

## Research Article

# New Network Selection Algorithm Based on Cosine Similarity Distance and PSO in Heterogeneous Wireless Networks

Said Radouche  and Cherkaoui Leghris 

Computer Science Department, RTM Team, FST Mohammedia, Hassan II University of Casablanca, BP 146, Mohammedia 220650, Morocco

Correspondence should be addressed to Said Radouche; [said.radouche@yahoo.com](mailto:said.radouche@yahoo.com) and Cherkaoui Leghris; [cherkaoui.leghris@fstm.ac.ma](mailto:cherkaoui.leghris@fstm.ac.ma)

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Future wireless communication networks will be composed of different technologies with complementary characteristics. Thus, vertical handover (VHO) must support seamless mobility in such heterogeneous environments. The network selection is an important phase in the VHO process and it can be formulated as a multiattribute decision-making problem. So, the mobile terminal equipped with multiple interfaces will be able to choose the most suitable network. This work proposes an access network selection algorithm, based on cosine similarity distance, subjective weights using Fuzzy ANP, and objective weights using particle swarm optimization. The comprehensive weights are based on the cosine similarity distance between the networks and the ideal network. Finally, the candidate network with the minimum cosine distance to the ideal network will be selected in the VHO network selection stage. The performance analysis shows that our proposed method, based on cosine similarity distance and combination weights, reduces the ranking abnormality and number of handoffs in comparison with other MADM methods in the literature.

## 1. Introduction

Nowadays, mobile users usually move into heterogeneous environments, which are composed of different wireless access technologies, such as 5G, long-term evolution (LTE), universal mobile telecommunication system (UMTS), wireless local area networks (WLANs), and Worldwide Interoperability for Microwave Access (WiMAX). One of the trending challenges is to exploit the complementary characteristics of these different technologies in terms of coverage, cost, security, etc.

The transfer process of mobile terminal connectivity in a seamless way, from one network to another, is called handover and is divided into three main phases: handover initiation phase, handover decision phase (network selection), and finally handover execution phase. When this

process is performed between two networks with different access technologies, it is called vertical handover (VHO).

The handover decision can be controlled by the mobile or the network; we can distinguish between several handover categories [1]. So, in MCHO (mobile-controlled handover), the mobile is responsible for the handover decision, based on the measurements that it makes, without any participation of the network. When handover management is completely dedicated to the network, without any involvement of the mobile, it is referred to as the NCHO (network-controlled handover). In addition, when the handover decision is made by the mobile, based on the measurements received from the network, it is NAHO (network-assisted handover). Unlike the NAHO, in the MAHO (mobile-assisted handover), the decision of the handover is taken by the network but based on the measurements received from the mobile.

Seamless integration of different radio access networks, in heterogeneous wireless networks, requires efficient handover decision management. So, the implementation of the network selection algorithm into the mobile avoids a single point of failure and allows network scalability [2].

In the handover decision process, the mobile terminal selects the best available network available in a heterogeneous environment. This process of network selection uses some mathematical tools, such as MADM methods, game theory, Markov chains, fuzzy logic, artificial neural network algorithms in the field of machine learning [3–5], and utility functions used in two important issues in the integration of heterogeneous wireless networks, vertical handover decision, and optimal resource allocation for the handover [6–8]. Several conflicting criteria are involved in the network selection scheme, such as the quality of service (QoS), energy consumption, load, security, and user preferences.

An important challenge for the network selection procedure is determining the degree of importance (i.e. the weight) of every network decision criterion. So, the weighting techniques that have been used to calculate criteria weight are subjective weighting methods, such as AHP (analytical hierarchy process) [9], ANP (analytic network process) [10], FAHP (fuzzy analytic hierarchy process), and FANP (fuzzy analytic network process), and objective weighting methods, such as the entropy technique.

The addition of the objectiveness in the determination of the criteria weights requires minimizing (or maximizing) an objective function. So, metaheuristic techniques will be used instead of classic methods to identify the weight of each criterion when the resolution of the optimization problem becomes complex.

Moreover, network selection techniques are often used to rank the available networks with eventual optimization of some evaluation parameters. This paper aims to use a novel technique for the best network selection based on the following evaluation parameters such as:

- (i) Ranking abnormality: The ranking order of candidate networks changes when one alternative is added or removed from the candidate list. This phenomenon can make the network selection decision inefficient.
- (ii) Number of handover: Unnecessary handoffs should be minimized as they waste network resources and increase processing overheads.

The rest of this paper is organized as follows: Section 2 presents some related works. In Section 3, we present MADM methods, used in the context of vertical handover, within a multiaccess environment. In Section 4, the metaheuristic techniques will be presented. Our proposed algorithm will be introduced in Section 5, while simulation results are presented in Section 6. Finally, the study is concluded, and some perspectives are addressed.

## 2. Related Works

In the context of vertical handover, the research is focused on the handover decision phase, and especially, on the

optimization of a network selection algorithm, to support different services, with the best QoS. Several strategies have been proposed by researchers in the literature, to select the best network, some of them use one single criterion, and other more complex schemes use multiple criteria.

Multiattribute decision-making (MADM) methods are mathematical tools used to solve the problems that require decision-making, such as economics, statistics, and computer science. The MADM methods are used to identify the best alternative that is defined by a finite set of conflicting attributes. In the context of the vertical handover decision, the alternatives represent the access networks available in the mobile terminal environment and the attributes represent the criteria used in the network selection process.

In the vertical handover decision, several MADM methods are used to rank the alternatives, such as SAW (simple additive weighting), MEW (multiple exponent weighting), TPOSI (technique for order preference by similarity to ideal solution), GRA (grey relational analysis), and VIKOR (VIsekriterijumsko KOMpromisno Rangiranje).

Obayiuwana and Falowo [11] presented a classification of the most used MADM methods in the network selection, in terms of algorithmic approach, handover-control point, the type of network utilities, types of calls, and cardinality of the decision criteria employed. Some weaknesses are also identified like abnormalities and weights sensitive for decision criteria.

