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Particle swarm optimization application for multiple attribute decision making in vertical handover in heterogenous wireless networks

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ABSTRACT

In wireless heterogenous networks, mobile terminals are covered by different wireless networks with varying quality of services to ensure the delivery of different classes of services. In this paper, Particle swarm optimization (PSO) was applied to the distance to ideal alternative (DIA) technique in the framework of network selection in a heterogenous wireless network. The PSO was applied to overcome the subjectivity and bias in the weights' assignment process used in multiple attribute decision making (MADM). The PSO was utilized to optimize the weights of the DIA method through the maximization of the absolute value of the summation of the ranking differences among candidate networks. In this regard, two different optimization functions were introduced and used to generate the optimum weights. The performance of the PSO-based handover for the DIA method was investigated in terms of ranking difference, ranking abnormalities, and network selection. The results show that the proposed PSO-based weights' assignment technique increased the ranking difference and reduced the ranking abnormalities without degrading the network selection when compared to the conventional DIA technique. The results of this paper are expected to widen the application of the DIA method and other MADM techniques to the handover process in wireless networks and other decision-based challenges in other fields.

Keywords: Vertical handover, network selection, multiple attribute decision making (MADM), heterogeneous wireless networks, distance to ideal alternative (DIA), Particle Swarm Optimization (PSO), ranking abnormality.

INTRODUCTION

Current and future wireless networks represent a heterogenous environment with different types of access points (AP) and technologies that have diverse requirements of quality of services (QoS), data rate, delay, and other performance parameters. Such coexistence of multiple networks with different types of QoS requires vertical handover (VHO) (Kassar, M., 2008; Bhuvaneswari, A., 2012; Yan, X., 2010) technologies to guarantee that the connection between mobile users and AP is maintained anytime and anywhere. In vertical handover, the mobile terminal (MT) is transferred manually or automatically between different types of networks.

Wireless network selection can be modeled by various techniques. The application of multiple attribute decision making (MADM), utility theory, game theory, fuzzy logic, and Markov chain to network selection has been surveyed in Wang, L. (2013). In heterogeneous wireless networks, vertical handovers may be triggered for convenience rather than connectivity reasons. This is due to the wide range of parameters that a decision-making algorithm considers and processes to ultimately come up with the most suitable decision. These parameters are categorized as static such as cost, security, and power consumption or dynamic such as bandwidth, data rate, latency, received signal strength, reliability, network load balancing, and velocity (Obayiuwana, E., 2017; Maroua Drissi, 2017). In this paper, six parameters are considered, namely, cost per byte (CB), data-rate (DR), security (S), packet delay (D), packet jitter (J), and packet loss (L). These attributes are widely used in the literature as in Maroua Drissi (2017), Anupama, K. S. S. (2018), Lahby (2012), and Almutairi, A. F. (2016a, 2016b), to mention a few. Furthermore; such attributes are selected to reflect such categorization (static and dynamic).

In Triantaphyllou, E. (2000), Obayiuwana, E. (2017), Maroua Drissi (2017), and Radhwan Mohamed Abdullah (2018), MADM techniques are known to be fast in decision speed, simple in implementation complexity, and highly precise; moreover, these techniques are known to be decentralized and user-centric when they are applied to VHO scenarios. These characteristics make MADM techniques useful for VHO in future heterogenous wireless networks and in internet of things (IoT) settings. However, a major drawback of MADM techniques is the inherited ranking abnormality. Ranking abnormality occurs when the ranking of the top network changes due to the drop of one of the low ranked networks (Anupama, K. S. S., 2018). MADM techniques have common characteristics, including alternatives, attributes, a decision matrix, and attribute weights (Wang, L., 2013; Triantaphyllou, E., 2000; Obayiuwana, E., 2017; Maroua Drissi, 2017; Radhwan Mohamed Abdullah, 2018). In the context of VHO, the alternatives represent the coexisting wireless networks that need to be ranked. Attributes represent the performance parameters, such as cost, data rate, security, delay, jitter, and packet loss, which are processed by MADM methods to rank alternatives. MADM formulation can be expressed by a matrix format (decision matrix), where the columns and rows represent the attributes and alternatives, respectively. Attributes' weights are calculated by different techniques (Lahby, 2012; Almutairi, A. F., 2016a, 2016b) to express the attributes' relative importance. The most popular weights assignment technique is the analytic hierarchy process (AHP) (Saaty, T. L., 2008).

