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A genetic algorithm approach for multi-attribute vertical handover decision making in wireless networks

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Abstract Mobile terminals can typically connect to multiple wireless networks which offer varying levels of suitability for different classes of service. Due to the changing dynamics of network attributes and mobile users' traffic needs, vertical handovers across heterogeneous networks become highly desirable. Multiple attribute decision making (MADM) techniques offer an efficient approach for ranking competing networks and selecting the best one according to specific quality of service parameters. In this paper, a genetic algorithm (GA) is applied to optimize network attributes' weighting by emphasizing ranking differences among candidate networks, thereby aiding correct decision making by reducing unnecessary handovers and ranking abnormalities. The performance of the proposed GA-based vertical handover is investigated with typical MADM techniques including Simple Additive Weighting (SAW) and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). The results show that the proposed GA-based weight determination approach reduces the abnormality observed in the conventional SAW and TOPSIS techniques substantially. The results of this paper will help ensuring the application of MADM methods to more dynamic and challenging decision making problems encountered in wireless network.

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1 Introduction

The wide diversity in wireless access technologies is manifested by the coexistence of various heterogeneous networks with different features and architectures as shown in Fig. 1. This diversity provides mobile terminals with different connectivity options depending on the offered quality of service (QoS) parameters and the mobile users' traffic classes. This flexibility gives rise to the need of transferring a mobile terminal connectivity from one network to another in a seamless way. When this process is executed between two networks with different architectures and air interface protocols, it is commonly described as "vertical" handover (VHO) [1,2]. A vertical handover process can typically be divided into three phases [3]; namely, Handover Initiation Phase, Handover Decision Phase, and Handover Execution Phase. Different handover management schemes are presented in [4–9].

The decision making problem in vertical handover execution takes into consideration several performance attributes to enable the selection of the most suitable network. Multiple attribute decision making (MADM) techniques are commonly used to take into account several attributes in order to evaluate a given set of competing alternatives. In the context of vertical handover, the main objective of these methods is to rank the set of candidate networks by considering some evaluation parameters in a structured and meaningful way. The application of several MADM algorithms for vertical handover has been addressed and the performance of typical algorithms has been investigated in [10,11]. This includes Simple Additive Weighting (SAW),