Tran and Boukhatem [12] presented a performance comparison between classical MADM methods, such as SAW, MEW, and TOPSIS. This work shows that TOPSIS has a problem of “ranking abnormality,” while SAW and MEW have a problem of “ranking identification.” When networks order changes if the worst alternative is removed from the candidate networks list, it is called a ranking abnormality problem. The ranking identification problem occurs when it is difficult to determine with precision the best alternative. They proposed the DIA (distance to ideal alternative) algorithm to eliminate ranking abnormality and have used Manhattan distance instead of the Euclidean distance used with TOPSIS.

Lahby et al. [13] proposed a vertical handover decision algorithm NMMD (novel method based on Mahalanobis distance) that combines Mahalanobis distance and the AHP method. They also proposed Fuzzy AHP with Mahalanobis distance (FADM) [14]. The simulation results show that their algorithms reduce the ranking abnormality and the number of handoffs. They provide the best performances than MADM methods used in the handover decision-making, such as SAW, MEW, TOPSIS, GRA, and DIA, for the traffic classes, namely conversational, interactive, streaming, and background.

Almutairi et al. [15] proposed the genetic algorithm approach to determine dynamic weights that maximize the total difference among the value of the networks. This approach reduces the abnormalities produced by SAW and TOSIS and adds objectiveness to criteria decision weights.

Al-Gharabally et al. [16] proposed the PSO technique to determine dynamic weights of attributes in the DIA method

that maximize the absolute value of the ranking difference among alternatives. This method adds objectiveness in the weights' assignment process and outperformed the conventional AHP-based DIA method in terms of ranking abnormality in all classes of services.

Goyal et al. [17] proposed a novel fuzzy analytic hierarchy process (AHP)-based network selection in heterogeneous wireless networks. Triangular fuzzy numbers are used to represent the elements in the comparison matrices for voice, video, and best-effort applications with many criteria that are not considered in the decision-making process. To overcome this problem, a new nonlinear fuzzy optimization model for deriving crisp weights from fuzzy comparison matrices for network selection is presented.

Baghla and Bansal [18] proposed a vertical handover decision algorithm based on the VIKOR method, and vector-normalized preferred performance-based normalization technique. The V-VPP algorithm reduces the number of handoffs and ranking abnormality and outperforms a traditional MADM method.

Yu et al. [19] proposed a network selection algorithm that selects an appropriate access network for each traffic class. It is based on chi-square distance to rank candidate networks and combines entropy theory and criteria importance through intercriteria correlation (CRITIC) and AHP to assign weights to decision criteria. However, it did not use the ranking abnormality and number of handovers as performance evaluation metrics of vertical handover decision.

Radouche and Leghris [20] proposed an access network selection algorithm method-based multiple attribute decision-making approach. This developed method is based on the cosine similarity measure and integrated weights that combines subjective and objective weights. The FANP and entropy methods are used for the calculation of subjective and objective weights, respectively. This developed method gives the best performances in terms of the average of the number of handoffs and ranking abnormality and outperforms the conventional MADM methods, such as TOPSIS, VIKOR, and GRA.

### 3. MADM Methods

The handover decision process, based on MADM methods, uses the same approach to select the best network. In the first step, the selection attributes set and alternatives are identified. The decision matrix  $D$  contains  $m$  rows and  $n$  columns. The rows represent the list of the candidate networks  $A = \{A_i, i = 1, 2, 3, \dots, m\}$ , the columns indicate the list of the criteria  $C = \{C_j, j = 1, 2, 3, \dots, n\}$ , and  $x_{ij}$  represents the performance of the network  $A_i$  with the criterion  $C_j$ .

$$D = \begin{pmatrix} x_{11} & x_{12} & \cdots & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & \cdots & x_{2n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & \vdots & x_{mn} \end{pmatrix}. \quad (1)$$

In the next step, the normalized decision matrix  $R$  is determined. Several normalization methods are used to unify the decision attributes with a different unit of measurement, such as Euclidean distance, Sum, Min, Max, and Max-Min. In the normalization phase, it is necessary to distinguish between cost and benefit attributes. The utility of the benefit criterion is monotone increasing like throughput, but the utility of cost criterion is monotone decreasing like cost.

$$R = \begin{pmatrix} r_{11} & r_{12} & \cdots & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & \cdots & r_{2n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ r_{m1} & r_{m2} & \cdots & \vdots & r_{mn} \end{pmatrix}. \quad (2)$$

For each criterion  $C_j$ , we associate a weight  $w_j$  that represents its degree of importance. The methods such as AHP, FAHP, ANP, or FANP are used to calculate criteria weights. The weighted normalized decision matrix  $V$  is

$$V = \begin{pmatrix} v_{11} & v_{12} & \cdots & \cdots & v_{1n} \\ v_{21} & v_{22} & \cdots & \cdots & v_{2n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ v_{m1} & v_{m2} & \cdots & \vdots & v_{mn} \end{pmatrix}, \quad (3)$$

$$v_{ij} = w_j * r_{ij} \text{ with } \sum_{j=1}^n w_j = 1.$$

Finally, a method is used to rank the alternatives. The following MADM methods are used for vertical handover in the network selection phase.

**3.1. TOPSIS (Technique for Order Preference by Similarity to Ideal Solution).** TOPSIS method was introduced by Yoon and Hwang [21]. This method is the most used in the context of vertical handover and is also the basis of several improvements to optimize the network selection problem. The basic concept of this method is that the selected alternative that is closest to the positive ideal solution and the farthest distance from the negative ideal solution using Euclidean distance.

