, we introduce a new formulation for weights assignment techniques as a multi-objective optimization problem. Secondly, we expose the Multi-objective Whale optimization algorithm used to obtain the suitable decision criteria weights. Finally, we introduce our algorithm, called Multi-Objective Whale Optimization Algorithm for NIS (MOWOA-NIS), to overcome the limitations of MADM-NIS according to different traffic classes, the HWN environment and the used MADM-NIS approaches, namely TOPSIS and SAW.

5.1 Subjectivity/objectivity weight assessment technique model

In this part, we define the commonly used networks attributes as decision criteria for networks ranking in HWN. Subsequently, the four important traffic classes of the network services are described. Finally, the introduced formulation applied to model the subjective/objective attribute weighting techniques as a multi-objective optimization problem is presented.

Decision criteria

Traditionally, the vertical handover decision uses Revived Signal Strong (RSS) parameter to select the best network. In the latter, the user's equipment ranks the list of the available networks, after comparing the RSS values of each one, and connects it to the wireless network having the biggest RSS value. However, this method does not satisfy the user's and/or service requirements [57, 58]. To overcome this weakness, many metrics were defined to quantify and identify the capacities of the wireless networks and help the mobile users choose, during the vertical handover process, the best network according to these metrics. The latter are classified, in this study, into two types: benefit decision criteria and cost decision criteria. The former (the cost) are requested to be maximized/minimized by the user equipment. In the current work, we consider the six following network attributes as decision criteria (cost per Byte, Security, Data-Rate, Packet Delay, Jitter and Packet Loss) because they are among the widely network attributes-based on the NIS process [1], where:

- Cost per Byte (CB): designates the amount of money spent to upload or download a certain amount of bytes.
- Security (S): is a benefit decision criterion showing the confidence and/or the integrity of data against unauthorized and malicious access attempts.
- Data-Rate (DR): is a benefit decision criterion that expresses the bandwidth offered to each end-user.
- Packet Delay (D): is a cost decision criterion revealing the transfer time of a packet between two interfaces. It is expressed in (ms).
- Packet Jitter (J): depicts the variation of the delay between two consecutive packets.
- Packet Loss (L): is the proportion of packet loss during a given time (expressed in per 10^6).

Traffic classes

- Conversational traffic class: It involves the real-time two-dimensional service. This type of service permits the interaction between two or more end-users. The conversational services have a high requirement for packet jitter and delay.
- Background traffic class: This class includes the non-real-time one-dimensional services run in the background. Background services require rapid reception of data with low packet loss.
- Interactive traffic class contains non-real-time two-dimensional services that require lower packet loss rate and lower packet delay.
- Streaming traffic class: This class involves one-dimensional real-time services usually referring to multimedia content. It needs higher data rate and lower packet loss.

Table 1 shows the four traffic classes, their critical decision criteria and an example of the services belonging to each traffic class.

Problem formulation

As mentioned previously, MADM-NIS suffers from two drawbacks: the rank reversal problem and the lack of QoS consideration when computing the network

Table 1 Traffic classes and QoS requirements in 3GPP

Traffic classes	Description	Critical decision criteria	Application examples
Conversational	Real-time	Packet delay	Video games
	Two-dimensional transport	Jitter	Voice
			Video telephony
Background	Non-real-time	Packet loss	E-mail
	One-dimensional transport		Electronic postcard
Interactive	Real-time	Packet delay	Web browsing
	Two-dimensional transport	Packet loss	Network games
Streaming	Real-time	Data rate	Streaming multimedia
	One-dimensional transport	Packet loss	

attributes' weights assigned by using subjective or objective techniques. The former are based on the experience of the decision-makers, while the latter use mathematical methods to calculate weights based on the initial data.

In this section, we introduce a new formulation to represent subjective/objective attribute weighting techniques modelled as a multi-objective optimization problem. We divide our formulation into three objective functions to combine the subjectivity and objectivity of weights. The first one is applied to reduce the rank reversal problem. However, the second and the third objective functions are used to satisfy the preferences of the application/user by maximizing or minimizing the benefit (cost) of the network attributes. The three objective functions are defined below:

- The first objective function (OF_1) aims at reducing the rank reversal problem resulting from the MADM-NIS approaches. In [43], Almutairi et al. proved that maximizing the summation of the ranking differences of the candidate networks can reduce the rank reversal problem in MADM approaches. Based on this work and through the first objective function, the summation of the absolute value (SV) of the ranking values differences of the candidate networks increases, in the present study, by optimizing and selecting the suitable weights. The SV of the ranking is also improved to reduce the rank reversal problem and achieve the NIS objectivity.

  The used heterogenous wireless networks is composed of N networks and M network attributes. The equation of the SV is given below [43]:

$$\mathrm{OF}_1 = \mathrm{SV} = \sum_{i=1}^{N} \sum_{j=i+1}^{N} |N_i - N_j| \tag{19}$$

  where N_i represents the score of the ith network. As stated above, this model is proposed to optimize the rank reversal of any MADM approach.

  In this study, we address TOPSIS and SAW approaches because they are intensively applied to solve the NIS problem. In the former, N_i is replaced with the TOPSIS coefficient of each network represented in Eq. (14). Thus, the objective function equation for TOPSIS is given as follows [43, 54]:

$$\mathrm{OF}_1 = SV_{\mathrm{TOPSIS}} = \sum_{i=1}^{N} \sum_{j=i+1}^{N} \left| \frac{S_i^-}{S_i^- + S_i^+} - \frac{S_j^-}{S_j^- + S_j^+} \right| \tag{20}$$

where the (S_i^+) and (S_i^-) are outlined by using Eqs. (12) and (13), respectively.

However, the objective function equation for SAW is formulated by substituting the N_i of Eq. (19) by the SAW scoring equation outlined in Eq. (18). It is defined as follows [43, 55]:

$$\mathrm{OF}_1 = SV_{\mathrm{SAW}} = \sum_{i=1}^{N} \sum_{j=i+1}^{N} \left| \sum_{k=1}^{N} r_{ik} W_k - \sum_{k=1}^{N} r_{jk} W_k \right| \tag{21}$$

where W_{ij} designates the weight of the ith network for the jth criteria.

As previously mentioned, the weight vector W was optimized to maximize the summation of the absolute value of the ranking values differences.

- The second objective function (OF_2): aims at providing the QoS required by the user and/or service during the vertical handover by maximizing the critical decision criteria weights of the traffic class ran by the user equipment. Therefore, it Achieves the NIS objectivity and meets the user and/or service preferences. In fact, this objective function is applied to maximize the critical decision criteria of each traffic class summarized in Sect. 5.1 [59, 60]. The objective functions for the Conversational, Background, Interactive, and Streaming traffic classes are defined as follows:

$$\begin{aligned}
\mathrm{OF}_{2\,\text{for Conversational}} &= \text{maximize}(w_{\text{Packet delay}} + w_{\text{Jitter}}) \\
\mathrm{OF}_{2\,\text{for Background}} &= \text{maximize}(w_{\text{Data rate}}) \\
\mathrm{OF}_{2\,\text{for Interactive}} &= \text{maximize}(w_{\text{Packet delay}} + w_{\text{Packet loss}}) \\
\mathrm{OF}_{2\,\text{for Streaming}} &= \text{maximize}(w_{\text{Data rate}} + w_{\text{Packet loss}})
\end{aligned} \tag{22}$$

- The third objective function(OF_3): is used to satisfy the user's and/or service requirements (similar to the second objective function), to minimize the uncritical decision criteria and, thus, to achieve NIS objectivity according to the chosen traffic class. The third objective functions of the Conversational, Background, Interactive, and Streaming traffic classes are written below:

$$\begin{aligned}
\mathrm{OF}_{3\,\text{for Conversational}} &= \text{minimize}(w_{\text{Data rate}} + w_{\text{Packet loss}} + w_{\text{Cost per byte}}). \\
\mathrm{OF}_{3\,\text{for Background}} &= \text{minimize}(w_{\text{Data rate}} + w_{\text{Jitter}} + w_{\text{Packet Delay}} + w_{\text{Cost per byte}}). \\
\mathrm{OF}_{3\,\text{for Interactive}} &= \text{minimize}(w_{\text{Data rate}} + w_{\text{Jitter}} + w_{\text{Cost per byte}}). \\
\mathrm{OF}_{3\,\text{for Streaming}} &= \text{minimize}(w_{\text{Jitter}} + w_{\text{Delay}} + w_{\text{Cost per byte}}).
\end{aligned} \tag{23}$$

PS: The second and third objective functions aims at meeting the service requirements. To satisfy the user's requirements, the list of critical and uncritical networks' attributes should be determined, according to the preferences of the user equipment, and the objective functions have to be formulated.