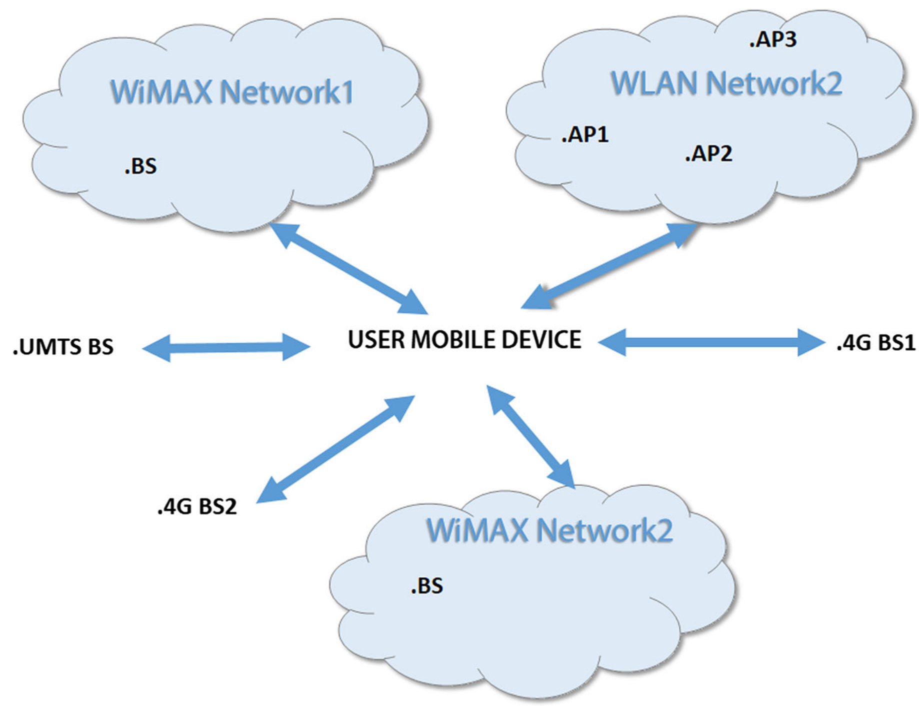

Fig. 1 Simulation topology of heterogeneous wireless networks

Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), Multiplicative Exponent Weighting (MEW), Grey Relational Analysis (GRA), ELimination and Choice Expressing REality (ELECTRE), and Weighted Markov Chain (WMC). Performance comparisons are also given among several MADM algorithms such as SAW, MEW, TOPSIS, GRA, ELECTRE and WMC with different traffic classes [12]. The handover metrics considered include cost per byte, total bandwidth, available bandwidth, security, utilization, delay, jitter and packet loss. A different approach based on two-stage vertical handover process was suggested in [13]. On the other hand, different works, as in [14–16], focused on suitable attribute weighting techniques such as Analytic Hierarchy Process (AHP), Fuzzy Analytic Hierarchy Process (FAHP), Analytic Network Process (ANP), Fuzzy Analytic Network Process (FANP), and Random Weighting (RW) which are studied and compared for different mobile users' traffic classes, including conversational, streaming, interactive and background traffic. The results reported in [14–16] show that different weighting techniques, namely; AHP, FAHP, ANP, FANP and RW, give widely varying performance when combined with the TOPSIS, DIA and GRA MADM algorithms. It should however be noted that the attributes' weights selection in these weighting techniques are set by decision-makers in heuristic (arbitrary) ways, leading to subjective network selection and increased ranking fluctuation, or *ranking abnormality*, which refers to the rapid changes in ranking order when a low ranked alternative is removed. This constitutes a major drawback as it leads to frequent (and unnecessary) handover initiations, thereby causing instabilities, delay and/or loss of service, and drainage of system resources due to increased computational and power consumption loads. As such, more robust MADM algorithms are needed to maintain the best alternative irrespective of the removal or addition of other alternatives [12], and there has been some recent interest in mitigating the ranking abnormality problem as discussed in [17–24]. The authors in [25] also proposed a two-step VHO decision algorithm based on dynamic weight compensation by introducing self-adaptive correction matrix. However, the challenge of ranking abnormality still needs further improvement. Such a challenge motivates the work presented in this paper, where we introduce a different approach to reduce ranking abnormality by targeting the weights assignment rather than looking at the normalization techniques [24]. A genetic algorithm (GA) weight assignment technique is proposed to reduce the ranking abnormality through maximizing the summation of the ranking differences of candidate networks. In contrast with the previously mentioned ranking abnormality reduction techniques, the proposed GA-based technique can be applied to any MADM method irrespective of the attributes and normalization techniques used. Furthermore, since attributes' weights are commonly assigned based on the (subjective) decision maker's experience which can affect the ranking and selection of alternatives, the proposed GA approach mitigates this problem by automating the weight generation process through the maximization of the summation of the ranking differences among candidate alternatives. The proposed GA-based algorithm will be evaluated and validated by thorough comparisons with conventional techniques by using metrics based on the ranking abnormality, attributes' weights, and ranking difference summation.

The rest of the paper is organized as follows. MADM methods are presented in Sect. 2. The genetic algorithm details are highlighted in Sect. 3. Section 4 introduces the GA-based technique for optimizing attributes' weighting. Numerical results and discussions are presented in Sect. 5. A summary of the work findings and conclusions are given in Sect. 6.

2 Multiple attribute decision making methods

As noted in the introduction, we consider for comparative purposes the SAW and TOPSIS methods combined with AHP, and assess their merits in terms of ranking abnormality, attributes' weight values, and ranking difference summation. We then show that the proposed GA-based weight assignment approach provides distinctively better performance. For completeness, the AHP, SAW and TOPSIS mathematical formulations are first highlighted before introducing our proposed method next. By the same token, the relevant formulations are also specified for the problem at hand, namely the vertical handover decision among competing wireless networks.

2.1 Analytic Hierarchy Process (AHP)

The Analytical Hierarchy Process is a procedure that gives a numerical weight to each decision alternative according to how well that alternative fulfills the criteria set for decision making [26]. The generated weights depend on the importance of each attribute compared to other attributes. The method attempts to establish a consistent way through pair-wise comparisons, and relies on experts' experience for constructing a *decision matrix*. The AHP steps are summarized below [26]:

(1) *Step 1: Problem decomposition*
First, the problem is decomposed into a hierarchy that contains three levels: (i) the topmost level consists of the overall objective, (ii) the subsequent level represents the decision factors, and (iii) the alternative solutions are located at the bottom level.
(2) *Step 2: Construction of a pair-wise comparison matrix*
The second step attempts to construct a pair-wise comparison matrix to give a measurable assessment of the importance of decision criteria vis-à-vis each other. In our specific case, the network quality-of-service (QoS) parameters are assessed pair-wise. This assessment is quantified according to Saaty's 9-point scale which maps the qualitative judgments into numerical relative priorities [26], as shown in Table 1. For example, if attribute A is decisively more important than B and was assigned the scale 7, then attribute B, being relatively less important, is assigned 1/7. The matrix main diagonal is set to 1 as this reflects any given parameter importance compared with itself. The non-diagonal entries display inverse symmetry with respect to the main diagonal because of the reason outlined above.
After the construction of the comparison matrix, columns are summed and each entry is normalized by the column weight. Next, each row of the normalized comparison matrix is summed and divided by the number of elements in the row. The result gives a weight vector which contains the percent weight of each criterion when compared to the other ones.
(3) *Step 3: Measurement of consistency of the weights*
The last step forms the sum of each column of the pair-wise comparison matrix and places it in the last row. The resultant matrix is then normalized to form a Normalized Comparison matrix by making the elements of the sum row as 1. A Consistency Ratio (CR) is obtained as outlined in [26]. It is recommended that the value of CR does not exceed 0.1, in which case the pair-wise comparison matrix is said to be consistent. The determination of the most suitable normalization procedure to normalize different criteria is one of the main challenges in MADM techniques. The performance of MADM techniques with different normalization is investigated in [27–30].