The following steps are performed by the TOPSIS algorithm to rank different alternatives:

- (1) Determine the decision matrix  $D$ .
- (2) Determine the normalized decision matrix  $R$  using the Euclidean distance method; therefore, the normalized value  $r_{ij}$  is obtained according to the following equation:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_i x_{ij}^2}}. \quad (4)$$

- (3) Determine weighted normalized decision matrix  $V$ .
- (4) Determine the ideal solution  $A^+$  and the negative ideal solution  $A^-$ :

$$\begin{aligned} A^+ &= [V_1^+, V_2^+, \dots, V_n^+], \\ A^- &= [V_1^-, V_2^-, \dots, V_n^-]. \end{aligned} \quad (5)$$

(i) For the benefit criteria:

$$\begin{aligned} V_j^+ &= \max_{i \in M} v_{ij}, \\ V_j^- &= \min_{i \in M} v_{ij}. \end{aligned} \quad (6)$$

(ii) For the cost criteria:

$$\begin{aligned} V_j^+ &= \min_{i \in M} v_{ij}, \\ V_j^- &= \max_{i \in M} v_{ij}. \end{aligned} \quad (7)$$

(5) The similarity distances between each alternative  $A^+$  and  $A^-$  are calculated as follows:

$$\begin{aligned} S_i^+ &= \sqrt{\sum_{j=1}^n (V_j^+ - v_{ij})^2}; \quad i \in M, \\ S_i^- &= \sqrt{\sum_{j=1}^n (v_{ij} - V_j^-)^2}; \quad i \in M. \end{aligned} \quad (8)$$

(6) The relative closeness to the ideal solution is given by

$$C_i^* = \frac{S_i^-}{S_i^+ + S_i^-}; \quad i \in M. \quad (9)$$

(7) Ranking alternatives: classifying the alternatives as a function of the decreasing values of  $C_i^*$ , the network with the highest value of  $C_i^*$  is selected.

$$A_{\text{TOPSIS}}^* = \arg \max_{i \in M} C_i^*. \quad (10)$$

**3.2. GRA (Grey Relational Analysis).** The GRA method is based on the Grey system theory [22]. The GRA method consists of calculating the GRC similarity distance of each of the alternatives to the ideal solution and choosing the solution that approximates the ideal alternative. The GRA process is described as follow:

- (1) Determine the decision matrix  $D$ .
- (2) Determine the normalized decision matrix  $R$  using the Max-Min method; therefore, the normalized value of  $r_{ij}$  is calculated as follows for benefit criteria:

$$r_{ij} = \frac{x_{ij} - x_j^{\min}}{x_j^{\max} - x_j^{\min}}. \quad (11)$$

For cost criteria, the  $r_{ij}$  is calculated as follows:

$$r_{ij} = \frac{x_j^{\max} - x_{ij}}{x_j^{\max} - x_j^{\min}}. \quad (12)$$

(3) Determine the positive ideal solution  $R^*$ .

$$R^* = [R_1^*, R_2^*, \dots, R_m^*]. \quad (13)$$

(i) For the benefit criteria,

$$R_j^* = \max_{i \in M} r_{ij}. \quad (14)$$

(ii) For the cost criteria,

$$R_j^* = \min_{i \in M} r_{ij}. \quad (15)$$

(4) Calculate the grey relational coefficient (GRC) of each alternative from the positive ideal solution. The value of the coefficient is defined as follows:

$$\text{GRC}_{ij}^* = \frac{\Delta_{\min} + \rho \Delta_{\max}}{\Delta_i + \rho \Delta_{\max}}, \quad (16)$$

where  $\Delta_i = |R_j^* - r_{ij}|$ ,  $\Delta_{\max} = \max_{i \in M, j \in N} \Delta_i$ .

$\Delta_{\min} = \min_{i \in M, j \in N} \Delta_i$ , the identification coefficient  $\rho = 1$  and  $r_{ij}$  is calculated using the Max-Min method.

(5) Calculating the degree of grey relational coefficient of each alternative from the positive ideal solution using the following equation:

$$\text{GRC}_i^* = \sum_j w_j * \text{GRC}_{ij}^*. \quad (17)$$

(6) Ranking the alternatives: the alternatives are ordered according to the decreasing values of  $\text{GRC}_i^*$ . The network with the highest value of  $\text{GRC}_i^*$  will be selected.

$$A_{\text{GRA}}^* = \arg \max_{i \in M} \text{GRC}_i^*. \quad (18)$$

**3.3. VIKOR (VIsekriterijumsko KOMpromisno Rangiranje).** VIKOR is the MADM method that focuses on ranking and selecting from a set of alternatives with the presence of conflicting criteria. Tzeng et al. [23] presented a comparative study between VIKOR and TOPSIS. The VIKOR method process is as follows:

- (1) Determine the decision matrix  $D$ .
- (2) Determine the positive ideal solution  $F^*$  and negative ideal solution  $F^-$ :

$$\begin{aligned} F^* &= [F_1^*, F_2^*, \dots, F_m^*], \\ F^- &= [F_1^-, F_2^-, \dots, F_m^-]. \end{aligned} \quad (19)$$

(i) For the benefit criteria,

$$F_j^* = \max_{i \in M} r_{ij}, F_j^- = \min_{i \in M} r_{ij}. \quad (20)$$

(ii) For the cost criteria,

$$F_j^* = \min_{i \in M} r_{ij}, F_j^- = \max_{i \in M} r_{ij}. \quad (21)$$

(3) Calculate  $S_i$  and  $R_i$  for  $i \in M$  given by

$$S_i = \sum_j^n w_j \frac{(F_j^* - r_{ij})}{(F_j^* - F_j^-)},$$

$$R_i = \max_{j \in N} \left( w_j \frac{(F_j^* - r_{ij})}{(F_j^* - F_j^-)} \right). \quad (22)$$

(4) Calculate  $Q_i$  for  $i \in M$  as

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

$$S^* = \min_{i \in M} S_i, S^- = \max_{i \in M} S_i, \quad (23)$$

$$R^* = \min_{i \in M} R_i, R^- = \max_{i \in M} R_i.$$

$\vartheta$  represents the weight for the strategy of maximum group utility, while  $(1 - \vartheta)$  is the weight of the individual regret.

(5) Rank the alternatives: sorted by the values  $Q$  in increasing order.

$$A_{\text{VIKOR}}^* = \arg \min_{i \in M} Q_i. \quad (24)$$

## 4. Metaheuristic Algorithms

Metaheuristics algorithms are used to solve difficult optimization problems, for which conventional methods are not applicable. Many metaheuristic algorithms, inspired by biology behavior, are proposed to solve optimization problems. The most popular algorithms are the genetic algorithm (GA), artificial bee colony algorithm (ABC), and particle swarm optimization (PSO) algorithm.