5.2 Multi-objective whale optimization algorithm for network interface selection

In this section, we define the developed new technique, named multi-objective whale optimization algorithm for NIS (MOWOA-NIS), applied to obtain the suitable decision criteria of the networks' attribute according to the user and/or service requirements and, therefore, improve the performance of MADM-NIS approaches by reducing (or avoiding) the rank reversal problem and meeting the user/service characteristics. This technique uses an extended version of the whale optimization algorithm, called Guided Population Archive Whale Optimization Algorithm (GPAWOA), utilized to solve the multi-objective problem introduced in Sect. 5.1.

In the latter, we first highlight the main mechanisms used in GPAWOA algorithm. Then, we illustrate how GPAWOA is modelled to solve the proposed multi-objective problem and compute the appropriate weights of the decision criteria in order to overcome the MADM approaches limitations. In our work, we try to enhance two MADM approaches: TOPSIS and SAW.

5.2.1 Multi-objective whale optimization algorithm

Guided Population Archive Whale Optimization Algorithm (GPAWOA) [56] extends the original whale optimization algorithm [61] by adding two new components: an external archive and a leader selection strategy. The GPAWOA uses Pareto dominance and crowding-distance computation to obtain the Pareto front. In the following sub-sections, the mechanisms used in the proposed algorithm are described.

External archive

To solve a single objective problem, a meta-heuristic optimization algorithm chooses, for each iteration, only one leader optimal solution. Nevertheless, in multi-objective objective problems, the objective of a meta-heuristic optimization algorithm is to find the Pareto front defined by a set of non-dominated solutions.

The external archive is applied in GPAWOA to store and retrieve the non-used solutions in order to find Pareto optimal front. This mechanism is composed of two parts: an archive controller and a crowding distance approach employed to maintain the diversity of the proposed solutions.

The former is used to control the external archive. It is responsible for adding (or removing) a new-dominated solution to (from) the external archive. When a new non-dominated solution is generated, the archive controller applies the rules stated below:

- If the new non-dominated solution is neither dominated by any archive member nor dominates it, it should be added to the archive.
- If the new non-dominated solution dominates some element(s) of the archive residence(s), the archive controller allows the new non-dominated solution to enter the archive and replace the dominated archive residence(s).
- If, at least, one archive dominates the new non-dominated solution, the archive controller will not add the new non-dominated solution.

- If the external archive is full and a new non-dominated solution should be added to the external archive, the most crowded archive element is removed from the archive and replaced by the new non-dominated solution. The crowding distance computation algorithm is also applied to calculate each archive element's crowding value and maintain the diversity of Pareto front [62].

Crowding distance Computation Crowding distance allows assessing a solution's density according to its surrounding solutions [63]. Thus, to compute the crowding distance value of the objective function solutions, the latter are sorted in descending order. Then, the first and the last solutions having the biggest and the lowest objective function values are given an infinite crowding distance value. After that, the crowding distance of solution S_i is considered as the average distance of its two neighbouring solutions S_{i+1} and S_{i-1}, as shown in Fig. 1. Finally, the final crowding distance of each solution is computed by summing all the crowding distances in each objective function. The pseudo-code used in the crowding distance algorithm is described in algorithm 1.

Algorithm 1 Crowding distance computation algorithm

Inputs: P: set of non-dominated solutions, N: size of the non-dominated solutions (P), M: number of the objective functions.
Output: Crowding distance of the non-dominated solutions $P[i]_{crowding\_distance}$

```
for i ← 1...N do
    P[i]_crowding_distance ← 0;
end for
for each objective function m do
    I ← Sort(P,m);
    for i ← 2to(M − 1) do
        P[i]_crowding_distance ← P[i]_crowding_distance + (I[i + 1] − I[i − 1]);
    end for
    I[1] ← ∞;
    I[M] ← ∞;
end for
    return P[i]_crowding_distance
```

5.2.2 Multi-objective whale optimization algorithm for network interface selection

The Guided Population Archive Whale Optimization Algorithm (GPAWOA) is applied, in the proposed technique MOWOA-NIS, to compute and optimize decision criteria weights of the NIS problem. the GPAWOA in NIS is modelled as follows:

– Each weight is represented by a number in the interval [0,1].

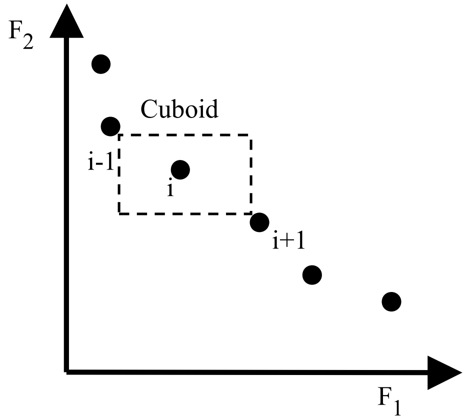


Fig. 1 Crowding distance computation

- An agent (whale) is an array of weights $W_{[M]}$ where M is the maximum number of the network attributes, and W_i, denotes the weight of the ith network attribute. All the whales should respect the following constraints:

$$\sum_{i=i}^{M} W_i = 1 \tag{24}$$

$$\sum_{i=i}^{M} 0 \leq W_i \leq 1 \tag{25}$$

- The external archive is represented by a matrix $A_{sm}, m \leq M, s \leq S_{\text{ext}}$ where S_{ext} designates the size of the archive. The introduced technique is based on the assumption that the number of whales is equal to the archive size.

The different steps of the MOWOA-NIS technique are detailed below:

- Inputs:

1. $HWN_{[NM]}$: the matrix of the parameters which represents the HWNs environment. It is composed of N networks and M decision criteria.
2. The type of service ran in the user's equipment (the traffic class).
3. The type of MADM-NIS approach applied to rank the available candidate networks located in the HWN environment (either TOPSIS or SAW).

In fact, the vertical handover process consists of three phases: handover information gathering, handover decision and handover execution. The input values are collected (sometimes estimated) in the first phase of vertical handover.

- Step 1: Classifying the decision criteria into two lists according to the traffic class ran by the user equipment during the vertical handover (as described in Sect. 5.1):
  - L_{critical} : List of critical decision criteria.
  - $L_{\text{uncritical}}$: List of uncritical decision criteria.
- Step 2: Calculating and optimizing the weights of the suitable decision criteria by using the GPAWOA algorithm. As mentioned above, the weights are optimized using the following metrics: the type of MADM-NIS approach applied to rank the candidate networks, the type of the traffic class run during the network interface selection process, the list of the critical and uncritical decision criteria, and the HWN environment. The first parameter is used to determine the first objective function (Eq. 19); whereas the second and third metrics are applied to determine the second and the last objective functions Eqs. (20) and (21). However, the last metric is employed to optimize the weights of decision criteria and rank the candidate wireless networks composed of the HWN environments (as described in Sect. 3). The suitable weights are obtained by :

  1. Determining the size of the external archive S_{ext} and the number of iterations $T_{\max}$.
  2. Specifying the objective functions according to the MADM-NIS approach used to rank the candidate networks and based on the traffic class of the service run in the user's equipment (as shown in Sect. 5.1).
  3. Initializing the GPAWOA Algorithm through generating randomly an initial population represented by a vector of decision criteria weights $Int_{[I_s,M]}$ where I_s is the size of the initial population and M denotes the number of the decision criteria problems. To maintain a better diversity between the decision criteria weights of the initial population's elements, the size of the initial population must be bigger than (or equal to) the size of the external archive ($S_{\text{ext}} \leq I_s$). Each element of the initial solution, should respect:
     - $Int_{i,L_{\text{critical}}} > Int_{i,L_{\text{uncritical}}}$ to meet the traffic class requirements.
     - The constraints mentioned in Eqs. (24) and (25) .
  4. Finding the non-determined elements from the initial generation, and storing them in the external archive by using the crowding distance computation algorithm, as described in Sect. 5.2.1.
  5. For each iteration $t_{\max}$:
     (a) Sort the external archive solutions in a descending order depending on the crowding distance value to achieve the diversity and great convergence for Pareto front [56]. The crowding distance value is obtained by applying the three objective functions described in Sect. 5.1.
     (b) Select one of the less crowded solutions to achieve the diversity of solutions in the Pareto front (one of the 40% highest solution). The selected solution is used as a leader (best solution) to guide the popu-

lation toward a very accurate approximations of the true Pareto front. The crowding distance is calculated as described in Sect. 5.2.1.

