IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received January 11, 2019, accepted January 30, 2019, date of publication February 14, 2019, date of current version March 5, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2899405

Joint Access Selection and Bandwidth Allocation Algorithm Supporting User Requirements and Preferences in Heterogeneous Wireless Networks

GEN LIANG[1], HEWEI YU[2], XIAOXUE GUO[1], AND YONG QIN[3]

[1]College of Electronic and Information Engineering, Guangdong University of Petrochemical Technology, Maoming 525000, China
[2]School of Computer Science and Engineering, South China University of Technology, Guangzhou 510006, China
[3]School of Computer Science, Dongguan University of Technology, Dongguan 523808, China

Corresponding author: Hewei Yu (hwyu@scut.edu.cn)

This work was supported in part by the Natural Science Foundation of Guangdong Province under Grant 2017A030307035, in part by the Innovative Research Project of the Education Department of Guangdong Province under Grant 2017KTSCX127, and in part by the Key Collaborative Innovation Project among Industry, University, and Institute of Guangzhou under Grant 201604010001.

ABSTRACT The next generation of heterogeneous wireless networks (HWNs) will integrate various radio access technologies, which will make how to connect mobile users based on the performance parameters of each wireless network and the quality of service requirements (as to enable mobile users to be connected to the most suitable wireless network) a hot topic for HWNs. This paper designs an algorithm for joint access selection and bandwidth allocation in HWNs. Taking into account the environment in which worldwide interoperability for microwave access, long term evolution, and wireless local area network may co-exist, the algorithm uses received signal strength, network load, and user rate requirements as input decision parameters and adjusts the parameters of the membership function in the five-layer fuzzy neural network structure through supervised learning to obtain the score and bandwidth allocation value for each candidate network. The simulation results show that the proposed algorithm can enable users to choose the most suitable network to access and may modify the fuzzy rules and adjust the resource utilization of different networks based on user preferences.

INDEX TERMS Access selection, heterogeneous wireless networks, fuzzy neural networks, resource allocation.

I. INTRODUCTION

In recent years, various radio access technologies (RAT) have been rapidly developed with different transmission characteristics (i.e. signal coverage, bandwidth, delay, frequency, etc.). For example, the Universal Mobile Telecommunications System (UMTS) can provide a wide range of signal coverage and lower bandwidth. In addition, such systems as Long Term Evolution (LTE) and Worldwide Interoperability for Microwave Access (WiMAX) use key transmission technologies, namely orthogonal frequency division multiplexing (OFDM) and multi-input & multi-output (MIMO), to improve spectral efficiency and data transmission rates while providing a large range of signal coverage [1]. Moreover, the wireless local area network (WLAN) technology based on the IEEE 802.11 standard can provide high-speed data transmission within small signal coverage [2].

Within the signal coverage of cellular networks, a variety of other wireless access networks are deployed, forming heterogeneous wireless networks (HWNs) with overlapping areas of signal coverage [3], [4]. The co-existence and mutual integration of different wireless networks using different access technologies have become the development trend of HWNs. Due to the differences in wireless network transmission performance and the diversity of user services, it is necessary to rely on the access selection algorithm to provide the most suitable connection service for mobile users in a HWN environment [5], [6]. Therefore, access selection has become a hot topic for HWNs.

In the design of the access selection algorithm for HWNs, some papers use the received signal strength (RSS) as the

The associate editor coordinating the review of this manuscript and approving it for publication was Ghufran Ahmed.

main decision parameter for network selection, with which mobile users choose to access the network with the highest RSS. The RSS-based access selection algorithm is low in complexity and easy to implement, but it often causes a more serious ping-pong effect [7]. Some papers connect users to the network with the lowest load when designing the access selection algorithm to achieve a balancing load. Although this kind of algorithm improves the resource utilization of HWNs, the algorithm does not take into account the performance of the network link, and the user may be connected to the network with poor link quality. Therefore, the QoS requirements of user service cannot be effectively guaranteed [8].

Some papers have considered multiple decision parameters in the design of the access selection algorithm (e.g. RSS, bandwidth, network load (NL), delay, delay jitter, packet loss ratio, moving speed, service price, energy consumption, etc.) and modeled the access selection as a Multiple Attribute Decision Making (MADM) issue [9], [10]. This MADM first collects data for each decision parameter. Then, it normalizes the data and calculates all attributes based on the weight of each decision parameter. Finally, the candidate networks are ranked.