Table 1 AHP importance scale [26]

Intensity of importance	Definition	Description
1	Equal importance	Element A_i and A_j are equally important
3	Weak importance of A_i over A_j	Experience and judgments slightly favors A_i over A_j
5	Essential or strong importance	Experience and judgments strongly favors A_i over A_j
7	Demonstrated importance	A_i is very strongly favored over A_j
9	Absolute importance	The evidence favoring A_i over A_j is of the highest possible order of affirmation
2, 4, 6, 8	Intermediate importance	When compromise is needed

2.2 Simple Additive Weighting (SAW) method

SAW [12] is among the conventional MADM techniques used for producing candidate' scores and ranking alternatives. To illustrate the method, we assume a number of candidate networks denoted by "*m*" and a number of decision attributes denoted by "n". A context matrix A_{SAW} is then defined by:

$$A_{SAW} = \begin{bmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{m1} & \cdots & a_{mn} \end{bmatrix} \tag{1}$$

where a_{ij} denotes attribute j of candidate network i. With respect to the decision parameters, it is observed that they can be classified into two categories: benefit and cost parameters, where the higher the value of a benefit parameter, the better the outcome, and vice versa for a cost parameter. For our purpose, data rate, security and bandwidth are considered benefit parameters, and st, delay, and jitter are cost parameters. With this classification, the context matrix A is then normalized to produce a matrix $\bar{A}$ using the following equations:

For the benefit criteria:

$$\bar{a}_{ij} = \frac{a_{ij}}{\sum_{i=1}^{m} a_{ij}} \tag{2}$$

For the cost criteria:

$$\bar{a}_{ij} = \frac{\sum_{i=1}^{m} a_{ij}}{a_{ij}} \tag{3}$$

The normalized context matrix ($\bar{A}$) is given by:

$$\bar{A} = \begin{bmatrix} \bar{a}_{11} & \cdots & \bar{a}_{1n} \\ \vdots & \ddots & \vdots \\ \bar{a}_{m1} & \cdots & \bar{a}_{mn} \end{bmatrix} \tag{4}$$

On the other hand, for every traffic profile, a given weights' vector is assigned and denoted by $\boldsymbol{W}$ with its elements w_j's representing the weights of criteria j = 1,…,n. For normalization, the sum of w_j's is set to 1.

$$\boldsymbol{W} = [w_1 \cdots\cdots w_n] \tag{5}$$

Then, a new matrix $\bar{\bar{A}}$ is formed by multiplying each column of the $\bar{A}$ matrix that represents any given attribute by that attribute's weight. This matrix is given by:

$$\bar{\bar{A}} = \begin{bmatrix} \bar{a}_{11} * w_1 & \cdots & \bar{a}_{1n} * w_n \\ \vdots & \ddots & \vdots \\ \bar{a}_{m1} * w_1 & \cdots & \bar{a}_{mn} * w_n \end{bmatrix} \tag{6}$$

The SAW model finally evaluates all candidate networks and ranks the alternatives with a numerical score. The network with the highest score is then selected.

$$S_{SAW} = \sum_{j=1}^{n} \bar{a}_{ij} * w_j \tag{7}$$

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

The TOPSIS model is another common MADM method used for ranking alternative candidates [12]. It defines an index that compares the separation of each network to the best and worst network which indicate ideal and bad solution, respectively. The context matrix A_{TOPSIS} for a given set context of m candidate networks and n decision criteria is constructed as follows:

$$A_{TOPSIS} = \begin{bmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{m1} & \cdots & a_{mn} \end{bmatrix} \tag{8}$$

where the normalization of attributes is given by:

$$\bar{a}_{ij} = \frac{a_{ij}}{\sqrt{\sum_{i=1}^{m} a_{ij}^2}} \tag{9}$$

The weight normalized matrix ($\bar{\bar{A}}_{TOPSIS}$) is obtained by multiplying each context criteria by their class weights:

$$\bar{\bar{A}}_{TOPSIS} = \begin{bmatrix} \bar{a}_{11} * w_1 & \cdots & \bar{a}_{1n} * w_n \\ \vdots & \ddots & \vdots \\ \bar{a}_{m1} * w_1 & \cdots & \bar{a}_{mn} * w_n \end{bmatrix} \tag{10}$$

To identify the best and worst alternatives with respect to a given context criterion (with index j), we find the highest and lowest values among all $\left(\bar{a}_{ij}\right)$, respectively. The following equations illustrate this.

$$\bar{a}_j^{Best} = Max\left(\bar{a}_{ij}\right), i = 1, \ldots, m \tag{11}$$

$$\bar{a}_j^{Worst} = Min\left(\bar{a}_{ij}\right), i = 1, \ldots, m \tag{12}$$

The distances of each candidate network from the best and worst solutions are then obtained as:

$$S_i^{+} = \sqrt{\sum_{j=1}^{n} \left(\bar{a}_{ij} - \bar{a}_j^{Best}\right)^2} \tag{13}$$

$$S_i^{-} = \sqrt{\sum_{j=1}^{n} \left(\bar{a}_{ij} - \bar{a}_j^{Worst}\right)^2} \tag{14}$$

To identify the best alternative, the highest value of S_{TOPSIS} is found after ranking based on the relative distances from best and worst solutions.

$$S_{TOPSIS} = \frac{S_i^-}{S_i^+ + S_i^-} \tag{15}$$

3 Genetic algorithm optimization

Genetic Algorithms (GA) have been successfully adopted for various optimization applications in many fields of science and engineering (see, e.g., [30–33]). These algorithms can be applied to solve different types of optimization problems, including both constrained and unconstrained ones, by relying on the principles of natural selection and genetics.