In addition to AHP, there are other popular MADM techniques such as simple additive weighting (SAW) (Mi, Z., 2010), technique for order preference by similarity to ideal solution (TOPSIS) (Savitha, K., 2011a), multiplicative exponent weighting (MEW) (Savitha, K., 2011b), and Grey rational analysis (GRA) (Almutairi, A. F., 2016a). The performance of the DIA technique in terms of ranking abnormality and the differences of ranking values has been compared to that of SAW, WP, and TOPSIS in Tran, P. (2008). It has been found that the DIA outperforms TOPSIS in terms of ranking abnormality and outperforms SAW and WP in terms of the differences of ranking values. The performance of DIA with different weighting techniques has been investigated in Almutairi, A. F. (2016b). It has been shown that the use of different weighting techniques with the DIA method has resulted in varying performance in terms of network selection and ranking abnormalities. Such variations in the performance of the DIA are due to the subjectivity in the weights' assignment process and the generation of constant weights. Due to the advantages of the DIA, presented in Tran, P. (2008), and considering the results presented in Almutairi, A. F. (2016b), the work in this paper further investigates the performance of the DIA when the weights are dynamic and generated by PSO. The application of MADM techniques to vertical handover has been investigated in Tran, P. (2008) and Stevens-Navarro, E. (2006). There are many weighting techniques (Charilas, D. E., 2009; Mahmoodzadeh, S., 2007; Lee, J. W. & Kim, S. H., 2000; Beckmann, M., 2009; Sipahi, S., 2010) associated with these MADM methods. AHP, fuzzy analytic hierarchy process (FAHP), analytic network process (ANP), fuzzy analytic network process (FANP), and random weighting (RW) can be used to determine the weights for MADM methods. It has been found in Lahby, M. (2012) and Almutairi, A. F. (2016a, 2016b) that the use of different weighting techniques with the same MADM method will result in different performances. This is due mainly to the subjectivity and bias of the decision makers in the weights' assignment process. To overcome such subjectivity, a genetic algorithm (GA) approach has been proposed in Almutairi, A. F. (2018) to generate dynamic weights and reduce abnormalities associated with the SAW and TOPSIS methods.

There are many challenges inherited in MADM techniques. The weights assignment process is subjective, and the weights are assigned based on the decision maker experience. However, the conventional weights' assignment techniques presented in Charilas, D. E. (2009), Mahmoodzadeh, S. (2007), Lee, J. W. & Kim, S. H. (2000), Beckmann,

M. (2009), and Sipahi, S. (2010) are viewed as subjective assignment methods; hence, objective selection of the most appropriate network might be limited. Another drawback of the classical MADM techniques is that the previously mentioned weighing techniques generate static weights. Such static weights do not reflect the dynamic nature of wireless services. In addition, In MADM techniques, the ranking value differences among different candidate are small, which make it hard for the decision maker to choose the best candidate. Furthermore, MADM techniques suffer from ranking abnormalities when the ranking of the top network changes due to the drop of one of the low ranked networks. Ranking abnormalities are more challenging in the sitting of vertical handover due to the dynamic nature of wireless environment. Ranking abnormalities result in frequent handovers that consume network resources, increase computational overhead, delay decision making, interrupt services, and consume more power (Huszák, Á., 2010). With the new generations of wireless services and due to the high scalability of future networks, such effects are expected to be more severe. These challenges motivated the work presented in this paper. A different approach to generate the weight has been introduced. The weights generated in this approach are dynamic and change to maximize the summation of the ranking differences among candidate networks, which is expected to reduce the ranking abnormalities. PSO technique is used to optimize the summation of the ranking differences through the assignment of a dynamic weights for the attributes. The use of PSO is motivated by the fact that MADM is a multiobjective conflicting criteria problem. DIA technique in the framework of network selection in a heterogenous wireless network, which is an example of a MADM, uses attributes such as cost, data rate, security, delay, jitter, and packet loss, which are processed by MADM methods to rank alternatives. This creates what is known as a nonconvex multiobjective optimization. Due to the nature of wireless channel, these attributes have a lot of subjectivity, irregularity, and fluctuation. Optimizing such attributes will create different single nonconvex problem after linear scalarization. So, in general, this problem is hard to be solved using techniques such as Lagrangian decomposition (LD) or Nash bargaining solution (NBS).