In addition, different users have different satisfaction levels with the same decision parameter value due to the diversity of user services. Therefore, some papers use the utility theory to quantify user satisfaction with decision parameters [11], [12]. The concept of a utility-function-based access selection algorithm is to design different utility functions and convert the actual values of decision parameters into utility values to calculate the comprehensive utility value for each candidate network, rank these values, and finally access the network with the highest utility value. In addition, some papers use models such as game theory [13]–[15], the Markov chain [16], [17], and the optimization method [18], [19] to design access selection algorithms.

Most of the above access selection algorithms based on RSS, MADM, utility theory, and other methods need an accurate description of decision parameters; however, not all decision parameters can be accurately modeled in a HWN environment. Moreover, in order to adapt to the dynamic environment of HWNs, the operating parameters of these algorithms need to be manually corrected, resulting in the manual intervention process and limiting the practical application of these algorithms [20]–[22].

The fuzzy logic system is suitable to deal with imprecise, nonlinear, and other issues. Moreover, it is good at expressing knowledge of a fuzzy or qualitative analysis, has a strong ability to process natural language, and may closely reach that of human reasoning. Thus, it can use the design of the access selection algorithm as its basis. Its ability to self-learn and self-adapt, however, is where it falls short [23], [24]. Additionally, the neural network can learn directly from samples. Although the neural network-based access selection algorithm has the advantages of a high fault tolerance and adaptive learning, such algorithms are not applicable to the expression of rule-based knowledge [25]. Therefore, how to combine fuzzy logic system with a neural network to realize both fuzzy and qualitative knowledge as a fuzzy system and learning ability of a neural network, to design HWN access selection algorithm based on a fuzzy neural network, and to realize resource allocation to users in the access process has become the research motivation of this paper.

The rest of this paper is organized as follows. Section 2 reviews the research work related to this article. Section 3 provides a detailed description of the algorithm framework. And then the detailed calculation steps are also introduced. In addition, Section 4 configures simulation environment parameters and discusses the experimental results. Furthermore, Section 5 summarizes the article and introduces further research.

II. RELATED STUDIES

Since some fuzzy information that is difficult to be quantized is used in making decisions on access selection of HWNs, a calculation method based on fuzzy logic can be used when making the access selection decision. The main idea of this kind of algorithm is to fuzzify the input parameters first. Then, it generates fuzzy sets of output parameters according to the fuzzy rules. Finally, it obtains the scores of the candidate networks by defuzzification [26].

Khan *et al.* [27] designed a vertical handover scheme combining fuzzy logic and MADM. The scheme is divided into three stages. The first stage focuses on the handover triggering approach. Meanwhile, the second stage uses a fuzzy system to delete unsuitable candidate networks, and the third stage sorts out candidate networks using the TOPSIS approach. That paper considers various parameters such as delay, jitter, bit error rate (BER), packet loss, communication cost, response time, and NL to select the best network.

Ahuja *et al.* [28] proposed a network selection algorithm combining utility function and fuzzy logic. The algorithm uses the utility function to calculate the utility values of RSS, available bit rate, signal to noise ratio, throughput, and bit error rate. It also utilizes the particle swarm optimization (PSO) to calculate the weights. Finally, the output results are calculated through the fuzzy logic system. This algorithm reduces unnecessary handoffs between networks.

Yan *et al.* [29] proposed a dynamic imprecise-aware network selection algorithm in view of the complexity and fluctuation of the wireless network in the high-speed railway scenario, with which the imprecise statuses are inferred by fuzzy rules, the network selection is made by the state monitoring module, and the utility functions are designed to calculate the user's quality of service (QoS).

In addition, some papers use the neural network model to design access selection algorithms. Such algorithms are a progressive optimization process, with which the optional network selection results are obtained by performing multiple iterations.

Chen *et al.* [30] considered the quality of experience (QoE) in the algorithm design of the vertical handover algorithm, used a random neural network to calculate QoE and determine the correlation between QoE and QoS in heterogeneous networks, and designed a Q-learning-based vertical handoff algorithm to maximize the QoE utility of users. This algorithm has better QoE performance than other algorithms in terms of service charges and terminal power consumption.