For our purpose, the application of GAs as a search method to solve the weight optimization problem is investigated in this work to reduce ranking abnormality in VHO applications. In the GA framework, solutions are transformed into coded forms called chromosomes. As with other optimization methods, a candidate solution viability is rated by an objective function. In the GA approach, each solution is tested by a fitness function that reflects its strength among all other solutions in the population. This fitness function can be viewed as the objective function [34–36]. After the problem is encoded into chromosomes and a fitness function has been chosen, the GA evolves solutions until the fitness accuracy is met, or a maximum number of generations are reached. More specifically, initial populations of candidate solutions are created randomly. Then the populations are mated and a sequence of new populations emerges. At each step, individuals in the current generation are used to create the next population. The GA-based specific processing steps applied in this work are summarized in the following:

(1) Evaluation and fitness assignment
The objective function values of the candidate solutions in the current population are evaluated. The algorithm uses the objective function values to determine the fitness values of the candidate solutions in the current population.
(2) Selection
The algorithm selects members, called parents, based on their fitness. The main idea of selection is to prefer better solutions to worse ones. There are different strategies to select the individuals to be copied over into the next generation. In the "elitism" technique, some of the individuals in the current population that have the best fitness values are chosen as elite individuals and are passed to the next population as children. The technique selects the first parents by the fitness order and they mate to produce next generation. In the "roulette wheel" selection technique, selection is represented as a game of roulette whereby each individual gets a slice of the wheel, but more fit ones get larger slices than less fit ones. With this selection method, the chance of a chromosome to be selected is calculated according to their fitness (cost) or according to their rank. In the "tournament" technique, a small subset of chromosomes is selected randomly and the one with the best fitness will become a parent. Parents can also be selected randomly.
Stochastic universal sampling is used in our case as it chooses several solutions from the population by setting a single random value to sample all of the solutions by choosing them at evenly spaced intervals. This gives weaker members of the population a chance to be chosen and thus reduces the unfair nature of fitness-proportional selection methods.
(3) Crossover (Recombination)
Crossover combines the vector entries or genes of two parents to form potentially better solutions (offspring) for the next generation. Different strategies of crossover are developed and used according to the optimization problem at hand. In one-point crossover, a single crossover point on both parents' organism strings is selected. All data beyond that point in either organism string is swapped between the two parent organisms. The resulting organisms are the children. In two-point crossover**,** two points are selected on the parent organism strings. Everything between the two points is swapped between the parent organisms, rendering two child organisms. On the other hand, uniform crossover uses a fixed mixing ratio or a predefined rule between two parents. If the mixing ratio is 0.5, the offspring has approximately half of the genes from first parent and the other half from second parent, which is the approach used in this paper.
(4) Mutation
Mutation applies random changes to one or more genes of an individual parent to form children. It is performed with a low probability in the range 1–20%. Mutation is a divergence operation. It is intended to occasionally break one or more members of a population out of a local minimum/maximum space and potentially discover a better one. The end goal is to bring the population to convergence, mutation, being a divergence operation, should happen less frequently, and typically effects a few members of a population in any given generation. Types of mutations includes: flip bit mutation where the bits of the chosen genome are inverted. Boundary mutation is another type where the genome is replaced with lower/upper bounds randomly. This can be used for integer and float genes. Uniform mutation is another approach where the value of the chosen gene is replaced with a uniform random value selected between user-specified upper and lower bounds. Gaussian mutation is also used whereby the operator adds a unit Gaussian distributed random value to the chosen gene. If it falls outside of the

user-specified lower or upper bounds for that gene, the new gene value is clipped. This mutation operator can only be used for integer and float genes.

Due to the nature of our problem, adaptive feasible mutation is chosen to randomly generate directions that are adaptive with respect to the last successful or unsuccessful generation. The mutation chooses a direction and step length that satisfies bounds and linear constraints.

(5) Reproduction

This final step accounts for the reproduction of children through by selection, crossover, and mutation to form the next generation.

4 GA-based weight vector determination

In MADM techniques, the weights are often determined by decision makers' experience, and this could lead to subjectivity in network selection. Another drawback is that the ranking differences of evaluation values are small in some environments. This will make it difficult for a decision maker to choose the best alternative, which leads to the previously mentioned ranking abnormality.

In conventional MADM algorithms, the degree of importance (i.e., weight) of every attribute must be determined. The larger the weight, the higher the importance of the attribute corresponding to that weight, and vice versa. In the current MADM, decision makers rely on users' requirements and other subjective experience to set the weights of attributes. For example, the AHP method is widely used to determine the weight of each attribute [26]. Other weighting techniques are also presented in [14–16]. However, these techniques are found to be subjective assignment methods. As a consequence, the objective selection of the most appropriate network is not always achieved. Thus, one of the major limitations of these conventional MADM methods is the absence of objectiveness with regards to weight assignment, and hence overall decision making.