(c) Run the whale optimization algorithm to discover new agents (decision criteria weights) by employing the exploitation and exploitation phases defined in [64].
(d) Save all the obtained solutions in a temporary matrix.
(e) Remove the solutions that do not respect the above-cited constraints.
(f) Update the external archive by using the function described in Sect. 5.2.1.
(g) The output of this step is the residents of the external archive (the suitable decision criteria weights of the NIS problem) representing the Pareto front.

The output of this step is the residents of the external archive (the suitable decision criteria weights of the NIS problem) representing the Pareto front.

- Step 3: Selecting a random solution (weight) from the external archive. This solution will be used as decision criteria weights for the current configuration. All solutions located inside the external archive are considered as suitable weights for solving the current NIS problem.

After selecting the suitable decision criteria, the chosen MADM-NIS approach ranks the best candidate network located in the HWN according to the score of each network. Afterwards, the network having the highest ranking score will be selected.

5.2.3 Complexity analysis

In this section, we analyse the computational and the space complexity of our proposal.

Computational complexity

The computational complexity of MOWOA-NIS is mainly induced by the first and the second steps because, in the third step of the proposed technique, a simple selection method that takes a constant time $O(1)$ is used, as illustrated in Table 2. Thus, complexity of this 3d step can be neglected and the overall computational complexity of MOWOA-NIS can be expressed as follows:

$$O(\text{MOWOA-NIS}) = O(Step_1 + Step_2) \tag{26}$$

where $Step_1$ and $Step_2$ denote the time complexity of the first and second steps, respectively.

In the first step, the decision-maker determines the list of critical decision criteria L_{cl} and that of uncritical decision criteria L_{uc} (PS: $\|L_{uc} + L_{uc}\| = M$ where M

Table 2 The complexity of MOWOA-NIS approach

MOWOA-NIS approach steps	Time complexity	Space complexity
Inputs: $HWN_{[N,M]}$, the type of service ran in the user's equipment, the type of MADM-NIS approach used to select the best candidate network.	$O(1)$	$O(M \times N)$
Step 1: Determining the list of critical and uncritical decision criteria.	$O(M)$	$O(M)$
Step 2:		
Initialization:		
– Specifying S_{ext}, $T_{\max}$, and I_s.	$O(1)$	$O(1)$
– Determining the objective functions.	$O(F)$	$O(F)$
– Determining the upper and lower bounds of multi-objective problem.	$O(2M)$	$O(2M)$
Applying the GPAWOA algorithm for $T_{\max}$ times to optimize the external archive $Ext_{[S,M]}$ and, thus, to obtain the suitable decision criteria weights of the NIS problem .	$O(OjbCost \times {S_{\mathrm{ext}}}^2)$	$O(I_s + 2S_{\mathrm{ext}})$
Step 3: Selecting randomly a suitable solution (a vector M of weights) from the external archive.	$O(1)$	$O(M)$

represents the number of decision criteria). Thus, the computational complexity of the first step is calculated as demonstrated below:

$$O(Step_1) = O(M) \tag{27}$$

The second step consists mainly in initializing the GPAWOA algorithm and, then, applying it to obtain the suitable weights of the networks' attributes of the heterogeneous wireless environment $HWN_{[N,M]}$ where N corresponds to the number of networks (alternatives). Besides, the complexity of the second step is expressed as follows:

$$O(Step_2) = O(Cost_{\text{of}} Initialitation + Cost_{\text{of}} GPAWOA) \tag{28}$$

where $Cost_{\text{of}} Initialitation$ and $Cost_{\text{of}} GPAWOA$ refers to the complexity of the initialization and the GPAWOA algorithm, respectively.

The computational complexity of the initialization sub-step, as illustrated in Table 2, is accomplished as follows:

$$O(Cost_{\text{of}} Initialitation) = O(F + 2M) = O(M) \tag{29}$$

where F represents the total number of objective functions. In the introduced technique, $O(F)$ can be realized in constant time because 3 objective functions ($F = 3$) are used.

However, complexity of GPAWOA algorithm is $O(OjbCost \times {S_{\text{ext}}}^2)$, as proven in [56] where $OjbCost$ refers to the complexity of the objective functions and S_{ext} denotes the size of the external archive. Thus, GPAWOA complexity in the introduced technique MOWOA-NIS is calculated as follows:

$$\begin{aligned} O(Cost_{\text{of}} GPAWOA) &= O(\text{GPAWOA}) \\ &= O((OjbCost1 + OjbCost2 + OjbCost3) \times {S_{\text{ext}}}^2) \end{aligned} \tag{30}$$

where $OjbCost1$, $OjbCost2$ and $OjbCost3$ refer to the complexity of the first (19), second (22) and third (23) objective functions, respectively.

The complexity of the first objective function (Eq. 19) depends on the applied MADM approach to sum the absolute values of the ranking values of the candidate networks. Therefore, it is calculated as demonstrated below:

- if using TOPSIS, to calculate the first objective function, defined in Eq. (20), $2N^2$ should be added and $2N^2$ must be multiplied [43]. Moreover, it requires $2M$ additions and $2M$ multiplications to compute the S_i^+ and S_i^- defined in Eqs. (12) and (13), respectively. Subsequently, the computational complexity of the first objective function obtained using TOPSIS as a ranking method is:

$$\begin{aligned} O(\text{OjbCost1}_{\text{TOPSIS}}) &= O(2M + 2M + 2N^2 + 2N^2) \\ &= O(4M + 4N^2) \\ &= O(M + N^2) \end{aligned} \tag{31}$$

- when using SAW approach, as described in Eqs. (19) and (21), the first objective function requires $2 \times M$ multiplications and $2 \times M \times N^2$ additions [43]. Besides, the computational complexity of the first objective function obtained when using SAW as a ranking method is presented below:

$$\begin{aligned} O(\text{OjbCost1}_{\text{SAW}}) &= O((2 \times M) + (2 \times M \times N^2)) \\ &= O(2 \times M \times N^2) \\ &= O(M \times N^2) \end{aligned} \tag{32}$$

The complexities of the second and third objective functions are constant. They are accomplished in constant time ($O(1)$) because they are composed of simple addition operators, as illustrated in Eqs. (22) and (22).

Therefore, from the above-determined Eqs. (26) to (32), we can conclude that the computational complexity of the introduced technique (MOWOA-NIS) is obtained as follows:

- In case of applying TOPSIS as a ranking approach:

$$\begin{aligned} O(\text{MOWOA-NIS}) &= O(Step_1 + Step_2) \\ &= O(Step_1 + Cost_{\text{of}} Initialitation + Cost_{\text{of}} GPAWOA) \\ &= O(M + M + (M + N^2) \times {S_{\text{ext}}}^2) \\ &= O(2M + M \times S^2 + N^2 \times {S_{\text{ext}}}^2) \end{aligned} \tag{33}$$

- In case of applying SAW as a ranking approach:

$$\begin{aligned} O(\text{MOWOA-NIS}) &= O(Step_1 + Step_2) \\ &= O(Step_1 + Cost_{\text{of}} Initialitation + Cost_{\text{of}} GPAWOA) \\ &= O(M + M + (M \times N^2) \times {S_{\text{ext}}}^2) \\ &= O(2M + M \times N^2 \times {S_{\text{ext}}}^2) \\ &= O(M \times N^2 \times {S_{\text{ext}}}^2) \end{aligned} \tag{34}$$