Calhan and Ceken [31] proposed an artificial-neural-network-based handoff decision algorithm, which uses data rate, cost, and RSS as input decision parameters to determine whether it is necessary to handoff to other networks, and to select the best access network among the candidate networks. This algorithm reduces such handoff latency.

Mahira and Subhedar [32] proposed a HWN handover decision algorithm based on a multi-layer feedforward artificial neural network, with which the network selection is made according to data rate, service cost, RSS indicator (RSSI), and velocity of the mobile device, thus reducing the number of handoffs.

As fuzzy logic systems and neural networks have different advantages and disadvantages, some papers combine fuzzy logic systems with neural networks to design access selection algorithms.

Giupponi *et al*. [33], [34] designed a joint radio resource management (JRRM) mechanism in a HWN environment. The fuzzy neural JRRM algorithm proposed in that paper contains three different radio access technologies (RATs). The first step of the algorithm is to construct a combination of cells using the three available RATs. The second step is to help users choose the most appropriate RAT, assign an appropriate bit rate to each user, and control the user dissatisfaction probability using reinforcement learning mechanisms.

Chen *et al*. [35] proposed an admission control method based on fuzzy Q-learning for multimedia traffic in HWNs composed of WCDMA and WLAN. The fuzzy Q-learning admission control system consists of a neural-fuzzy inference system (NFIS) admissibility estimator, NFIS dwelling estimator, and decision maker. This algorithm reduces the blocking probabilities and the handoff rate.

Mar *et al*. [36] designed a rate controller for the HWN environment based on an adaptive neural fuzzy inference system to adapt to the changing traffic loads and user speed. This approach can reduce the probabilities of new call blocking and handoff failure and can support a heavier traffic load.

At present, although some other papers have used fuzzy logic, neural network, or combination of fuzzy logic and neural networks to design access selection algorithms for HWNs, such papers have either not taken into account both network performance and user requirements simultaneously, or have not taken into account resource allocation in access selection, or have not taken into account the user preferences, etc. Additionally, those algorithms usually only give a ranking of scores for candidate networks. In this paper, a framework of access selection and a bandwidth allocation algorithm based on fuzzy neural network in the environment are designed where WiMAX, LTE, and WLAN co-exist. The framework includes an input module, a fuzzy logic decision module, an output module, and a learning module. The input module considers the three aspects, including wireless link status, network performance, and user requirements. It also uses RSS, NL, and user rate requirements as input decision parameters. The fuzzy logic decision module obtains the scores and bandwidth allocation values of candidate networks through three steps of fuzzification, fuzzy inference, and defuzzification. In addition, the learning module corrects the parameters of the membership function in the fuzzy neural network structure through supervised learning. This algorithm can allow users to select the most suitable network and get the bandwidth allocation value. Furthermore, it can adjust the resource utilization of different networks according to user preferences, which is the main contribution and feature of this paper.

III. ALGORITHM DESIGN AND IMPLEMENTATION

A. ALGORITHM FRAMEWORK DESIGN

In the HWN scenario presented herein, there are three candidate networks (i.e. WiMAX, LTE, and WLAN) and the signal coverage of these wireless networks overlap. There are several mobile users in the scenario, and these users move in random directions within the signal coverage. Assume that users can obtain parameter values of each network, and that these users are multi-mode mobile terminals with the ability to process all wireless access technologies and to access any wireless network.

As shown (Fig. 1), this paper presents an access selection and bandwidth allocation algorithm framework based on the fuzzy neural network, which includes an input module, a fuzzy logic decision module, an output module, and a learning module. The newly entered users or connected users periodically acquire network parameter values and input these values to the fuzzy logic decision module. The fuzzy logic decision module calculates and outputs the scores and bandwidth allocation values of each candidate network so that users can select the most appropriate network and control the allocation of bandwidth resources of each network. The learning module adjusts the parameters of the membership function of the fuzzifying step and the defuzzifying step in the fuzzy logic decision module according to the training samples.