**4.1. Particle Swarm Optimization Algorithm.** Proposed by Kennedy and Eberhart [24], particle swarm optimization (PSO) is a population-based stochastic optimization technique inspired by the social behavior of bird flocking and fish schooling.

The standard PSO algorithm uses a population of particles. The particles fly through the  $n$ -dimensional domain space to find the minimum value (or maximum) returned by the objective function. Each particle is represented by its position  $x_i = (x_{i1}, x_{i2}, \dots, x_{in})$  and velocity  $v_i = (v_{i1}, v_{i2}, \dots, v_{in})$  that they are updated.

All the particles remember their best position  $p_i = (p_{i1}, p_{i2}, \dots, p_{in})$ . They also know the best position of all the particles of the swarm  $p_g = (p_{g1}, p_{g2}, \dots, p_{gn})$ . During every iterations, each particle is updated by the aforementioned two "best" values.

Each particle's velocity is updated using equation (25):

$$v_i^{k+1} = wv_i^k + c_1 r_1 (p_i - x_i^k) + c_2 r_2 (p_g - x_i^k), \quad (25)$$

where  $w$  is the inertial coefficient;  $c_1$  and  $c_2$  are two constants, called acceleration coefficients;  $r_1$  and  $r_2$  are two random values  $0 \leq r_1, r_2 \leq 1$  regenerated every velocity update.

The three key parameters to PSO used in the velocity update equation are

- (i)  $wv_i^k$  corresponds to the momentum component, where the inertial constant  $w$  controls how much the particle remembers its previous velocity.
- (ii)  $c_1 r_1 (p_i - x_i^k)$  corresponds to the cognitive component. Here, the acceleration constant  $C_1$  controls how much the particle heads toward its personal best position.
- (iii)  $c_2 r_2 (p_g - x_i^k)$  referred to as the social component, draws the particle toward the swarm's best position; the acceleration constant controls this tendency.

The position of the particle  $i$  is defined by

$$x_i^{k+1} = x_i^k + v_i^{k+1}. \quad (26)$$

The main steps of the procedure are illustrated in the following flowchart (Figure 1) [25].

**4.2. Artificial Bee Colony.** The artificial bee colony (ABC) algorithm was introduced by Dervis Karaboga [26]. It is a population algorithm based on the foraging of bees. In this algorithm, a candidate solution to the optimization problem is represented by a food source. Each food source has a quantity of nectar that characterizes its quality (fitness).

The colony population is divided into three groups of bees: employed bees, onlooker bees, and scout bees. The number of employed bees and scout bees corresponds to the number of food sources. The algorithm's main steps are illustrated in the following flowchart (Figure 2) [25].

**4.3. Genetic Algorithm.** Genetic algorithms (GAs) are stochastic optimization algorithms inspired by the mechanisms of natural selection and genetics. They have been adapted for optimization by John Holland [27]. The vocabulary used is the same as that of the theory of evolution and genetics; we use the term individual (potential solution), population (set of solutions), genotype (a representation of the solution), gene (part of the genotype), parent, child, reproduction, crossing, mutation, generation, and so on. Their operation is extremely simple, starting from a population of potential solutions (chromosomes) initial, arbitrarily chosen, their relative performance (Fitness) are evaluated. Based on these performances, a new population of potential solutions is created by using simple evolutionary operators: selection, crossing, and mutation. The best-adapted individuals are expected to survive and reproduce more than others. This cycle is repeated until a satisfactory solution is found. The basic algorithm is summarized in Figure 3 [25].

## 5. Proposed Method

The cosine similarity measure is one of the important tools for the degree of similarity between objects [28]. The similarity measure has been introduced in many areas, such as automatic classification, decision science, and citation analysis.

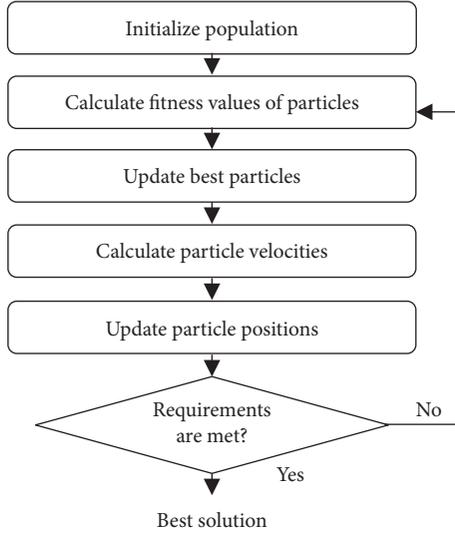


FIGURE 1: Flowchart of particle swarm optimization algorithm.

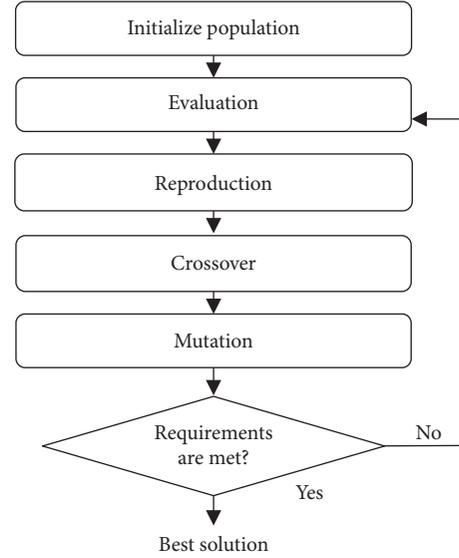


FIGURE 3: Flowchart of genetic algorithm.

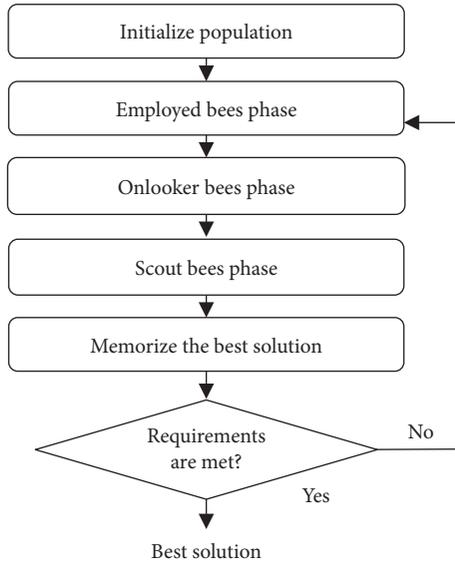


FIGURE 2: Flowchart of artificial bee colony algorithm.