The limitations of MADM techniques presented previously have motivated the work in this paper. The paper investigates the application of the DIA method to vertical handover when the weights are generated using PSO. Such dynamic generation of the weights will eliminate the subjectivity in the process of weights' assignment inherited in the conventional MADM techniques. In addition to using PSO, we proposed different optimization functions based on the absolute values of the ranking differences. The proposed weight optimization was applied to the DIA method. The performance of the proposed technique with different optimization functions was investigated in terms of the total ranking separation, ranking abnormalities, and network selection.

The rest of the paper is organized as follows. The DIA algorithm is presented in Section 2. In Section 3, the PSO algorithm is highlighted. The PSO-based weights assignment technique for the DIA method is introduced in Section 4. Numerical results and discussion of the proposed technique are presented in Section 5. Conclusions are drawn in Section 6.

DISTANCE TO IDEAL ALTERNATIVE ALGORITHM

MADM mathematical formulation can be expressed in the matrix format (decision matrix). "n" columns in the decision matrix represent the attributes, and "m" rows represent the alternatives (wireless networks). The DIA is a MADM technique that calculates the "Manhattan" distance, instead of the Euclidian distance, to the positive and negative ideal solutions. The DIA method is introduced in Tran, P. & Boukhatem, N. (2008). The following steps are taken by the DIA method to rank the alternatives.

1. Construct the decision matrix, D

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

2. Normalize the entries of the decision matrix, d_{ij}, using Euclidian normalization, to generate a normalized matrix, R, with each element, r_{ij}, given by

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

3. Construct the weighted normalized matrix, *B*. The elements of *B* are generated by multiplying each column of matrix *R* by its corresponding weight, w_j, as follows:

$$b_{ij} = w_j * r_{ij}\ , \qquad \text{where} \sum_{j=1}^{n} w_j = 1 \tag{3}$$

4. Calculate the positive ideal solution, A^+, and negative ideal solution, A^-:

$$A^+ = [b_1^+, \ldots, b_n^+] \quad and \quad A^- = [b_1^-, \ldots, b_n^-] \tag{4}$$

For benefit criteria:

$$\begin{aligned} b_j^+ &= \max_i\{b_{ij}, i = 1, \ldots, m\} \\ b_j^- &= \min_i\{b_{ij}, i = 1, \ldots, m\} \end{aligned} \tag{5}$$

For cost criteria:

$$\begin{aligned} b_j^+ &= \min_i\{b_{ij}, i = 1, \ldots, m\} \\ b_j^- &= \max_i\{b_{ij}, i = 1, \ldots, m\} \end{aligned} \tag{6}$$

5. Calculate the Manhattan distance between attribute values and the positive and negative ideal values of each attribute:

$$D_i^+ = \sum_{j=1}^{n} \left|b_{ij} - b_j^+\right| \quad , i = 1, \ldots, m \| 1 D_i^- = \sum_{j=1}^{n} \left|b_{ij} - b_j^-\right| \quad , i = 1, \ldots, m \tag{7}$$

6. Determine the positive ideal alternative (PIA):

$$\text{PIA} = \{\min(D_i^+), \max(D_i^-)\} \tag{8}$$

7. Find the distance of an alternative from the PIA:

$$R_i = \sqrt{\left(D_i^{\pm} min(D_i^+)\right)^2 + \left(D_i^- - max(D_i^-)\right)^2} \tag{9}$$

8. Rank the alternatives in an increasing order of Ri.

In the context of VHO, the top-ranked network with the smallest value of R_i is selected, and the handover process is initiated. Due to the dynamic of the wireless environment, the value of the attributes, and hence the ranking of the networks, changes.

PARTICLE SWARM OPTIMIZATION

PSO is a simple, computationally efficient and effective optimization technique that found wide applications in wireless communication networks. PSO technique has been applied to improve routing scheme (Wang, J., 2019), energy efficiency (Wang, X., 2007), localization (Zhang, Y., 2016), and other functionalities of wireless networks (Kulkarni, R. V., 2010). In Goudarzi, S. (2015), PSO is used to predict the signal strength to facilitate the vertical handover process. The study in Goudarzi, S. (2017) proposes a hybrid intelligent handover decision algorithm based on artificial bee colony (ABC), as well as particle swarm optimization to select best wireless network during vertical handover process.