Considering the parameters that affect the scores and bandwidth allocation values, the decision parameters used in this algorithm are mainly considered from the three aspects, namely the wireless link state, network performance, and user requirements, which are described in detail as follows:

(1) RSS: The main function of this parameter is to characterize the state of wireless links. This paper uses RSS_{WiMAX}, RSS_{LTE}, and RSS_{WLAN} to represent the signal quality between users and the WiMAX, LTE, and WLAN network access points respectively. Users aim to access networks with higher RSS. The higher the RSS, the higher the network score. Since the signal strength ranges of different networks are different, it is first necessary to normalize the collected RSS

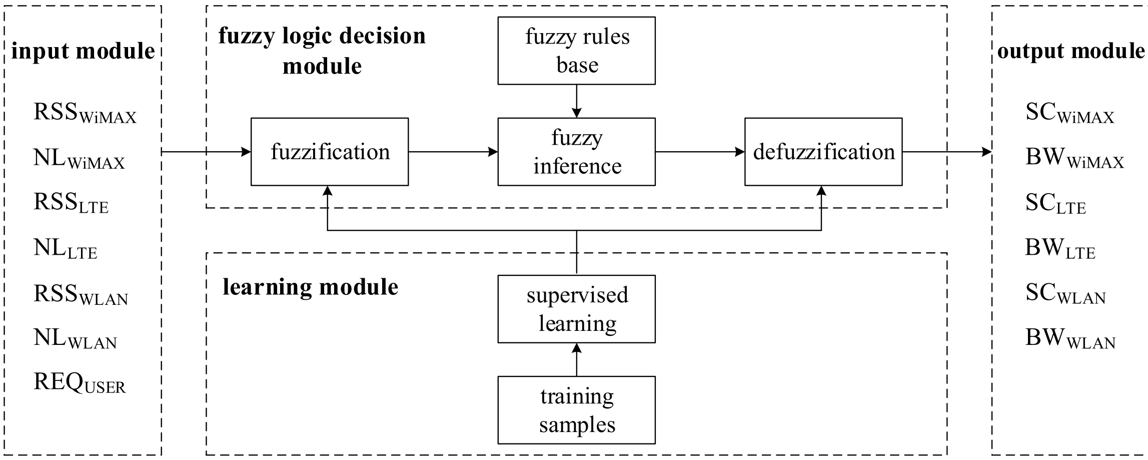

FIGURE 1. Access selection and bandwidth allocation algorithm framework based on fuzzy neural networks.

parameter values of each network, and then input them to the fuzzy logic decision module. In addition, according to the Shannon formula [19], if the user service rate is a certain value, the network with the higher RSS only needs to allocate less bandwidth to the user, while the network with the lower RSS needs to allocate more bandwidth to meet the user's rate requirement. Therefore, the RSS parameters will also affect the bandwidth allocation value.

(2) NL: The main function of this parameter is to characterize the resource usage of each network. This paper uses NL_{WiMAX}, NL_{LTE}, and NL_{WLAN} to represent the loads of WiMAX, LTE, and WLAN networks, respectively. Users aim to access networks with a low network load and avoid accessing networks with a high load as much as possible in order to obtain a better performance.

(3) User Service Rate Requirement (REQ_{user}): This parameter is mainly used to distinguish the suitability of each network under different rate requirements and is represented in this paper as REQ_{user}. For example, for a lower rate requirement, WiMAX, LTE, and WLAN can achieve the same level of satisfaction, while WLAN can provide a better level of satisfaction for higher rate requirements.

The output of the proposed algorithm is divided into two groups, which are the evaluation scores of candidate networks and the bandwidth values allocated by the candidate networks to users, which are described in detail as follows:

(1) The candidate networks are scored based on the RSS, NL, and REQ_{user}. This papers uses SC_{WiMAX}, SC_{LTE}, and SC_{WLAN} to represent the scores of WiMAX, LTE, and WLAN respectively, and the value range of the score is [0,1]. Then, the scores of these networks are ranked, and the user selects and accesses the network with the highest score.

(2) This paper uses BW_{WiMAX}, BW_{LTE}, and BW_{WLAN} to represent the bandwidth values allocated by the WiMAX, LTE, and WLAN networks to users. This value represents the ratio of the bandwidth value allocated to the user to the bandwidth available for allocation by a network. The value range is [0,1].

B. FUZZY LOGIC DECISION MODULE

The main function of the fuzzy logic decision module is to calculate the output values based on the input parameter values, which mainly include three steps: fuzzification, fuzzy inference, and defuzzification.