The main goal of the network selection process is to select the best network among networks present in the mobile environment. In this paper, the developed method is based on cosine similarity distance between each alternative  $A_i$  and the ideal alternative  $A^+$  to rank the networks. So, the best network is the one that has the shortest cosine similarity distance to the ideal network.

Another contribution of the proposed method is to determine the weights for each criterion using both subjective weights obtained with the fuzzy ANP method and objective weights obtained from the objective technique based on the PSO algorithm. This metaheuristic algorithm

has been successfully applied in many areas. It is also easy to implement, and there are few parameters to be adjusted.

The following steps are performed by the proposed method to rank different networks:

- (1) Determine the decision matrix.

$$D = \begin{pmatrix} x_{11} & x_{12} & \cdots & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & \cdots & x_{2n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & \vdots & x_{mn} \end{pmatrix}. \quad (27)$$

- (2) Construct the normalized decision matrix  $R$  using the Max method:

$$R = \begin{pmatrix} r_{11} & r_{12} & \cdots & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & \cdots & r_{2n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ r_{m1} & r_{m2} & \cdots & \vdots & r_{mn} \end{pmatrix}. \quad (28)$$

The normalized value of  $r_{ij}$  is calculated as follows:

- (i) For the benefit criteria,

$$r_{ij} = \frac{x_{ij}}{x_j^{\max}}. \quad (29)$$

- (ii) For the cost criteria,

$$r_{ij} = \frac{x_j^{\min}}{x_{ij}}, \quad (30)$$

$$x_j^{\max} = \max_{i \in M} x_{ij}, x_j^{\min} = \min_{i \in M} x_{ij}.$$

- (3) The weighted normalized decision matrix  $V$  is calculated using combination weights:

$$V = \begin{pmatrix} v_{11} & v_{12} & \cdots & \cdots & v_{1n} \\ v_{21} & v_{22} & \cdots & \cdots & v_{2n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ v_{m1} & v_{m2} & \cdots & \vdots & v_{mn} \end{pmatrix}, \quad (31)$$

where  $v_{ij} = w_j^* \cdot r_{ij}$  with  $\sum_{j=1}^n w_j^* = 1$ .

In this contribution, we propose a comprehensive combination that integrates both objective and subjective weightings. Subjective weights  $w_j^s$  are calculated using user experience, while objective weights  $w_j^o$  are directly determined from attribute values of alternative networks.

The objective weights  $w_j^o$  are obtained by solving an optimization problem.

$$\min \sum_{i=1}^m \sum_{j=1}^n \left[ w_j^o \left( 1 - \frac{r_{ij} * r_j^+}{rr^+} \right) \right]^2, \quad (32)$$

subject to  $\sum_{j=1}^n w_j^o = 1,$

subject to  $w_j^o \geq \varepsilon, \quad j = 1, \dots, n$  and  $\varepsilon > 0,$

where  $w_j^o$  is the weight or importance of a  $j$ th criterion. The small quantity  $\varepsilon$  is suggested to avoid any criterion being neglected.

To determine the importance of subjective and objective weights, combination weights can be expressed as

$$w_j = \alpha w_j^s + \beta w_j^o. \quad (33)$$

An optimal mathematical model can be considered to solve  $\alpha$  and  $\beta$ .

$$\min \sum_{i=1}^m \sum_{j=1}^n \left( 1 - \frac{r_{ij} * r_j^+}{rr^+} \right) (\alpha w_j^s + \beta w_j^o). \quad (34)$$

Subject to  $\alpha^2 + \beta^2 = 1$  and  $\alpha, \beta \geq 0$ .

$r_j^+$  is the normalized value of the  $j$ th best attribute, and  $r_{ij}$  is the normalized value of the  $j$ th attribute of the  $i$ th network.

The equation (34) can be obtained as

$$\alpha = \frac{\sum_{i=1}^m \sum_{j=1}^n (1 - ((r_{ij} * r_j^+) / rr^+)) w_j^s}{\sqrt{[\sum_{i=1}^m \sum_{j=1}^n (1 - ((r_{ij} * r_j^+) / rr^+)) w_j^s]^2 + [\sum_{i=1}^m \sum_{j=1}^n (1 - ((r_{ij} * r_j^+) / rr^+)) w_j^o]^2}}, \quad (35)$$

$$\beta = \frac{\sum_{i=1}^m \sum_{j=1}^n (1 - ((r_{ij} * r_j^+) / rr^+)) w_j^o}{\sqrt{[\sum_{i=1}^m \sum_{j=1}^n (1 - ((r_{ij} * r_j^+) / rr^+)) w_j^s]^2 + [\sum_{i=1}^m \sum_{j=1}^n (1 - ((r_{ij} * r_j^+) / rr^+)) w_j^o]^2}}.$$

Substitute  $\alpha$  and  $\beta$  into equation (33); combination weight  $w_j$  can be determined.

The final weight  $w_j^*$  is determined by this formula

$$w_j^* = \frac{w_j}{\sum_{j=1}^n w_j}. \quad (36)$$

- (4) Calculate cosine similarity distance using weighted normalized decision matrix  $V$ . This measure is described as follows:

Let  $V_i = (v_{i1}, v_{i2}, \dots, v_{in})$  and  $V^+ = (v_1^+, v_2^+, \dots, v_n^+)$  be two  $n$ -dimensional vectors with positive components which represent respectively the alternative  $A_i$  and the ideal alternative  $A^+$ .

$$A^+ = [V_1^+, V_2^+, \dots, V_n^+]. \quad (37)$$

- (i) For the benefit criteria,

$$V_j^+ = \max_{i \in M} v_{ij}, V_j^- = \min_{i \in M} v_{ij}. \quad (38)$$

- (ii) For the cost criteria,

$$V_j^+ = \min_{i \in M} v_{ij}, V_j^- = \max_{i \in M} v_{ij}. \quad (39)$$

The cosine similarity distance of two vectors  $V_i$  and  $V^+$  defined as

$$\text{Cosine distance}(V_i, V^+) = 1 - \frac{V_i \cdot V^+}{|V_i| \cdot |V^+|}. \quad (40)$$

Finally, the alternatives are ranked according to the increasing values of cosine similarity distance.