PSO is a powerful computational method that obtains a competitive solution for optimization problems by iteratively enhancing a preliminary set of potential solutions in parallel with reference to a given measure of quality. PSO is a type of swarm intelligence (SI) methodology (Eberhart, R., 1995) and is based on the metaphor of bird flocking. In general, the potential set of solutions in PSO mimics a flock of birds, as information is shared among the flock, so each member can individually benefit from that information (Parsopoulos, K. E., 2002). In addition to a connection to SI theory, PSO is associated with artificial life (A-life). Specifically, a group of arbitrary candidate solutions, which represent 'particles,' are initially fed into the PSO algorithm. Within a given problem space, each particle is assigned a random location and a random velocity and made to move iteratively through it. The particles are then attracted, simultaneously, towards the areas of both the best fitness achieved by itself and the best fitness achieved by the entire population.

Suppose the total population of the swarm is denoted by N, the dimension of the problem-to-be-solved is denoted by M, and the position and velocity of the i^{th} particle are $x_i = [x_i^1, \dots, x_i^n, \dots, x_i^M] \in R^M$ and $v_i = [v_i^1, \dots, v_i^n, \dots, v_i^M] \in R^M$ in M –dimensional space, respectively. Therefore, the position and velocity of the particle i would vary depending on the following equations:

$$v_i^{m+1} = v_i^m + \alpha_1 * rand_1(0 \to 1) * (p_i^m - x_i^m) + \alpha_2 * rand_2(0 \to 1) * \left(p_g^m - x_i^m\right) \qquad (10)$$

$$x_i^{m+1} = x_i^m + v_i^m \qquad (11)$$

where α_1 and α_2 are two acceleration coefficients; $rand_1(.)$ and $rand_2(.)$ are two uniformly distributed random values, which are independently generated in range [0,1]; $p_i = [p_i^1, \dots, p_i^n, \dots, p_i^M] \in R^M$ refers to the best previous position of the particle I; and $p_g = [p_g^1, \dots, p_g^n, \dots, p_g^M] \in R^M$ refers to the best previous position discovered by all particles (Du, W. B., 2015). A general description of PSO pseudocode is shown in Figure 1.

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for each particle $i = 1, \dots, N$ **do**

Initialize the particle's position x_i randomly

Initialize the particle's best-known position p_i to its initial position

Update the swarm's best-known position p_g

Initialize the particle's velocity: v_i randomly

while a termination criterion is not met **do**:

for each particle $i = 1, \dots, N$ **do**

for each dimension $m = 1, \dots, M$ **do**

Update the particle's velocity using Eq. (10)

Update the particle's position using Eq. (11)

Update the particle's best-known position

Update the swarm's best-known position

Figure 1. General PSO algorithm.

The total complexity of the PSO algorithm can be calculated using the total number of computations required to obtain the cost of a candidate solution and the computations required to use the updated values of the particles, which include the position and the velocity (Sohail, M. S., 2014).

The complexity for the various steps in PSO algorithm is as follows. The generation of the random population of the n particles, as well as the calculations of the fitness for the i^{th} particle, is n times. The weight factor is initialized once, and the loop required to find the best fitness between all particles uses sorting and, hence, has at best $N.log(N)$ complexity. To calculate the velocity and position of the $k+1$ particle, we need to compute Eq. (10) and Eq. (11) for M times and, hence, $M.C1$, where $C1$ is a constant factor to accommodate for the computation of both equations. After the calculation, the complexity is $N.log(N).(M.C1)$. In summary, the total complexity is $O(N.M.Log(N))$ (Papadimitriou, C. H., 1998). The PSO has two nested loops that run through the entire population and another outer loop for the general iterations. Therefore, the complexity of this algorithm is $O(N.M.Log(N).t)$, where t is the iterations number.