Space complexity Firstly, the proposed technique needs $O(M \times N)$ to store the HWNs environment, as illustrated in Table 2. Moreover, space complexity of the first step can to store theHWNs environment, as illustrated in Table 2. Moreover, space complexity of thefirst step can be expressed by:

$$O(L_{\text{cl}} + L_{\text{un}}) = O(M) \tag{35}$$

because the introduced algorithm requires a vector of M size to save the list of critical and uncritical decision criteria. The space complexity of the second step is defined as:

$$O(F + 2M + I_s + 2S_{\text{ext}}) \tag{36}$$

where $O(F)$ and $O(2M)$ are applied to memorize the objective functions and the upper and lower bounds of the multi-objective problem, $O(I_s)$ is used to store the

Table 3 Decision criteria weights computed by AHP

	CB	S	DR	D	J	PLR
$W_{\text{conversational}}$	0.036	0.124	0.104	0.325	0.307	0.102
$W_{\text{Background}}$	0.085	0.155	0.441	0.051	0.079	0.186
$W_{\text{Interactive}}$	0.078	0.174	0.092	0.309	0.050	0.294
$W_{\text{Streaming}}$	0.101	0.195	0.297	0.092	0.119	0.192

Table 4 Attributes values for the candidate networks

Tech-nolo-gies	Cost per byte	Security (%)	Data rate (mbps)	Packet delay (ms)	Packet jitter (ms)	Packet loss ratio (10^{-6} ms)
WIFI	5–10	50	1–11	100–150	10–20	20–80
WiMax	40–50	60	1–60	60–100	3–10	20–80
UMTS	60–80	70–90	0.1–2	25–50	5-10	20–80
LTE	40–50	60	2–100	50–300	3–12	20–80

generated initial population where I_s refers to the size of the initial population, and $O(S_{\text{ext}})$ is employed to memorize the external archive. Finally, the last step has a constant space complexity because the random vector selected from the external archive is used as weights decision criteria to solve the NIS problem. Therefore, the space complexity of the MOWOA algorithm is expressed as follows:

$$O(\text{MOWOA-NIS}) = O(F + 3M + I_s + 2S_{\text{ext}} + M \times N) \tag{37}$$

6 Experimental results

We expose, in this section, the performance of our proposed technique when combined with MADM-NIS approaches, namely TOPSIS and SAW. We used MATLAB to simulate HWN environments. We considered four types of radio access networks; each of which has six network attributes (Cost per Byte (CB), Data-Rate (DR), Security (S), Packet Delay (D), Packet Jitter (J) and Packet Loss (L)). These attributes are defined as shown in Tables 3, 4.

We conducted simulations rather than considering a real testbed environment for two important reasons. Firstly, to evaluate NIS algorithm by using a testbed, the user equipment spends long time to gather and estimate the information of each candidate wireless networks located in the HWN environment (the gathering information phase of vertical handover process). In addition, the ranking as well as the creation of links between the user's equipment and the chosen wireless network (Handover execution phase) and, consequently, the communication and connection between the user equipment and the different candidate wireless networks are time consuming. Secondly, simulations allow obtaining the results faster than testbeds. However, as the calculation of the average of rank reversal phenomena (for example) for 10^3 iterations is time consuming when a testbed is used, most of the research works solved the network interface selection problem by simulations to evaluate the performance of their contributions.

MATLAB was used as a simulator because it is a matrix-based language, and the HWN environments were modelled as a matrix of N networks and M decision criteria. In addition, the MADM approaches utilized the notion of the matrix to solve the multi-objective problems.

To evaluate the performances of MOWOA-NIS, we performed two simulations. The first simulation ran for 10^3 iterations. In this simulation, we calculated the rank reversal ratio of the four traffic classes according to the number of networks by applying the two following scenarios:

- Removing the worst network scenario: It consists first in ranking the original matrix of candidate networks and, then, removing the network having the lowest scoring value. Afterwards, the obtained matrix was re-ranked. Finally, to test the occurring of rank reversal ratio, the rank of candidate networks of the original and the obtained matrices were compared.
- Removing the best network scenario: In this scenario, the network having the highest score rank was deleted instead of the lowest scoring value.

The second simulation was run for 10^3 iterations. We evaluated, in this simulation, the performance of the proposed technique in term of satisfying the application requirements by calculating the average selected networks' attribute values for a streaming service.

In the two simulations, the performances of MOWOA-NIS were compared with that of the conventional weight technique method (AHP) when used with TOPSIS and SAW approaches for the four traffic classes. Therefore, TOPSIS-MOWOA-NIS and SAW-MOWOA-NIS were compared to the conventional NIS approaches (TOPSIS-AHP and SAW-AHP) for the four traffic classes.

For the conventional TOPSIS and SAW approaches, the weights obtained by the AHP technique were used in all iterations. However, new decision criteria weights were obtained at each iteration according to the type of the MADM approach and that of the traffic class. Moreover, Eqs. (20) and (21) were considered as the first objective functions in TOPSIS and SAW, respectively. In all simulations, the size of the external archive was randomly equal to 100, and the number of initial generations and the number of iterations was 200.

In the analytical hierarchy process (AHP), a weighting assessment technique was used in MADM approaches to obtain the weights of decision criteria, depending on the importance of each decision criterion compared to other decision criteria. The AHP decision criteria weights considered in the four used traffic classes are shown in Table 3. They are based on [43].

6.1 Simulation 1: Study of the rank reversal ratio

The simulation results of rank reversal ratio obtained by TOPSIS-NIS and SAW-NIS approaches are depicted respectively in Figs. 2, 3, 4, and 5 simulating the removal of the worst network and that of the best network scenarios. Each figure represents the rank reversal ratio of the conversational, background, interactive and streaming traffic classes. The performance of the suggested technique (MOWOA-NIS) is compared with that of AHP technique.

In the scenario of removing the worst network, MOWOA reduced the RRP for TOPSIS. Hence, the rank reversal ratio varied between 0% and 3% regardless of the number of candidate networks, as shown in Fig. 2. In SAW, MOWOA technique avoided the occurring of RRP, as depicted in Fig. 3. Except in rare cases, if the number of candidate networks was, for instance, less than 5, the ratio of RRP could range from 1% to 4%. However, only the conventional TOPSIS and SAW approaches, which use the AHP technique to obtain the decision criteria, provided a rank reversal ratio directly proportional to the number of the candidate networks. For example, the rank reversal ratio was 13% if the HWN was