(1) Step 1: Fuzzification of input variables

In this paper, there are seven linguistic variables (i.e. RSS_{WiMAX}, RSS_{LTE}, RSS_{WLAN}, NL_{WiMAX}, NL_{LTE}, NL_{WLAN}, and REQ_{user}). The role of fuzzification is to convert the precise quantities of these seven inputs into fuzzy quantities and map them into the fuzzy set on the universe of discourse. For each linguistic variable, its value is a set of linguistic names, which constitute a term set. Each linguistic name corresponds to a fuzzy set. In this paper, the number of fuzzy sets for each linguistic variable is set to 3 (i.e. low, medium, and high), which are represented by low (L), medium (M), and high (H), respectively.

To map the numeric value into a fuzzy set, it is necessary to determine the membership function. The common membership functions include the triangle-shaped membership function, the bell-shaped membership function, the trapezoidal membership function, the Gaussian membership function, etc. Since the membership function needs to be derived in the learning phase, and the Gaussian membership function is easy to derivate, it is more efficient in the learning phase. Therefore, the Gaussian function is chosen as the membership function, which is defined as follows:

$$f(x) = e^{-\frac{(x-c)^2}{\sigma^2}} \tag{1}$$

The parameters c and σ in the above formula represent the mean and the variance of the function, respectively.

(2) Step 2: Fuzzy inference

The fuzzy rule base consists of a series of fuzzy rules. The fuzzy rule in this paper takes the form: IF (meeting a set of conditions) THEN (deducing a set of conclusions). As shown (Table 1), the preconditions and consequences in

TABLE 1. Example of fuzzy rules.

IF							THEN					
RSS_{WiMAX}	NL_{WiMAX}	RSS_{LTE}	NL_{LTE}	RSS_{WLAN}	NL_{WLAN}	REQ_{user}	SC_{WiMAX}	BW_{WiMAX}	SC_{LTE}	BW_{LTE}	SC_{WLAN}	BW_{WLAN}
L	L	M	L	H	L	H	M	H	M	H	H	M
L	H	H	L	L	H	L	M	M	H	M	L	M
M	L	H	L	L	H	M	M	M	H	M	L	M
H	L	M	L	L	H	M	H	M	M	M	L	M
H	H	L	H	H	M	L	M	L	L	M	H	L

the IF-THEN rule are both fuzzy concepts. The preconditions are the combination of fuzzy sets of input linguistic variables in the fuzzification step. The conclusion is the fuzzy set of scores and bandwidth allocation values of the candidate networks.

The fuzzy rule base R contains n rules of MIMO, which are in the form of:

$$R = \left\{R^1_{MIMO}, R^2_{MIMO}, \cdots, R^n_{MIMO}\right\} \tag{2}$$

The rule represented by R^i_{MIMO} in the above formula is as follows: IF (x is $A_i,\ldots,y$ is B_i) THEN (z_1 is $C_{i1},\ldots,z_q$ is C_{iq}). The precondition for R^i_{MIMO} is the fuzzy set on the product space $X \times \cdots \times Y$, the conclusion is q unions with the control role, which are independent of each other. The fuzzy implication that can be represented by rule R^i_{MIMO} is as follows: $R^i_{MIMO} : (A_i \times \cdots \times B_i) \to (C_{i1} + \cdots + C_{iq})$; therefore, R^i_{MIMO} can be expressed as q multiple input single output rules, namely:

$$\begin{aligned} R^i_{MIMO} &= \left\{(A_i \times \cdots \times B_i) \to \left(C_{i\,1} + \cdots + C_{iq}\right)\right\} \\ &= \{[(A_i \times \cdots \times B_i) \to C_{i\,1}], \\ &\quad \cdots, \left[(A_i \times \cdots \times B_i) \to C_{iq}\right]\} \end{aligned} \tag{3}$$

According to (3), the fuzzy rule base R can be expressed as:

$$\begin{aligned} R &= \left\{U^n_{i=1} R^i_{MIMO}\right\} \\ &= \left\{U^n_{i=1}\left[(A_i \times \cdots \times B_i) \to \left(C_{i\,1} + \cdots + C_{iq}\right)\right]\right\} \\ &= \left\{U^n_{i=1}\left[\left(A_j \times \cdots \times B_i\right) \to C_{i\,1}\right],\right. \\ &\quad \left.\cdots, U^n_{i=1}\left[(A_i \times \cdots \times B_i) \to C_{iq}\right]\right\} \\ &= \left\{U^q_{k=1} U^n_{i=1}\left[(A_i \times \cdots \times B_i) \to C_{ik}\right]\right\} \\ &= \left\{RB^1_{MISO}, RB^2_{MISO}, \cdots, RB^q_{MISO}\right\} \end{aligned} \tag{4}$$

Thus, the rule base R containing the MIMO rule structure can be regarded as consisting of q sub-bases RB, each of which consists of n multi-input & single-output (MISO) rules.