Typically, in MADM methods such as the DIA, fixed weight values are assigned in a subjective way based on the decision maker's experience using the AHP technique and the importance of the attribute. Attributes with higher importance are given larger weight values, and vice versa. In this paper, a PSO-based weights' assignment is suggested. The proposed technique is expected to improve the ranking and the selection process by optimizing the weights assigned to attributes to reduce the inaccuracy and the subjectivity in the weights' assignment process. PSO will initially work on weights obtained using the AHP technique (Saaty, T. L., 2008). Those weights are then optimized dynamically within $\pm 75\%$ around the initial weights. PSO will optimize those weights towards maximizing the summation of the absolute value of the ranking differences among alternatives. The following objective functions are proposed to control and direct the PSO optimization process:

$$\Delta 1 = \sum_{i=1}^{m} \sum_{s=i+1}^{m} |R_s - R_i| \tag{12}$$

$$\Delta 2 = \sum_{i=1}^{m} |R_{i+1} - R_i| \tag{13}$$

$$Maximize\ (\Delta i) \quad s.t \sum_{j=1}^{n} w_j = 1 \tag{14}$$

where $\Delta 1$ and $\Delta 2$ represent the summation of the ranking differences obtained by the PSO-based DIA method. These objective functions are proposed to increase the ranking differences, obtained by DIA, among alternatives. Such increase is expected to better distinguish among alternatives and hence will reduce ranking abnormalities.

To utilize the previous objective functions, the value of the ranking parameter, R_i, in Eq. (17) is substituted in the objective functions $\Delta 1$ and $\Delta 2$. The values of R_i are updated through the weights obtained by applying the PSO technique through an objective function to maximize the difference among ranking values as follows:

$$D_i^{\,+} = \sum_{j=1}^{n} \left| w_j * r_{ij} - max\left(w_j * r_j\right) \right| \tag{15}$$

$$D_i^{\,-} = \sum_{j=1}^{N} \left| w_j * r_{ij} - min\left(w_j * a_j\right) \right| \tag{16}$$

$$R_i = \sqrt{\sqrt{\left(D_i^{\pm} min(D_i^{+})\right)^2 + \left(D_i^{-} - max(D_i^{-})\right)^2}}\ ; \tag{17}$$

Figure 2 outlines the process of applying the PSO technique to obtain the dynamic weights, which can be used by the DIA method. The weights play a major part in the calculation of the ranking values of the different networks through Eqns. (Savitha, K., 2017a, 2017b; Tran, P., 2008) when the DIA method is used. When the ranking values of the networks are close, the removal of a network will make the process vulnerable to ranking abnormities. The function Δ1 maximizes the summation of the absolute value of the ranking difference among all alternatives, while Δ2 maximizes the summation of the absolute value of the ranking difference between consecutive alternatives. The objective functions represented by Δ1 and Δ2 are used as tools for the PSO technique to obtain weights that maximize the summation of the absolute value of the ranking difference and hence reduce the ranking abnormalities. In the subsequent numerical results, the objective functions Δ1 and Δ2 are used as a mean for the PSO technique to obtain an optimum weight that maximizes these objective functions.

- Let N be the size of the PSO population,
- $W[i]$ be the i^{th} particle of the PSO population and the weight vector for the network *I,*
- fitness $[W[i]]$ be the cost function of a particle according to Eq. (12) or (13),
- $W[i][j]$ be a Wj for the network *I,*
- $V[W[i]]$ be the velocity of a particle $W[i]$,
- and $P[W[i]]$ be the position of particle $W[i]$. Then:

Step1: (Initialization): for each particle $W[i]$ in the population:

- Initialize $W[i][j]$ using AHP technique.
- Initialize both $V[W[i]]$ and $P[W[i]]$ randomly.
- Evaluate fitness $[W[i]]$
- Initialize $Gbest$ with a copy of the particle with the highest fitness among the population.
- Initialize $Pbest[i]$ with a copy of each particle's best location.

Step2: Repeat until a number of generation (t) is passed:

- Step2.1: Find $Gbest$ such that fitness $[Gbest] >= fitness[W[i]] \;\forall i <= N$ & $Gbest \in W[]$.
- Step2.2: for each particle i: $Pbest[i] = W[i] \; iff. \; fitness[W[i]] > fitness[Pbest[i]] \;\forall i <= N$
- Step2.3: for each particle i: update $V[W[i]]$ and $P[W[i]]$ according to Eqs. (10) and (11).

Figure 2. A description of the implementation algorithm of the proposed PSO-based weights' assignment techniques for the DIA method.

RESULTS AND DISCUSSIONS

Four different candidate networks are considered in the simulation setup to represent the heterogenous network setting. The candidate networks are UMTS, WLAN, WIMAX, and LTE. Each network is associated with six attributes: cost per byte (CB), data-rate (DR), security (S), packet delay (D), packet jitter (J), and packet loss (L). The candidate networks and the values of the attributes are shown in Table 1.