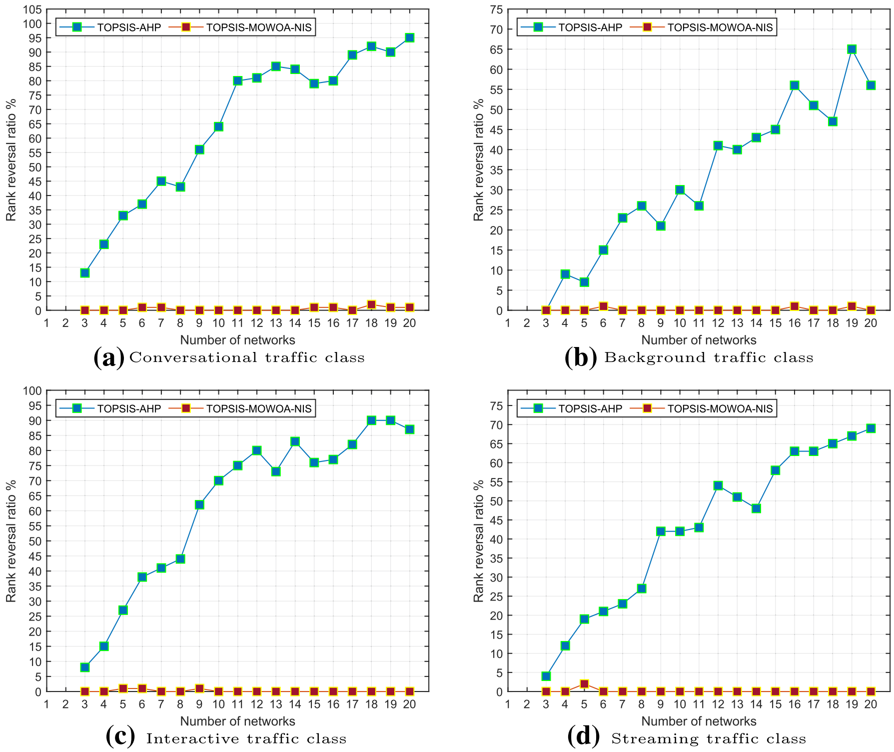
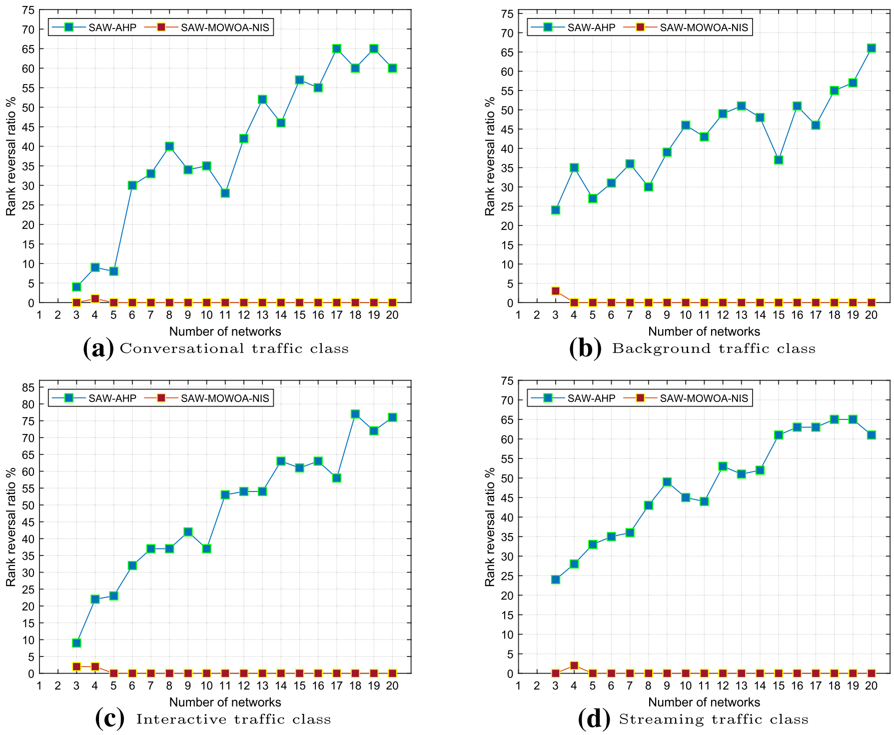


Fig. 2 Rank reversal ratio when removing the worst network for TOPSIS-NIS



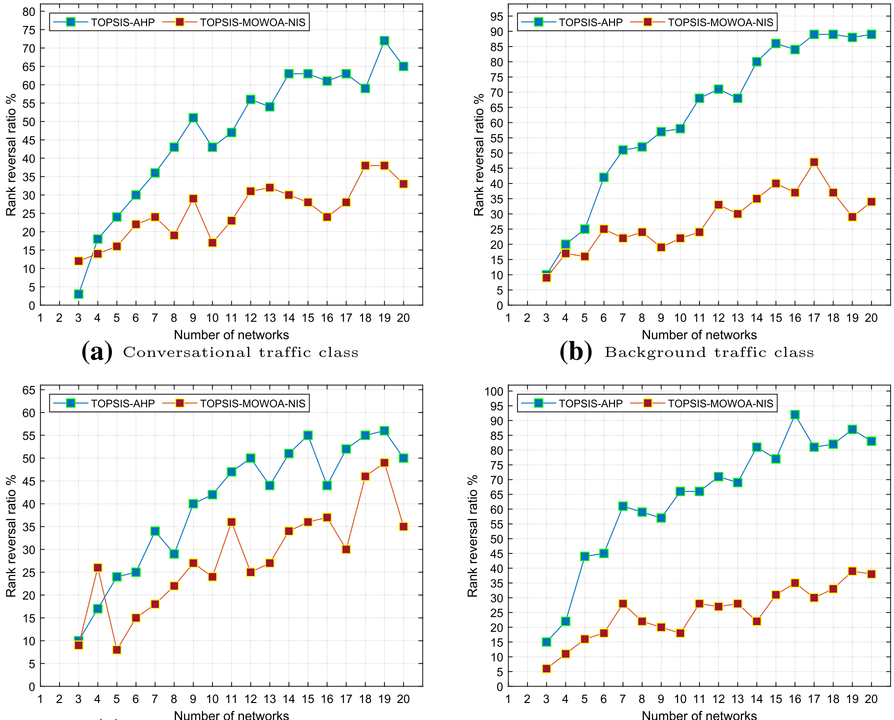
(a) Conversational traffic class
(b) Background traffic class
(c) Interactive traffic class
(d) Streaming traffic class

Fig. 3 Rank reversal ratio when removing the worst network for SAW-NIS

composed of 3 networks. However, it reached 95% when the number of networks was equal to 20, as displayed in Fig. 2a.

Interestingly, the percentage of the rank reversal problem obtained by the conventional MADM approaches was high in the best network removal scenario, as illustrated in Figs. 4 and 5. In fact, a positive correlation between the latter and the increase in the number of networks was observed. For example, by applying TOPSIS, the percentage of rank reversal was enhanced from 3% to 72%, from 10% to 89%, from 10% to 56%, and from 15% to 92%, as shown in Fig. 5. However, the developed technique reduced the percentage of rank reversal phenomenon in TOPSIS to the following values (12%-38%, 9%-47%, 8%-49%, 6%-39%) in conversation, background, interactive, and streaming traffic classes, respectively. Nevertheless, in some rare cases, the performance of the conventional TOPSIS was better than that of TOPSIS-MOWOA-NIS, especially when the number of networks was lower than 5 for the conversational and interactive traffic classes. On the other hand, the MOWOA avoided completely the rank reversal in SAW approach. Except in rare cases, if the number of wireless networks was, for instance, less than 6, the ratio of rank reversal could range from 1% to 4%.

The main conclusions of this first simulation are summarized below:



(a) Conversational traffic class

(b) Background traffic class

(c) Interactive traffic class

(d) Streaming traffic class

Fig. 4 Rank reversal ratio when removing the best network for TOPSIS-NIS

- The number of networks affected the rank reversal ratio in a directly proportional manner for TOPSIS-AHP and SAW-AHP in the two scenarios of all traffic classes.
- For the two scenarios, TPOPSIS-AHP and SAW-AHP suffered from rank reversal regardless of the type of the used traffic class. On the other hand, by combining the introduced technique (MOWOA-NIS) with TOPSIS and SAW, the rank reversal ratio was reduced for all traffic classes, except in some rare cases (e.g. removing the best network scenario, in conversational and interactive traffic classes where the HWNs are composed of 3 or 4 networks).
- The MOWOA-NIS avoided the rank reversal ratio when SAW approach was used in the two scenarios: removing the worst and removing the best networks.
- The MADM-NIS approaches were not affected by the number of networks when MOWOA-NIS was used, unlike AHP technique.

We conclude that, by applying MOWOA-NIS technique, the performance of MADM approaches (especially TOPSIS and SAW approaches) can be improved by reducing more the risk of the rank reversal problem, compared to the original MADM approaches (TOPSIS-AHP and SAW-AHP).