In this paper, the weights are obtained by solving an optimization problem whose objective is to maximize the summation of the absolute value of the ranking differences among candidate networks. The determination of the weights of the attributes is achieved by the application of GA techniques, as discussed in the previous section.

To develop the GA-based approach, we let the parameter N_i represent the ranking value of a certain network I, assuming we have M networks with N attributes. The objective function needs to optimize "Δ", the summation of the absolute value of the ranking values differences of the networks, which is given by:

$$\Delta = \sum_{r=1}^{M} \sum_{s=r+1}^{M} |N_r - N_s| \tag{16}$$

In case of SAW:

$$\Delta_{SAW} = \sum_{r=1}^{M} \sum_{s=r+1}^{M} \left| \sum_{j=1}^{N} a_{rj} W_j - \sum_{j=1}^{N} a_{sj} W_j \right| \tag{17}$$

where the values of the weight vector W values are optimized to maximize Δ_{SAW}. More specifically, with the TOPSIS algorithm, the separation measurements of each network from the positive and negative ideal solutions are given by the following equations:

$$S_i^+ = \sqrt{\sum_{i=1}^{N} \left(w_j * a_{ij} - \left(w_j * a_j^{Best} \right) \right)^2} = \sqrt{\sum_{j=1}^{N} \left[w_j^2 * \left(a_{ij} - a_j^{Best} \right)^2 \right]} \tag{18}$$

$$S_i^- = \sqrt{\sum_{i=1}^{N} \left(w_j * a_{ij} - (w_j * a_j^{worst}) \right)^2} = \sqrt{\sum_{j=1}^{N} \left[w_j^2 * \left(a_{ij} - a_j^{worst} \right)^2 \right]} \tag{19}$$

In the TOPSIS framework, the ranking is then obtained by calculating the relation of each network to the best and worst solutions, as outlined in Sect. 2. The summation of the absolute value of the ranking values differences is given by:

$$\Delta_{TOPSIS} = \sum_{r=1}^{M} \sum_{s=r+1}^{M} \left| \frac{S_r^-}{S_r^+ + S_r^-} - \frac{S_s^-}{S_s^+ + S_s^-} \right| \tag{20}$$

In the subsequent numerical results, the objective functions represented by Δ_{SAW} and Δ_{TOPSIS} are used as cost metrics for the GA to obtain optimum weights that maximize these functions.

With respect to the computational complexity aspects of the proposed GA-based VHO MADM algorithm, it can be seen from Eqs. (16), (17) that, for the case of the SAW-based approach, the main input fed to the GA optimization part consists of the delta metric, which requires an order of $2n$ multiplications and $2nm^2$ additions, where $n$is the number of decision criteria (i.e., length of the weight vector W) and m is the number of candidate networks. Similarly, for the TOPSIS implementation, the computation of each of the quantities S_i^+ and S_i^- based on Eqs. (18)–(20) requires $2n$ multiplications and $2n$ additions, while the computation of the delta metric in Eq. (20) adds on the order of $2m^2$ divisions and

Table 2 Attributes values for the candidate networks

#	Network	CB (%)	S (%)	DR (mbps)	D (ms)	J (ms)	L (per 10^6)
1	UMTS1	60	70	0.1–2	25–50	5–10	20–80
2	UMTS2	80	90	0.1–2	25–50	5–10	20–80
3	WLAN1	10	50	1–11	100–150	10–20	20–80
4	WLAN2	5	50	1–11	100–150	10–20	20–80
5	WIMAX1	50	60	1–60	60–100	3–10	20–80
6	WIMAX2	40	60	1–60	60–100	3–10	20–80
7	LTE1	50	60	2–100	50–300	3–12	20–80
8	LTE2	40	60	2–100	50–300	3–12	20–80

$2m^2$ additions. On the other hand, it is found that for typical implementations of Genetic Algorithms [33], the complexity requirements are estimated as O(gpn), with g denoting the number of generations, p the population size and n the size of the individuals (weights vector), respectively. Therefore, it can be seen that the computational complexity of our proposed algorithm is practically manageable given that the number of VHO candidate networks $m$is small for all practical purposes, and the number of decision criteria or attributes n is also limited (six attributes, in our assumed MADM model).

5 Results and discussions

5.1 Simulation setup

To investigate the performance of the proposed algorithm, a simulation environment was developed. Eight networks with six QoS attributes (as shown in Table 2) are assumed to be available in the coverage area. The six attributes which are used to evaluate this heterogeneous environment are: Cost per Byte (CB), Data-Rate (DR), Security (S), Packet Delay (D), Packet Jitter (J) and Packet Loss (L). Some of the attributes are modeled as uniform random variables with minimum and maximum values specified in Table 2. The randomness in the values of the attributes are essential to capture the dynamics of these networks and to reflect a more realistic scenario. In addition, the existence of two networks from each category introduces high probability for ranking abnormality to occur. Attribute values of the candidate networks are normalized using Linear Scale Transformation [26].

The simulation is run for 1000 iterations. For the conventional SAW and TOPSIS methods, the weights, shown in Table 3, are generated by the AHP technique and are maintained for all the runs. On the other hand, for the GA based technique, new weights are generated in every run based on the optimization approach specified in Eqs. (17) and (20).