Table 1. Attributes' Values for the Candidate Networks.

	#Network	CB (%)	S (%)	DR (mbps)	D (ms)	J (ms)	L (per 10^6)
1	UMTS	60	70	0.1-2	25-50	5-10	20-80
2	WLAN	10	50	1-11	100-150	10-20	20-80
3	WIMAX	50	60	1-60	60-100	3-10	20-80
4	LTE	40	60	2-100	50-300	3-12	20-80

As shown in table 1, some attributes are assigned fixed values, while others are represented by a uniform random variable with minimum and maximum limits. Such random representation is intended to reflect the change of the values of the attributes due to the dynamic of the wireless environment. The parameters (DR, D, J, L) are modeled as uniform random variables as shown in Table 1. For example, the data rate is modeled as a random variable uniformly distributed from 0.1 to 2 Mpbs. In each run of the simulation, a new value, within this range, is generated for the data rate, and the decision matrix in Eq. (1) is updated. Different classes of services are simulated through the weights' generation process. Attributes with higher importance are given higher values of weights. CB and S parameters are assigned the values shown in Table 1 to reflect the importance of these parameters the networks presented. For example, the CB for UMTS is assigned a value 6 times higher than that of WLAN. AHP technique is used to generate the initial weights as shown in Saaty, T. L. (2008) and Almutairi, A. F. (2018).

A major step in the weight generation process through the AHP technique is the construction of a pair-wise comparison matrix. Each class of service has different attributes that are more important than others. The importance of such attributes is reflected by their weights. The more important attributes are given higher weight values through the AHP process. For each class of service, a pair-wise comparison matrix is constructed using Saaty scale (Saaty, T. L., 2008). For example, for conversational traffic class, attributes such as delay and jitter are more important than the other attributes. After constructing the pair-wise matrix for this class and going through the AHP technique to generate the initial weights, the weight values assigned to delay and jitter are higher than those of the other parameters as shown in Table 2. The attributes values are normalized using Euclidian normalization using Eq. (2). For the conventional DIA method, the weight values are static and generated using AHP. For the proposed PSO-based technique, the weight values are initialized using AHP and then updated in every run using the PSO approach and the fitness functions presented earlier. Therefore, in the proposed technique, the weight values are dynamic and optimized based on Eq. (12) and Eq. (13). The adopted methodology is shown in Figure 3.

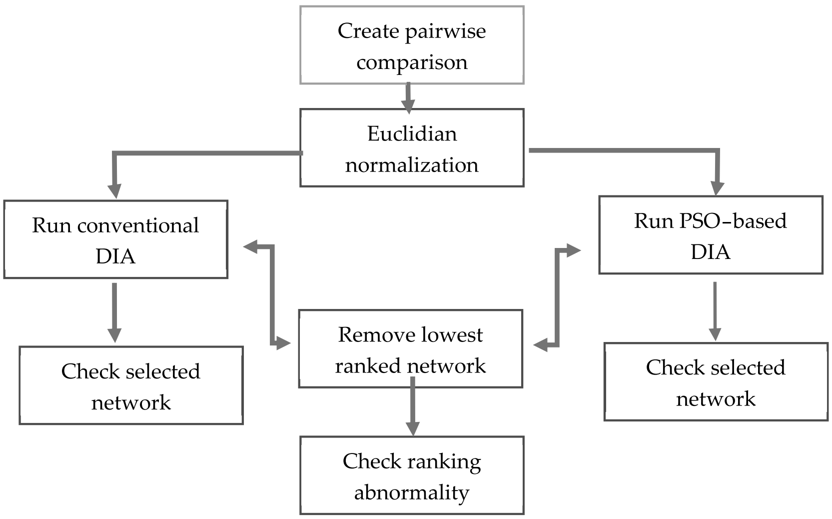

Figure 3. Block diagram of PSO-based DIA methodology.

The weights generated based on the AHP and the optimization functions presented in the previous sections are presented in Table 2 under the headings AHP, Δ1, and Δ2, respectively.

Table 2. AHP static weights and a sample of the two PSO-optimized dynamic weights for the DIA method.