## 6. Simulation and Results

To optimize the network selection decision problem in a heterogeneous wireless network environment, we propose a new method based on cosine similarity distance and the combination of subjective and objective weights. Our study will be divided into three parts: first, the fuzzy ANP method

TABLE 1: Attribute values for candidate networks.

Networks	Delay (ms)	Jitter (ms)	Loss rate (%)	Throughput (Mbps)	Load (%)	Cost [1-10]
LTE	40-60	3-12	1-3	40-100	20-80	9
UMTS	25-50	5-10	1-4	1-2	20-80	3
WiMAX	25-60	3-10	1-5	30-80	20-80	6
Wi-Fi	50-150	10-20	1-7	1-54	20-80	1

TABLE 2: Weight values for different attributes for all services using FANP.

	Delay	Jitter	Loss rate	Throughput	Load	Cost
Conv	0.1456	0.1783	0.0932	0.2614	0.2164	0.1051
Int	0.1770	0.1040	0.1572	0.2402	0.2164	.1051
Str	0.0820	0.1323	0.1055	0.3586	0.2164	0.1051
Back	0.1122	0.1398	0.1205	0.3060	0.2164	0.1051

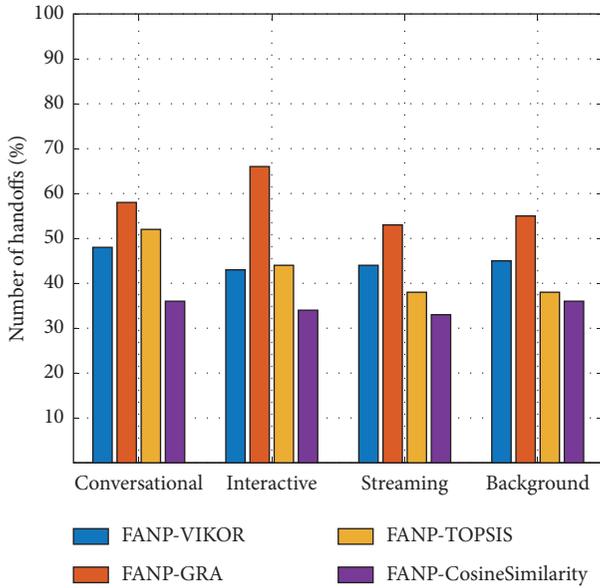


FIGURE 4: Average number of handoffs for MADM methods and cosine similarity method using subjective weights FANP.

is used to assign suitable subjective weights to different decision criteria according to network candidates. Secondly, the metaheuristic algorithm is used to identify objective weights. Finally, our method will be evaluated with combination weights. The proposed method will be compared to TOPSIS, GRA, and VIKOR methods in terms of the numbers of handovers and ranking abnormality.

The simulation environment is assumed to be covered by four access network technologies (candidates), such as LTE, UMTS, Wi-Fi, and WiMAX. An eventual mobile terminal, equipped with four interfaces, can choose an appropriate access network according to the selection process based on our method. Different conflicting decision criteria (attributes) are used in the VHO decision process in heterogeneous wireless networks such as delay ( $D$ ), jitter ( $J$ ), loss rate (LR), throughput ( $T$ ), load ( $L$ ), and cost ( $C$ ). In Table 1, the

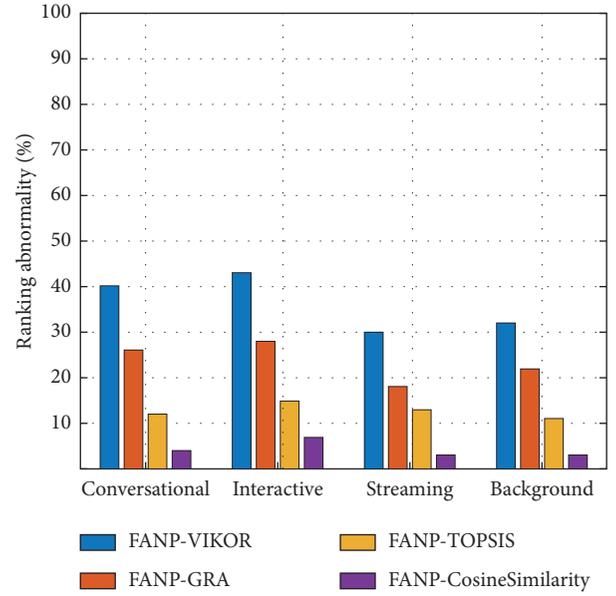


FIGURE 5: Average of ranking abnormality for MADM methods and cosine similarity method using FANP method.

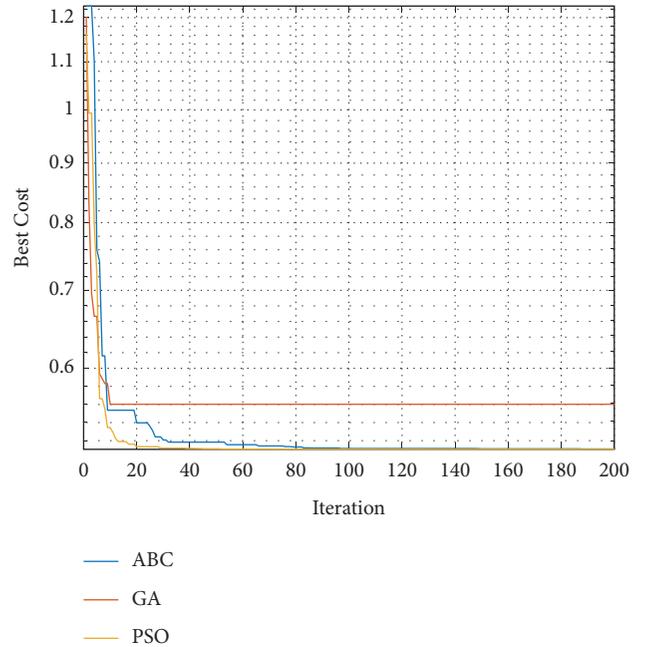


FIGURE 6: Convergence of optimization of algorithms.

values of these criteria (attributes) are generated randomly according to the interval indicated for each attribute. The simulation is repeated 100 times (100 points).