Table 3 Weight vectors associated with the criteria generated by AHP

	CB	S	DR	D	J	L
$W_{conversational}$	0.036	0.124	0.104	0.325	0.307	0.102
$W_{background}$	0.085	0.155	0.441	0.051	0.079	0.186
$W_{interactive}$	0.078	0.174	0.092	0.309	0.050	0.294
$W_{streaming}$	0.101	0.195	0.297	0.092	0.119	0.192

5.2 AHP criteria weights for traffic classes

The AHP method takes into account the user experience to build the decision matrix and to determine the weights of criteria [26]. Using the AHP procedure outlined in Sect. 2, the weights for each QoS of the different classes of traffic are generated as shown in Table 3. These set of weights will be used as a reference to the weights generated by applying the proposed GA approach.

5.3 Results

Using the attribute values and weight vector calculated from AHP, network selection is performed using SAW and TOPSIS techniques.

To investigate the performance of the GA based weight assignment technique, instead of relying on the AHP method of determining fixed attribute weights, the weights are allowed to vary within certain ranges to achieve the optimization of ranking separation. If the range is too small, ranking abnormality will not improve in a noticeable manner. Based on our investigation, it is found that the most suitable range is to allow the weights to vary within a $\pm 75\%$ window. This will allow the GA to maximize the summation of the differences of the ranking values according to Eqs. (17) and (20).

GA is then used to maximize the total difference between candidate networks ranking. The algorithm is applied in conjunction with SAW and TOPSIS in our case, but can be also used with other MADM methods. To reduce ranking abnormalities, the difference between networks final rank-

Table 4 AHP based static weights and GA optimized weights for SAW and topsis techniques

	Attribute	AHP	SAW	%Diff.	TOPSIS	%Diff.
Conversational traffic	CB	0.036	0.0129	64.17	0.0141	60.83
	S	0.124	0.118	4.84	0.137	10.48
	DR	0.104	0.1122	7.88	0.0956	8.08
	D	0.325	0.3659	12.58	0.3396	4.49
	J	0.307	0.2911	5.18	0.3055	0.49
	L	0.102	0.1002	1.76	0.1078	5.69
Background traffic	CB	0.085	0.0692	18.59	0.0548	35.53
	S	0.155	0.1175	24.19	0.134	13.55
	DR	0.441	0.5694	29.12	0.5646	28.03
	D	0.051	0.026	49.02	0.0268	47.45
	J	0.079	0.0702	11.14	0.07	11.39
	L	0.186	0.1479	20.48	0.1494	19.68
Interactive traffic	CB	0.078	0.0547	29.87	0.0499	36.03
	S	0.174	0.153	12.07	0.1644	5.52
	DR	0.092	0.0872	5.22	0.0746	18.91
	D	0.309	0.42	35.92	0.4253	37.64
	J	0.05	0.0393	21.40	0.0389	22.20
	L	0.294	0.246	16.33	0.2464	16.19
Streaming traffic	CB	0.101	0.082	18.81	0.0647	35.94
	S	0.195	0.1308	32.92	0.1535	21.28
	DR	0.297	0.4743	59.70	0.4652	56.63
	D	0.092	0.0636	30.87	0.0659	28.37
	J	0.119	0.1032	13.28	0.1027	13.70
	L	0.192	0.1461	23.91	0.1474	23.23

ing should be as large as possible. The GA is used to choose the values of the weights' vector within a set of predefined boundaries.

Table 4 represents the weights associated with the different criteria generated using the GA based optimization with the SAW and TOPSIS techniques. The results are to be compared to those of Table 3 where the weights generated by the conventional AHP technique. As can be seen from Table 4, the weights obtained by GA optimization still reflect the importance of the criteria in a given class of traffic. For example, for conversational traffic, AHP technique (Table 3) assigns large weights for Delay and Jitter and the same trend is observed when the GA based technique is used (Table 4). Another important observation is that in the GA-based technique, the weight assignments not only reflect the importance of the criteria but also optimize the summation of the differences among consecutive ranking values.

Tables 5 and 6 demonstrate the average difference in assigned final weight value. The total sum of the absolute rank differences is substantially increased by applying the proposed GA based optimization. One can notice that the total separation among the ranking value has increased. For example, in the case of SAW technique, the total rank value separation has increased by 32.60, 31.88, 49.00, and 64.57% for conversational, background, interactive, and streaming traffic classes; respectively. For the TOPSIS technique, the total rank value separation has increased by 33.05, 14.37, 55.51, and 36.78% for conversational, background, interactive, and streaming traffic classes; respectively. This improvement demonstrates the effectiveness of the proposed GA-based optimization in reducing ranking abnormalities.

Table 7 shows the ranking abnormality percentages for conversational, background, interactive and streaming traffic classes. The table compares the performance of SAW and TOPSIS when the GA based technique is used to that obtained by AHP technique. The abnormalities experienced by SAW and TOPSIS have been reduced substantially. For conversational traffic, the proposed GA based technique reduced ranking abnormality by 14.8% for SAW and 21.2% for TOPSIS. For background traffic, the proposed GA based

Table 5 Summation of absolute values of ranking differences for SAW with or without G.A.