	Attribute	AHP	Δ1	Δ2
Conversational Traffic	CB	0.0360	0.0148	0.0112
	S	0.1248	0.0820	0.0596
	DR	0.1045	0.0753	0.0670
	D	0.3251	0.4251	0.4431
	J	0.3071	0.3478	0.3742
	L	0.1024	0.0550	0.0449
Background Traffic	CB	0.0855	0.0417	0.0589
	S	0.1555	0.0891	0.0836
	DR	0.4416	0.7048	0.6947
	D	0.0518	0.0196	0.0211
	J	0.0793	0.0439	0.0397
	L	0.1863	0.1009	0.1020
Interactive Traffic	CB	0.0785	0.0374	0.0334
	S	0.1745	0.1490	0.1583
	DR	0.0927	0.0538	0.0805
	D	0.3095	0.4719	0.4551
	J	0.0505	0.0347	0.0389
	L	0.2944	0.2532	0.2337
Streaming Traffic	CB	0.1016	0.0724	0.0745
	S	0.1959	0.1363	0.1476
	DR	0.2975	0.4792	0.4708
	D	0.0929	0.0550	0.0716
	J	0.1198	0.1061	0.0988
	L	0.1923	0.1509	0.1367

For comparison, the weights of different classes, namely, conversational, background, interactive, and streaming classes, are presented. Although the trends of the weight values of the attributes are the same, each weighting technique gives a different set of weights' values. For example, for the conversational traffic class, AHP, Δ1, and Δ2 gave the highest weight values to delay and jitter. On the other hand, the proposed PSO optimization gave higher weight values to delay and jitter when compared to AHP-based weight. Such difference of weight values is expected to reflect positively on the performance of the proposed techniques in terms of ranking abnormality.

Table 3. Summation of ranking differences for DIA and the proposed PSO optimizations.

Class	DIA	Δ1	Δ2
Conversational	0.217	0.310	0.331
Background	0.357	0.594	0.611
Interactive	0.155	0.251	0.285
Streaming	0.218	0.396	0.413

Table 4. Percentage of ranking abnormalities of DIA with AHP and the proposed PSO optimizations.

Class	DIA	Δ1	Δ2
Conversational	4.6	1.8	1.2
Background	1.25	0.6	0.2
Interactive	5.70	0.4	0.3
Streaming	2.50	1.6	0.8

The performance of the proposed PSO optimization of the DIA technique has been investigated in terms of ranking abnormalities, and the results are shown in Table 4. The results support our observation that the improvements of the summation of the absolute values of the ranking differences will result in a reduction of ranking abnormalities for the PSO-based DIA method.

Δ1 and Δ2 have substantially lower abnormalities when compared to the conventional AHP-based DIA.

Table 5. Percentages of selection of desired networks of DIA with AHP and the proposed PSO optimizations.

Class	DIA	Δ1	Δ2
Conversational	99	100	99
Background	96	99	99
Interactive	93	93	94
Streaming	98	99	99

The performance in terms of the desired networks' selection is presented for different classes of services when the conventional AHP-based DIA and the two proposed PSO-based optimization techniques are presented in Table 5. The proposed PSO-based techniques did not degrade the excellent network selection capabilities of the conventional AHP-based DIA.

It is worth mentioning that the function Δ1 maximizes the summation of the absolute value of the ranking difference among all alternatives, while Δ2 maximizes the summation of the absolute value of the ranking difference between consecutive alternatives. Therefore, Δ1 will optimize differences that might not affect the performance parameters much, while the function Δ2 focus is in more important consecutive ranks. For this reason, the performance of Δ2 is better than that of Δ1.

CONCLUSION

In this paper, the PSO technique is applied to optimize the weights of attributes used in the DIA method. The application of PSO resulted in a better weights' assignment that changed based on the resources of the different wireless networks. Two optimization functions were proposed and applied to the DIA method. The proposed PSO optimizations outperformed the conventional AHP-based DIA method in terms of abnormality in all classes of services. On the other hand, the proposed PSO-based DIA techniques did not degrade the excellent network selection of the conventional AHP-based DIA method. Furthermore, such enhancement of the performance of the DIA method was possible by applying the PSO technique. The results of the paper are expected to widen the application of the DIA method and other MADM techniques to vertical handover problems in wireless networks and other decision-based challenges in other fields. This work can be extended in the future by using machine learning (ML) and artificial intelligence (AI) techniques to improve the performance of different MADM methods.

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