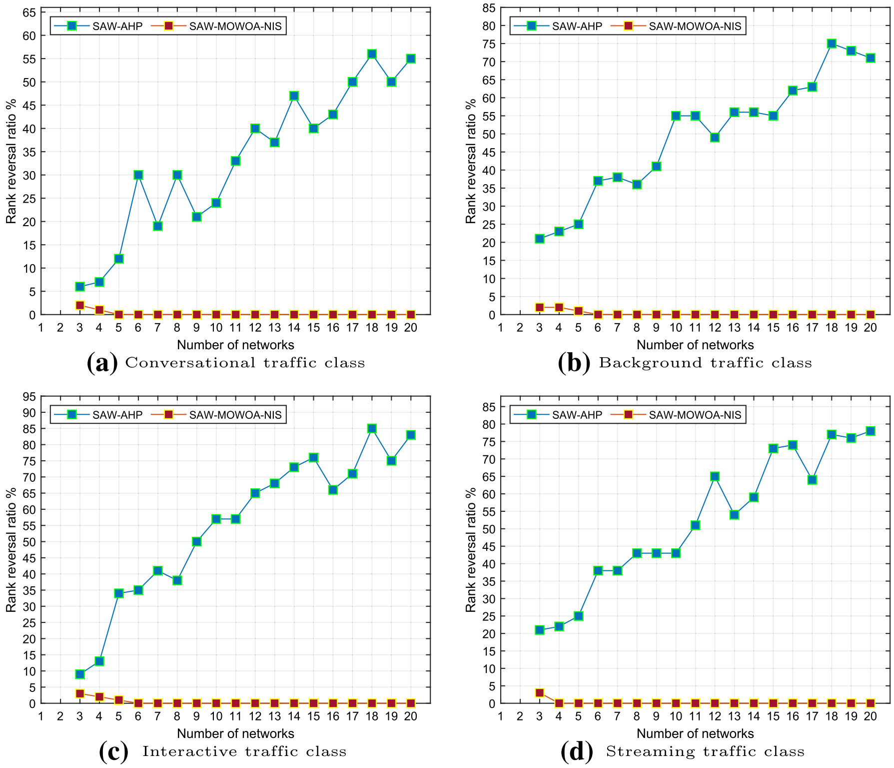


Fig. 5 Rank reversal ratio when removing the best network for SAW-NIS

6.2 Simulation 2 : QoS performances

Figure 6 depicts the mean values for selected network attributes of all algorithms (TOPSIS with AHP, TOPSIS with MOWOA-NIS, SAW with AHP and SAW with MOWOA-NIS) applied with a streaming traffic. Mini-figures (a), (b), (c), (d), (e) and (f) show the mean values of selected networks attributes of data rate, packet loss ratio, cost per byte, security, packet delay and packet jitter , respectively.

We compared the average selected networks attributes values provided by TOPSIS-AHP with those obtained by using TOPSIS-MOWOA-NIS and SAW-AHP with SAW-MOWOA-NIS. We notice that the proposed technique increased the data rate by 10 kbps and 14 kbps for TOPSIS and SAW, respectively. It also reduced the packet loss ratio of TOPSIS and SAW, respectively, by an average of 20×10^6 ms and $15.6ms \times 10^6$ ms, consequently, minimized the PLR of TOPSIS to 35.9×10^6 ms and SAW to 26×10^6.

Although the security, packet delay, and packet jitter are non-critical decision criteria, the MOWOA-NIS technique could optimize them in SAW approach (by an average of 8%, 4.8 ms, and 4.4 ms), it also minimized the packet jitter in TOPSIS approach (by an average of 5 ms), compared to the AHP technique.

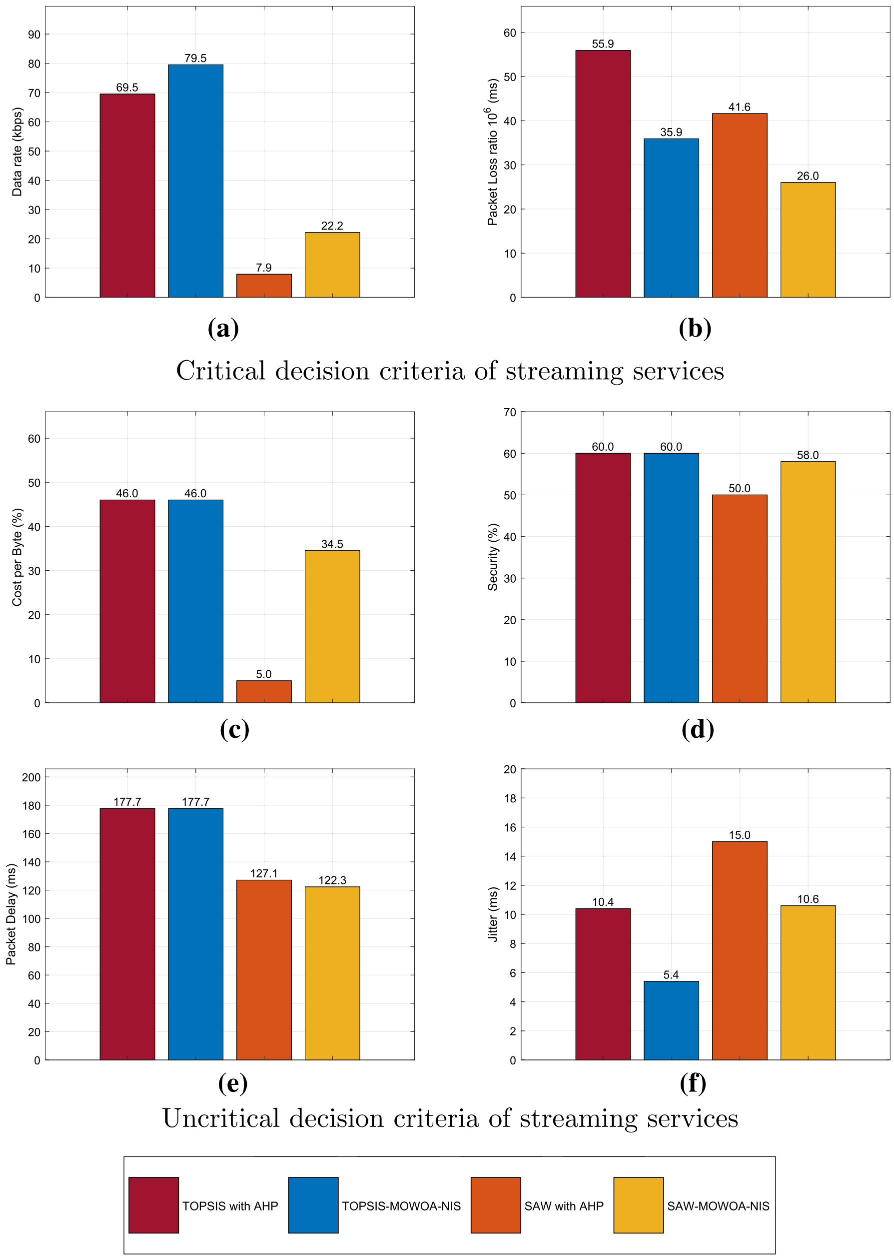


Fig. 6 Mean values of selected networks' attributes for streaming traffic class

From the simulation results, we conclude that, unlike the conventional TOPSIS and SAW approaches, the technique developed in this work can enhance the MADM-NIS approaches and allow meeting the service requirements.

Finally, it is obvious that combining the introduced method with MADM-NIS approaches, especially with TOPSIS and SAW approaches, made possible to achieve the NIS objectivity, by reducing the rank reversal problem, and the NIS subjectivity by meeting the service requirements. Therefore, MOWOA-NIS can overcome the MADM limitations and give better results than the conventional MADM-NIS approaches. However, in term of complexity, it is more difficult to implement and more time consuming than the AHP technique.

7 Conclusion

MADM-NIS are the most commonly used approaches to solve the network interface selection problem. Although they are easy to understand and implement and can support real-time scenarios and high decision making, they suffer from the rank reversal phenomena.

In this paper, we introduced a novel weighting assessment technique, called multi-objective whale optimization algorithm (MOWOA), that can overcome the MADM-NIS drawbacks. MOWOA can be combined with any multi-attribute decision-making approach to obtain the optimal decision criteria's weights, reduce the rank reversal problem and meet the user's/service requirements. The weights assignment techniques were first modelled as a multi-objective problem. Then, an extended version of the whale multi-objective whale optimization algorithm was applied to overcome the limitations of MADM approaches (TOPSIS and SAW).

We proved, through extensive MATLAB simulations, that our approach outperforms the AHP technique as it allowed reducing the rank reversal problem of TOPSIS and SAW approaches and satisfying the traffic classes requirements.

Furthermore, when applied in SAW approach, the introduced technique (MOWOA-NIS) avoided completely the rank reversal problem regardless of the number of candidate networks, the type of scenario (worst network removal or the best network removal scenarios) and the type of traffic classes (conversational, background, interactive, or streaming). Except in some rare situations, the average of rank reversal problem varied between 0% and 4%. However, the AHP technique suffered from this phenomenon in a directly proportional manner to the number of candidate networks.