For our simulations, we consider four traffic classes, such as conversational, interactive, streaming, and background. In Table 2, the weights associated with the criteria for each service are calculated using the fuzzy ANP method based on the AHP decision matrix and the AHP interdependence matrix for QoS parameters proposed by Faisal [29].

Figures 4 and 5 show, respectively, the average number of handoffs and the average of ranking abnormality performed, respectively, by the MADM methods and the cosine similarity method for each type of service. The ranking abnormality is the weak point of the MADM methods. However, the overall score of each alternative is affected by the removal of the worst alternative. Their methods are also weighting sensitive.

Figure 4 shows the average number of handoffs performed by the MADM methods and the proposed algorithm for the four traffic types. The fuzzy ANP method is used to assign a subjective weight to each parameter. The simulation results show that the proposed method reduces the average of ranking abnormality with a value of 36%, 34%, 33%, and 36% for conversational, interactive, streaming, and background respectively. The VIKOR handoffs averages are 48%, 43%, 44%, and 45%, respectively, while the GRA ones are 58%, 66%, 53%, and 55%, respectively, and the TOPSIS ones are 52%, 44%, 38%, and 38%, respectively.

In Figure 5, the proposed algorithm gives the best performance and reduces the ranking abnormality with a value of 4%, 7%, 3%, and 3% for conversational, interactive, streaming, and background services, respectively. The averages ranking abnormality of VIKOR are 40%, 43%, 30%, and 32%, respectively. The ranking abnormality averages of GRA are 26%, 28%, 18%, and 22%, respectively. The ranking abnormality averages of TOPSIS are 12%, 15%, 13%, and 11%, respectively.

Hence, for the subjective weights calculated by the FANP method based on the user's experience, the proposed method gives the best performance than other MADM methods in all traffic classes. In the next step, our proposal will be evaluated with objective weights.

In the first, we identify the efficient metaheuristic algorithm that minimizes the objective function. Figure 6 shows the convergence curves of the GA, PSO, and ABC algorithms using random points from Table 1. Tables 3 and 4 show that GA and ABC algorithms with a small population size could lead to premature convergence, while the PSO algorithm can converge to the minimum of the objective function, and it has the ability to finding the global minimum with fewer iterations and population size. Compared to GA and ABC, the advantages of PSO are that it needs a few parameters to adjust, and it is easy to implement. Therefore, we will use the PSO algorithm to calculate weights for each criterion.

Adding objectivity to the weight of the decision criteria minimizes the subjectivity introduced by the decision-maker and makes the VHO process more intelligent. The seamless handover demands real-time decisions to avoid undesired handover delay. In this work, we have used the original PSO-based optimization approach to calculate objective weights. The complexity of PSO optimization used in the VHO decision is acceptable, and the value is  $O(gpn)$ , where  $g$ ,  $p$ ,

TABLE 3: Criteria weights values using iteration = 100 and population size = 100 in the optimization techniques.

	$D$	$J$	LR	$T$	$L$	$C$	Weights sum
ABC	0.1436	0.1425	0.1921	0.2120	0.1726	0.1377	1.0005
GA	0.1632	0.1286	0.2314	0.2371	0.1230	0.1185	1.0017
PSO	0.1608	0.1382	0.1871	0.2109	0.1599	0.1431	1.0000

TABLE 4: Criteria weights values using iteration = 200 and population size = 200 in the optimization techniques.

	$D$	$J$	LR	$T$	$L$	$C$	Weights sum
ABC	0.1606	0.1462	0.1828	0.2141	0.1613	0.1351	1.0002
GA	0.1112	0.1128	0.2958	0.1726	0.1572	0.1516	1.0011
PSO	0.1582	0.1431	0.1887	0.2134	0.1600	0.1367	1.0000

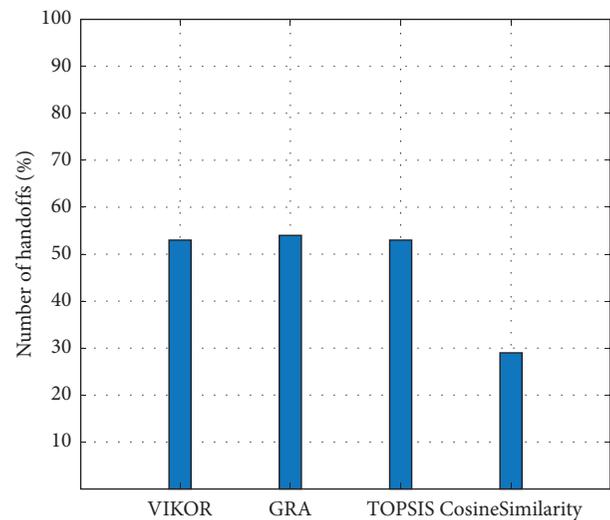


FIGURE 7: Average number of handoffs for MADM methods and cosine similarity method using objective weights with PSO.

and  $n$  represent the number of generations, the population size, and weights vector, respectively [15].

The simulations show that the cosine similarity method with the objective weights based on PSO optimization outperforms the MADM methods. In Figure 7, the cosine similarity, TOPSIS, GRA, and VIKOR algorithms reduce the average number of handoffs with a value of 29%, 53%, 54%, and 53%, respectively. In Figure 8, the cosine similarity, TOPSIS, GRA, and VIKOR algorithms reduce the ranking abnormality with a value of 9%, 23%, 23%, and 69%, respectively.