For ease of explanation, let's take the fuzzy rule of the two-input and one-output rule as an example. Suppose there are two fuzzy rules $R1$ and $R2$, which are defined as follows:

$$\text{R1 : IF} x \text{ is } A_1 \text{ and } y \text{ is } B_1 \text{ THEN } z \text{ is } C_1$$
$$\text{R2 : IF} x \text{ is } A_2 \text{ and } y \text{ is } B_2 \text{ THEN } z \text{ is } C_2$$

According to the fuzzy logic theory, the firing strength of $R1$ and $R2$ are α_1 and α_2, respectively. The calculation method is as follows:

$$\alpha_1 = \mu_{A_1}(x) \wedge \mu_{B_1}(y) \tag{5}$$
$$\alpha_2 = \mu_{A_2}(x) \wedge \mu_{B_2}(y) \tag{6}$$

In the above formula, $\wedge$ is the fuzzy AND operation. As shown in (7), the commonly used fuzzy AND operation is the minimum operation or the algebraic product.

$$\alpha_i = \mu_{A_i}(x) \wedge \mu_{B_i}(y) = \begin{cases} \min\left(\mu_{A_i}(x), \mu_{B_i}(y)\right) \\ \text{or} \\ \mu_{A_i}(x) \cdot \mu_{B_i}(y) \end{cases} \tag{7}$$

The rule i lead to the control decision with the membership function $\mu_{C'_i}(w)$:

$$\mu_{C'_i}(w) = \alpha_i \wedge \mu_{C_i}(w), \quad i = 1, 2 \tag{8}$$

The w in the above formula represents the support values of the membership function. Combining the results of $R1$ and $R2$, the output result obtained is as follows:

$$\begin{aligned} \mu_C(w) &= \mu_{C'_1}(w) \vee \mu_{C'_2}(w) \\ &= \left[\alpha_1 \wedge \mu_{C_1}(w)\right] \vee \left[\alpha_2 \wedge \mu_{C_2}(w)\right] \end{aligned} \tag{9}$$

In the above formula, $\vee$ is a fuzzy OR operation. As shown in (10), the most commonly used fuzzy OR operation is bounded sum or union.

$$\begin{aligned} \mu_C(w) &= \mu_{C'_1}(w) \vee \mu_{C'_2}(w) \\ &= \begin{cases} \min\left(1, \left(\mu_{C'_1}(w) + \mu_{C'_2}(w)\right)\right) \\ \text{or} \\ \max\left(\mu_{C'_1}(w), \mu_{C'_2}(w)\right) \end{cases} \end{aligned} \tag{10}$$

Therefore, taking the first rule in Table 1 as an example, the membership value output by the rule is defined as (11).

$$\begin{aligned} &\mu_M\left(\mathrm{SC_{WiMAX}}\right) \\ &= \mu_H\left(\mathrm{BW_{WiMAX}}\right) = \mu_M\left(\mathrm{SC_{LTE}}\right) \\ &= \mu_H\left(\mathrm{BW_{LTE}}\right) = \mu_H\left(\mathrm{SC_{WLAN}}\right) = \mu_M\left(\mathrm{BW_{WLAN}}\right) \\ &= \min\left[\mu_L\left(\mathrm{RSS_{WiMAX}}\right), \mu_L\left(\mathrm{NL_{WiMAX}}\right), \mu_M\left(\mathrm{RSS_{LTE}}\right),\right. \\ &\quad \mu_L\left(\mathrm{NL_{LTE}}\right), \mu_H\left(\mathrm{RSS_{WLAN}}\right), \mu_L\left(\mathrm{NL_{WLAN}}\right), \mu_H \\ &\quad \left.\left(\mathrm{REQ_{user}}\right)\right] \end{aligned} \tag{11}$$

Finally, the same fuzzy set of output linguistic variables in the fuzzy rule base is combined, and the membership value of the output fuzzy set can be obtained through the union of the membership values of these rules.