When applied in TOPSIS approach, the MOWOA-NIS technique reduced the rank reversal problem ratio in the worst removal and the best removal scenarios more than AHP technique by an average up to 94%. However, the AHP always suffered from the rank reversal in a directly proportional manner to the number of candidate networks.

In term of satisfying the service requirements, the MOWOA-NIS optimized the QoS requirements by reducing the packet loss ratio and increasing the data rate of streaming applications, thus, performing better than AHP technique. Moreover, it increased the data rate by 10 kbps and 14 kbps for TOPSIS and SAW, respectively. It also minimized the packet loss ratio of TOPSIS and SAW by an average up to 20×10^6 ms and 15.6×10^6 ms, respectively. In addition, the MOWOA-NIS enhanced non-critical decision criteria such as the security, packet delay, and packet

Table 5 List of abbreviations

Acronym	Explanation
ABC	Always best-connected
AHP	Analytical hierarchy process
AHP-NIS	Analytical hierarchy process -based approaches for NIS
ANN-NIS	Artificial neural networks-based approaches for NIS
CB	Cost per Byte
COCOSO-NIS	The combined compromise solution for NIS
CRITIC	Combined Chi-square distance algorithm with entropy method, criteria importance through intercriteria correlation
CV	Coefficient variation
D	Packet delay
DIA	The distance to the ideal alternative
DR	Data-rate
F	The number of objective functions
FAHP	Fuzzy analytic hierarchy process
FANP	Fuzzy analytic network process
FL-NIS	Fuzzy logic-based NIS
GPAWOA	The guided population archive whale optimization algorithm
GRA-NIS	Gray relational analysis-based approaches for NIS
GT-NIS	Game theory-based NIS
HWN	Heterogeneous wireless networks
$HWN_{[N,M]}$	A heterogeneous wireless networks environment of M decision criteria and N wireless networks
INFAHP	Intuitionistic normal fuzzy analytic hierarchy process
I_s	The size of the initial population
J	Packet Jitter rate
Kbps	Kilobits per second
L	Packet loss rate
L_{cl}	The size of the critical decision criteria list
L_{un}	The size of the uncritical decision criteria list
M	The number of decision criteria
MADM	Multi-attribute decision-making
MADM-NIS	Multi-attribute decision-making approaches-based NIS
MCDM	Multi-criteria decision-making
MDP-NIS	Markov decision process-based approaches for NIS
MOWOA	Multi-objective whale optimization algorithm
MOWOA-NIS	multi-objective whale optimization algorithm for the NIS problem
MPO	Multi-objective optimization problem
Ms	millisecond
N	The number of available wireless networks in the HWN environment
NIS	Network interface selection
OjbCost	The cost of the objective functions
QoS	Quality of service
Rats	Radio access technologies

Table 5 (continued)

Acronym	Explanation
RRP	Rank reversal problem
RSS	Received signal strength
S	Security
S_{ext}	The size of the external archive
SAW	Simple additive weighting
SAW-NIS	Simple additive weighting-based approaches for NIS
SD	Standard deviation
SI-MAAR	Simplified and improved multiple attributes alternate ranking
SV	The summation of the absolute value
T_{max}	The maximum number of GPAWOA iterations
TOPSIS	Technique for order preference by similarity to ideal solution
UF-NIS	Utility function-based NIS
VHO	Vertical handover process
VIKOR-NIS	ViseKriterijumsa Optimizacija I Kompromisno Resenje-based approaches for NIS
Wi-Fi	Wireless Fidelity
WiMAX	Worldwide interoperability for microwave access
WPM-NIS	Weighted product model-based approaches for NIS
2G	2nd Generation mobile networks
3G	3th Generation mobile networks
3GPP	The 3rd Generation partnership project
4G	4th Generation mobile networks
5G	5th Generation mobile networks
6G	6th Generation mobile networks

jitter in SAW approach (by an average of 8%, 4.8 ms, and 4.4 ms) and it reduced the packet jitter in TOPSIS by 5 ms.

8 Future works

As a future work, we are willing to investigate whether other optimization techniques would reduce time complexity. Moreover, we intend to apply other multi-objective meta-heuristic algorithms rather than the multi-objective whale optimization algorithm and compare their performances in terms of time complexity, rank reversal problem, and user/application requirements' meeting.

Furthermore, our research covered so far several HWN environments since we considered several common radio access technologies (Wi-Fi, WiMax, UMTS, and LTE). However, 5G heterogeneous ultra-dense networks may present specific characteristics and performances against the rank reversal problem and the QoS satisfaction. Further investigations and experimentation on 5G environments will be conducted in order to evaluate the performance of the introduced algorithm in a HWN environment involving 5G network (Table 5).

Funding Not applicable.

Availability of data and material Not applicable.

Code availability Not applicable.

Declarations

Conflict of interest Not applicable.

References

1. Wang L, Kuo GSG (2012) Mathematical modeling for network selection in heterogeneous wireless networks–a tutorial. IEEE Commun Surv Tutorials 15(1):271–292
2. Gustafsson E, Jonsson A (2003) Always best connected. IEEE Wirel Commun 10(1):49–55
3. Kassar M, Kervella B, Pujolle G (2008) An overview of vertical handover decision strategies in heterogeneous wireless networks. Comput Commun 31(10):2607–2620
4. Trestian R, Ormond O, Muntean GM (2012) Game theory-based network selection: Solutions and challenges. IEEE Commun Surv Tutorials 14(4):1212–1231
5. Senouci MA, Souihi S, Hoceini S, Mellouk A (2016) Qoe-based network interface selection for heterogeneous wireless networks: a survey and e-health case proposal. In: 2016 IEEE Wireless Communications and Networking Conference. IEEE; pp 1–6
6. Xiao K, Li C (2018) Vertical handoff decision algorithm for heterogeneous wireless networks based on entropy and improved TOPSIS. In: 2018 IEEE 18th International Conference on Communication Technology (ICCT). IEEE; pp 706–710
7. Zhong Y, Wang H, Lv H (2020) A cognitive wireless networks access selection algorithm based on MADM. Ad Hoc Netw 109:102286
8. Chattate I, Khaili M, Bakkoury J (2019) A new fuzzy-TOPSIS based algorithm for enhancing decision making in a heterogeneous network. J Commun. 14(3):194–201
9. Mansouri M, Leghris C (2020) A use of fuzzy TOPSIS to improve the network selection in wireless multiaccess environments. J Comput Netw Commun
10. Evangeline CS, Kumaravelu VB (2020) AHP-FVIKOR based access network selection in vehicular communications. In: Inventive Communication and Computational Technologies. Springer; pp 829–837
11. Singh P, Agrawal R (2019) AHP based network selection scheme for heterogeneous network in different traffic scenarios. Int J Inf Technol. pp 1–9
12. Zhou L, Jiang SM, Yan T (2021) A network selection scheme based on the analytic hierarchy process for marine internet. Wirel Commun Mobile Comput (2021)
13. Zhao S, Wang F, Ning Y, Xiao Y, Zhang D (2020) Vertical handoff decision algorithm combined improved entropy weighting with GRA for heterogeneous wireless networks. KSII Trans Internet Inf Syst 14(11)
14. Yu H, Guo M, Yu J (2020) A novel heterogeneous wireless network selection algorithm based on INFAHP and IGRA. J Interconnect Netw 20(03):2050010
15. Mefgouda B, Idoudi H (2021) COCOSO-based network interface selection algorithm for heterogeneous wireless networks. In: 2021 International Conference on Innovation and Intelligence for Informatics, Computing, and Technologies (3ICT). IEEE; pp 1–5
16. Mansouri M, Leghris C (2019) A comparison between MADM methods and utility functions in the network selection context. In: International Conference on Mobile, Secure, and Programmable Networking. Springer; pp 201–210