	Ranking differences summation without G.A.	Ranking differences summation with G.A.	Percent increase (%)
Conversational traffic	0.0914	0.1212	32.60
Background traffic	0.1719	0.2267	31.88
Interactive traffic	0.0753	0.1122	49.00
Streaming traffic	0.1129	0.1858	64.57

Table 6 Summation of absolute values of ranking differences for TOPSIS with or without G.A.

	Ranking differences summation without G.A.	Ranking differences summation with G.A.	Percent increase (%)
Conversational traffic	0.4714	0.6272	33.05
Background traffic	0.7198	0.8232	14.37
Interactive traffic	0.3920	0.6096	55.51
Streaming traffic	0.5441	0.7442	36.78

Table 7 Percentage of ranking abnormality occurrences for SAW and TOPSIS after using G.A. for weights optimization

	SAW		TOPSIS	
	Without G.A. (%)	With G.A. (%)	Without G.A. (%)	With G.A. (%)
Conversational traffic	39.7	24.9	47.9	26.7
Background traffic	21.5	12.7	23.6	16.9
Interactive traffic	51.4	26.9	59.2	26.7
Streaming traffic	35.0	18.4	36.0	22.7

technique reduced ranking abnormality by 8.8% for SAW and 6.7% for TOPSIS. For interactive class, the proposed GA based technique reduced ranking abnormality by 24.5% for SAW and 32.5% for TOPSIS. For streaming traffic, the proposed GA based technique reduced ranking abnormality by 16.6% for SAW and 13.3% for TOPSIS. These results confirm again that the application of the GA-based optimization leads to noticeable reduction in ranking abnormalities, especially when these abnormalities are high with other conventional methods.

6 Conclusion

This paper proposed the use of GA-based approach to optimize the weights of the network attributes to maximize the total difference among the rank values of the networks. As opposed to the conventional AHP technique, the proposed GA optimization is used to generate dynamic weights for SAW and TOPSIS MADM techniques. It is found that incorporating the GA in MADM methods reduces the subjectivity in assigning weight values. Furthermore; it is shown that the proposed approach results in generating dynamic weights values that represents the importance of the network attributes. The abnormalities of the SAW and TOPSIS techniques have been reduced for all classes of services when the GA based proposed technique is applied. In addition, the proposed approach can be applied to other MADM methods to reduce the ranking abnormalities.

References

1. Bhuvaneswari, A. (2012). An overview of vertical handoff decision making algorithms. *International Journal of Computer Network and Information Security*, *4*(9), 55–62.
2. Wang, H., Katz, R., & Giese, J. (1999). Policy-enabled handoffs across heterogeneous wireless networks. In *Proceedings of the second IEEE workshop on mobile computer systems and applications* (pp. 51–60).
3. Akhila, S., Murthy, J., Shankar, A., & Kumar, S. (2012). An overview on decision techniques for vertical handovers across wireless heterogeneous networks. *International Journal of Science and Engineering Research*, *3*(1), 1–6.
4. Arshad, R., Elsawy, H., Sorour, S., Al-Naffouri, T. Y., & Alouini, M.-S. (2017). Velocity-aware handover management in two-tier cellular networks. *IEEE Transactions on Wireless Communications*, *16*(3), 1851–1867.
5. Zhang, H., Ma, W., Li, W., Zheng, W., Wen, X., & Jiang, C. (2011). Signalling cost evaluation of handover management schemes in LTE-advanced femtocell. *2011 IEEE 73rd vehicular technology conference (VTC Spring)* (pp. 1–5).
6. Zhang, H., Jiang, C., Cheng, J., & Leung, V. C. M. (2015). Cooperative interference mitigation and handover management for