In Figure 9, the developed method based on combination weights reduces the average of number of handoffs with a value of 33%, 33%, 31%, and 33% for conversational, interactive, streaming, and background, respectively. The VIKOR numbers of handoffs averages are 51%, 47%, 52%, and 51%, respectively, while the GRA ones are 60%, 62%, 59%, and 64%, respectively, and the TOPSIS ones are 54%, 50%, 50%, and 52%, respectively.

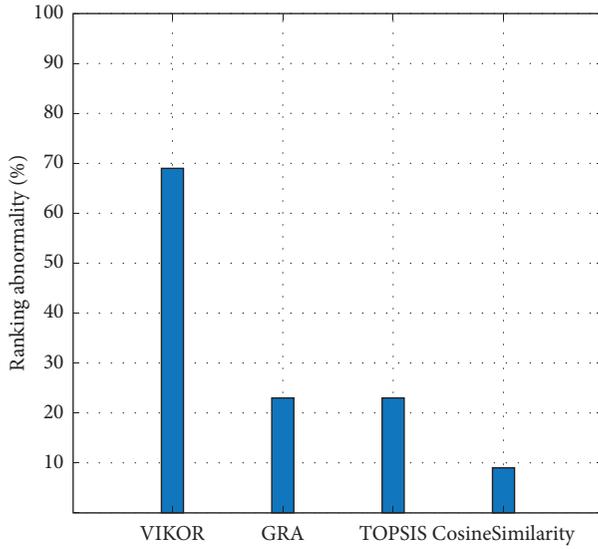


FIGURE 8: Average of ranking abnormality for MADM methods and cosine similarity method using objective weights with PSO.

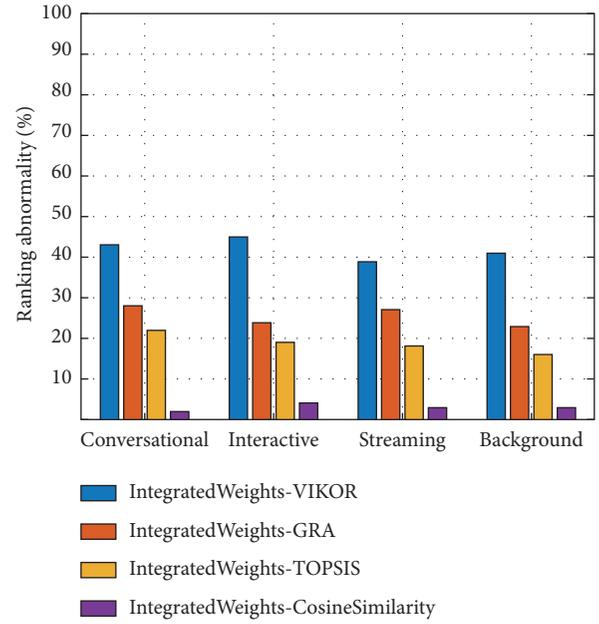


FIGURE 10: Average of ranking abnormality for MADM methods and cosine similarity method using integrated weights.

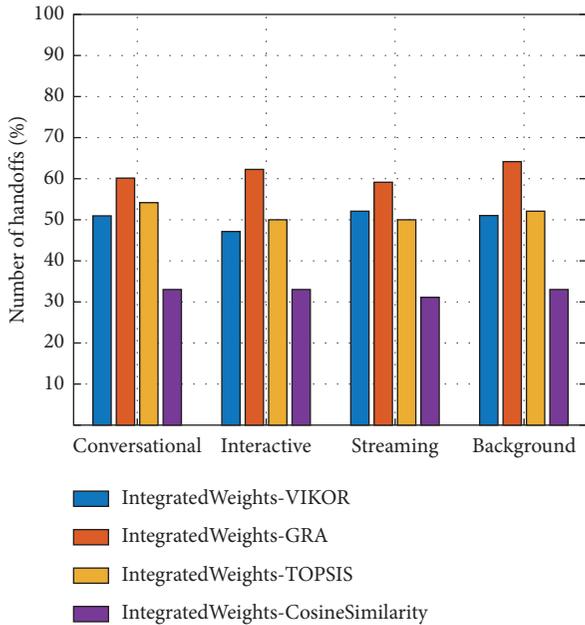


FIGURE 9: Average of number of handoffs for MADM methods and cosine similarity method using integrated weights.

In Figure 10, the proposed method reduces the average of ranking abnormality with a value of 2%, 4%, 3%, and 3% for integrated weight used for conversational, interactive, streaming, and background respectively. The ranking abnormality averages of VIKOR are 43%, 45%, 39%, and 41%, respectively. The ranking abnormality averages of GRA are 28%, 24%, 27%, and 23%, respectively. The ranking abnormality averages of TOPSIS are 22%, 19%, 18%, and 16%, respectively.

Hence, our proposed method based on the attribute weights obtained by the integration of the subjective and objective weights gives better results than the traditional MADM methods chosen in this paper.

## 7. Conclusion and Perspectives

In this paper, we propose an access network selection algorithm based on cosine similarity distance and PSO algorithm. The key property of the proposed approach is to minimize the cosine similarity distance between every candidate network and the ideal network. The proposed method is based also on the combination of subjective and objective weights, to minimize the uncertainty in the decision-maker preference. For each traffic class, we combine subjective weights calculated using FANP and objective weights got directly from data using PSO optimization. The comprehensive weights are the result of minimizing the total cosine distances between every network and the ideal one. Then, we measure the cosine similarity distance between every candidate network and the ideal to choose the network with the shortest distance as the best access network. The obtained results show that the ranking abnormality and number handoffs are reduced compared with conventional MADM methods, such as TOPSIS, GRA, and VIKOR. Indeed, the proposed solution performs better than MADM, but the biggest concern is the time overhead of the proposed solution because it relies on a metaheuristic optimization algorithm.

In future works, we plan to optimize our approach by reducing the generated time overhead which makes the principle PSO algorithm issue. Also, the use of this approach in real-time applications remains a good research subject.

## Data Availability

The data are available upon reasonable request from the corresponding author, Said Radouche, at said.radouche@yahoo.com.

## Disclosure

Some results of this works have been presented at the 2020 International Conference on Intelligent Systems and Computer Vision (ISCV).

## Conflicts of Interest

The authors declare that they have no conflicts of interest.

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