17. Khan S, Ahmad MI, Hussain F (2018) Exponential utility function based criteria for network selection in heterogeneous wireless networks. Electron Lett 54(8):529–531
18. Tan X, Chen G, Sun H (2020) Vertical handover algorithm based on multi-attribute and neural network in heterogeneous integrated network. EURASIP J Wirel Commun Netw 2020(1):1–21
19. Moreira PR, de Castro MC, de Boni MHL, Cardoso FF (2015) An approach for network selection based on artificial neural networks in heterogeneous wireless environments. ICWMC 2015:40
20. Chen L, Li H (2016) An MDP-based vertical handoff decision algorithm for heterogeneous wireless networks. In: 2016 IEEE Wireless Communications and Networking Conference. IEEE. pp 1–6
21. Xie J, Gao W, Li C (2020) Heterogeneous network selection optimization algorithm based on a Markov decision model. China Commun 17(2):40–53
22. Abbas N, Saade JJ (2015) A fuzzy logic based approach for network selection in WLAN/3G heterogeneous network. In: 2015 12th Annual IEEE Consumer Communications and Networking Conference (CCNC). IEEE. pp 631–636
23. Wang X, Liu B, Su X, Xu X, Xiao L (2019) Evolutionary game based heterogeneous wireless network selection with multiple traffics in 5G. In: 2019 26th International Conference on Telecommunications (ICT). IEEE. pp 80–84
24. Adiwal M, Singh NP (2019) RAT selection for a low battery mobile device for future 5G networks. Int J Commun Syst 32(13):e4055
25. Obayiuwana E, Falowo OE (2017) Network selection in heterogeneous wireless networks using multi-criteria decision-making algorithms: a review. Wireless Netw 23(8):2617–2649
26. Bendaoud F, Abdennebi M, Didi F (2018) Network selection in wireless heterogeneous networks: a survey. J Telecommun Inf Technol
27. Saaty TL (2008) Decision making with the analytic hierarchy process. Int J Serv Sci 1(1):83–98
28. Drissi M, Oumsis M, Aboutajdine D (2017) A multi-criteria decision framework for network selection over LTE and WLAN. Eng Appl Artif Intell 66:113–127
29. Saaty TL, Vargas LG (2013) The analytic network process. In: Decision Making with the Analytic Network Process. Springer. pp 1–40
30. Ayağ Z, Özdemir RG (2009) A hybrid approach to concept selection through fuzzy analytic network process. Comput Ind Eng 56(1):368–379
31. Barzilai J, Golany B (1994) AHP rank reversal, normalization and aggregation rules. INFOR Inf Syst Oper Res 32(2):57–64
32. Jahan A, Edwards KL (2015) A state-of-the-art survey on the influence of normalization techniques in ranking: Improving the materials selection process in engineering design. Mater Des (1980-2015) 65:335–342
33. de Farias Aires RF, Ferreira L (2019) A new approach to avoid rank reversal cases in the TOPSIS method. Comput Ind Eng 132:84–97
34. Senouci MA, Mushtaq MS, Hoceini S, Mellouk A (2016) TOPSIS-based dynamic approach for mobile network interface selection. Comput Netw 107:304–314
35. Chandavarkar BR, Guddeti RMR (2016) Simplified and improved multiple attributes alternate ranking method for vertical handover decision in heterogeneous wireless networks. Comput Commun 83:81–97
36. Senouci MA, Hoceini S, Mellouk A (2016) Utility function-based TOPSIS for network interface selection in heterogeneous wireless networks. In: 2016 IEEE International Conference on Communications (ICC). IEEE. pp 1–6
37. Baghla S, Bansal S (2018) VIKOR MADM based optimization method for vertical handover in heterogeneous networks. Adv Syst Sci Appl 18(3):90–110
38. Alhabo M, Zhang L, Nawaz N (2019) GRA-based handover for dense small cells heterogeneous networks. IET Commun 13(13):1928–1935
39. Yu HW, Zhang B (2019) A hybrid MADM algorithm based on attribute weight and utility value for heterogeneous network selection. J Netw Syst Manage 27(3):756–783
40. Mansouri M, Leghris C (2019) New Manhattan distance-based fuzzy MADM method for the network selection. IET Commun 13(13):1980–1987
41. Mefgouda B, Idoudi H (2022) A novel MADM based network interface selection approach with rank reversal avoidance in HWNs. In: 2022 IEEE Wireless Communications and Networking Conference (WCNC). IEEE. pp 2082–2087
42. Lu Y, Chen Y, Huang S, Zhang M (2021) An access network selection algorithm for terrestrial-satellite networks based on a QoS guarantee. Math Probl Eng (2021)

43. Almutairi AF, Hamed M, Landolsi MA, Algharabally M (2018) A genetic algorithm approach for multi-attribute vertical handover decision making in wireless networks. Telecommun Syst 68(2):151–161
44. Almutairi AF, Al-Gharabally M, Salman AA (2021) Particle swarm optimization application for multiple attribute decision making in vertical handover in heterogenous wireless networks. J Eng Res 9(1)
45. Yu HW, Zhang B (2018) A heterogeneous network selection algorithm based on network attribute and user preference. Ad Hoc Netw 72:68–80
46. Goyal RK, Kaushal S, Sangaiah AK (2018) The utility based non-linear fuzzy AHP optimization model for network selection in heterogeneous wireless networks. Appl Soft Comput 67:800–811
47. Priya B, Malhotra J (2020) 5GAuNetS: an autonomous 5G network selection framework for Industry 4.0. Soft Comput 24(13):9507–9523
48. Alhabo M, Zhang L (2018) Multi-criteria handover using modified weighted TOPSIS methods for heterogeneous networks. IEEE Access. 6:40547–40558
49. Yu H, Ma Y, Yu J (2019) Network selection algorithm for multiservice multimode terminals in heterogeneous wireless networks. IEEE Access. 7:46240–46260
50. Yu H, Chen L, Yu J (2020) Network selection algorithm based on chi-square distance in heterogeneous wireless networks. Wireless Pers Commun 111(3):1625–1643
51. Guo X, Omar M, Mohd Zaini K, et al. (2020) Multiattribute access selection algorithm supporting service characteristics and user preferences in heterogeneous wireless networks. Wirel Commun Mobile Comput
52. Radouche S, Leghris C (2020) Network selection based on cosine similarity and combination of subjective and objective weighting. In: 2020 International Conference on Intelligent Systems and Computer Vision (ISCV). IEEE; p. 1–7
53. Radouche S, Leghris C (2021) New network selection algorithm based on cosine similarity distance and PSO in heterogeneous wireless networks. J Comput Netw Commun (2021)
54. Behzadian M, Otaghsara SK, Yazdani M, Ignatius J (2012) A state-of the-art survey of TOPSIS applications. Expert Syst Appl 39(17):13051–13069
55. Savitha K, Chandrasekar C (2011) Vertical handover decision schemes using SAW and WPM for network selection in heterogeneous wireless networks. arXiv preprint arXiv:1109.4490
56. Got A, Moussaoui A, Zouache D (2020) A guided population archive whale optimization algorithm for solving multiobjective optimization problems. Expert Syst Appl 141:112972
57. Pollini GP (1996) Trends in handover design. IEEE Commun Mag 34(3):82–90
58. Pahlavan K, Krishnamurthy P, Hatami A, Ylianttila M, Makela JP, Pichna R et al (2000) Handoff in hybrid mobile data networks. IEEE Pers Commun 7(2):34–47
59. 3rd Generation Partnership Project (2003) Quality of Service (QoS) Concept and Architecture. 3GPP TS 23107
60. Habbal A, Goudar SI, Hassan S (2017) Context-aware radio access technology selection in 5G ultra dense networks. IEEE Access 5:6636–6648
61. Mirjalili S, Saremi S, Mirjalili SM, Coelho LS (2016) Multi-objective grey wolf optimizer: a novel algorithm for multi-criterion optimization. Expert Syst Appl 47:106–119
62. Raquel CR, Naval Jr PC (2005) An effective use of crowding distance in multiobjective particle swarm optimization. In: Proceedings of the 7th Annual Conference on Genetic and Evolutionary Computation. pp 257–264
63. Deb K, Pratap A, Agarwal S, Meyarivan T (2002) A fast and elitist multiobjective genetic algorithm: NSGA-II. IEEE Trans Evol Comput 6(2):182–197
64. Mirjalili S, Lewis A (2016) The whale optimization algorithm. Adv Eng Softw 95:51–67