heterogeneous cloud small cell networks. *IEEE Wireless Communications*, *22*(3), 92–99.
7. Zhang, H., Zheng, W., Wen, X., & Jiang, C. (2011). Signalling overhead evaluation of HeNB mobility enhanced schemes in 3GPP LTE-advanced. *IEEE vehicular technology conference* (pp. 1–5). Budapest.
8. Su, D., Wen, X., Zhang, H., & Zheng, W. (2010). A self-optimizing mobility management scheme based on cell ID information in high velocity environment. In *2010 2nd International conference on computer science and network technology* (pp. 285–288).
9. Zhang, H., Wen, X., Wang, B., Zheng, W., & Sun, Y. A novel handover mechanism between femtocell and macrocell for LTE based networks. In *2010 2nd International conference on communication software and networks* (pp. 228–231).
10. Stevens-Navarro, E., & Wong, V. (2006). Comparison between vertical handoff decision algorithms for heterogeneous wireless networks. In *IEEE 63rd vehicular technology conference* (Vol. 2, pp. 947–951).
11. Gondara, M. K., & Kadam, S. (2011). Requirements of vertical handover mechanism in 4G wireless networks. *The International Journal of Wireless & Mobile Networks*, *3*(2), 18–27.
12. Tran, P. N., & Boukhatem, N. (2008). Comparison of MADM decision algorithms for interface selection in heterogeneous wireless networks. In *16th International conference on software, telecommunications and computer networks* (pp. 119–124).
13. Alyousfi, E. A., & Alkhawlani, M. M. (2016). Optimization of vertical handover performance using elimination based MCDM algorithm. *Journal of Science and Technology*, *21*(1), 47–61.
14. Mohamed, L., Leghris, C., & Abdellah, A. (2012). A survey and comparison study on weighting algorithms for access network selection. In *9th Annual conference on wireless on-demand network systems and services (WONS)* (pp. 35–38).
15. Almutairi, A. F., Landolsi, M. A., & Al-Hawaj, A. O. (2016). Weighting selection in GRA-based MADM for vertical handover in wireless networks. In *2016 UKSim-AMSS 18th International conference on computer modeling and simulation (UKSim)* (pp. 331–336).
16. Almutairi, A. F., Landolsi, M. A., & Al-Mashmoum, H. Q. (2016). Performance of different weighting techniques with DIA MADM method in heterogeneous wireless networks. In *International wireless communications and mobile computing conference (IWCMC)* (pp. 921–925).
17. Bari, F., & Leung, V. (2007). Multi-attribute network selection by iterative TOPSIS for heterogeneous wireless access. In *Proceedings of 4th IEEE consumer communications and networking conference* (pp. 808–812).
18. Senouci, M. A., 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)* (pp. 1–6).
19. Wang, Y., & Elhag, T. M. (2006). An approach to avoiding rank reversal in AHP. *Decision Support Systems*, *42*(3), 1474–1480.
20. Radhika, K., & Reddy, A. V. (2011). AHP and group decision making for access network selection in multi-homed mobile terminals. *International Journal of Computational Science and Engineering*, *3*(10), 3412–3421.
21. Ren, L., Zhang, Y., Wang, Y., & Sun, Z. (2007). Comparative analysis of a novel M-TOPSIS method and TOPSIS. *Applied Mathematics Research eXpress, 2007*, abm005. doi:10.1093/amrx/abm005.
22. Mohamed, L., Leghris, C., & Abdellah, A. (2012). An intelligent network selection strategy based on MADM methods in heterogeneous networks. *The International Journal of Wireless & Mobile Networks*, *4*(1), 83–96.
23. Huszak, A., & Imre, S. (2010). Eliminating rank reversal phenomenon in GRA-based network selection method. In *IEEE international conference on communications* (pp. 1–6).
24. Jahan, A., & Edwards, K. L. (2015). A state-of-the-art survey on the influence of normalization techniques in ranking: Improving the materials selection process in engineering design. *Materials & Design*, *1980–2015*(65), 335–342.
25. Liu, C., Sun, Y., Yang, P., Liu, Z., Zhang, H., & Wen, Z. A two-step vertical handoff decision algorithm based on dynamic weight compensation. In *Communications workshops (ICC), 2013 IEEE international conference*, pp. 1031–1035.
26. Saaty, T. L. (2008). Decision making with the analytic hierarchy process. *International Journal of Services Sciences*, *1*(1), 83–98.
27. Lahby, M., Cherkaoui, L., & Adib, A. (2014). Performance analysis of normalization techniques for network selection access in heterogeneous wireless networks. In *9th International conference on intelligent systems* pp. (1–5).
28. Chakraborty, S., & Yeh, C.-H. (2009). A simulation comparison of normalization procedures for TOPSIS. In *International conference on computers and industrial engineering* (pp. 1815–1820).
29. Escobar, L., Navarro, A., Arteaga, A., Guerrero, F., & Salazar, C. (2010). Vertical handoff algorithms—A new approach for performance evaluation. In *IEEE Globecom workshops* (pp. 1724–1728).
30. Suhaimi, N. S., Kamarudin, S. N. K., Othman, Z., & Arbin, N. (2014). Multi-objective genetic algorithm in solving conflicted goals for questions generating problem. In *2014 5th International conference intelligent systems, modelling and simulation* (pp. 60–63).
31. Nag, K., & Pal, N. R. (2016). A multiobjective genetic programming-based ensemble for simultaneous feature selection and classification. *IEEE Transactions on Cybernetics*, *46*(2), 499–510.
32. Chandralekha, & Behera, P. K. (2010). Minimization of number of handover using genetic algorithm in heterogeneous wireless network. *The International Journal of Latest Trends in Computing*, *1*(2), 24–28.
33. Goldberg, D. E. (1989). *Genetic algorithms in search, optimization and machine learning*. Reading, MA: Addison-Wesley.
34. Nkansah-Gyekye, Y., & Agbinya, J. I. (2008). A vertical handoff decision algorithm for next generation wireless networks. In *3rd International conference of broadband communication, information technology and biomedical applications* (pp. 358–364).
35. Haoliang, P., Wenxiao, S., Shuxiang, L., & Chuanjun, X. (2012). A GA-FNN based vertical handoff algorithm for heterogeneous wireless networks. In *Proceedings of IEEE international conference on computer science and automation engineering (CSAE)* (Vol. *2*, pp. 37–40).
36. Elahi, A., Qureshi, I. M., Atif, M., & Gul, N. Interference reduction in cognitive radio networks using genetic and firefly algorithms. In *2017 International conference on communication, computing, and digital systems (C-CODE)* (pp. 96–100).

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