(3) Step 3: Defuzzification. The main task of this step is to convert the fuzzy output obtained by fuzzy inference to a crisp value. The commonly used defuzzification calculation methods include the mean of maximum method (MOM) and the center of area method (COA). The defuzzification

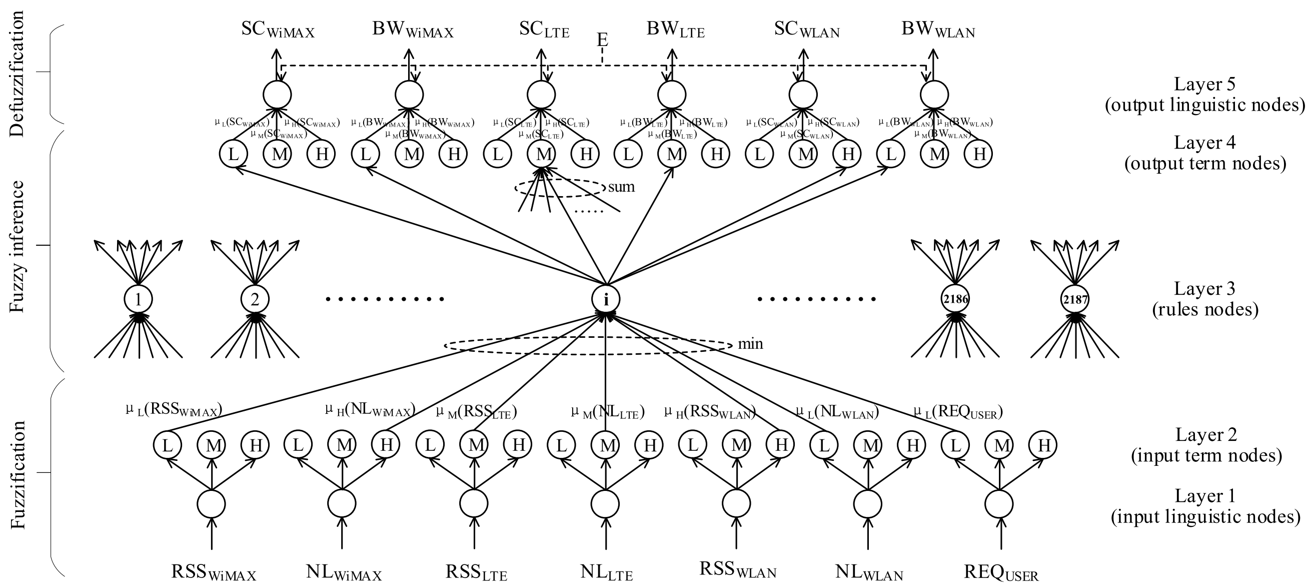

FIGURE 2. Fuzzy neural network structure.

method used in this paper is the center of area method, and its calculation is as follows:

$$\mathbf{z} = \frac{\sum_{j=1}^{n} \mu_C\left(w_j\right) \cdot w_j}{\sum_{j=1}^{n} \mu_C\left(w_j\right)} \tag{12}$$

The output obtained in this step is the exact value of the score of each candidate network and the bandwidth allocation values (i.e. SC_{WiMAX}, SC_{LTE}, SC_{WLAN}, BW_{WiMAX}, BW_{LTE}, and BW_{WLAN}.

C. FUZZY NEURAL NETWORK CONTROL MODULE

According to the fuzzy logic decision module in the previous section, since the input parameters, the membership functions of the input parameters, the fuzzy rules, the output parameters, and the membership functions of the output parameters are included in the module, this module is designed as a five-layer neural network (Fig. 2), where the layers of the neural network consist of a series of neuron nodes.

The specific structure of the neuron nodes (Fig. 2) is as shown below (Fig. 3). Suppose there are j input data on the node i at the k layer. Then, the input at the node can be represented as $I_i^{(k)} = f_i^{(k)}\left(x_{i,1}^{(k)}, x_{i,2}^{(k)}, \cdots, x_{i,j}^{(k)}\right)$, where $f_i^{(k)}$ represents the input data processing function, which processes the input data and then outputs that through the activation function $g_i^{(k)}$. In other words, the output value is $O_i^{(k)} = g_i^{(k)}\left(I_i^{(k)}\right)$.

The functions and the input and output calculation methods for each layer in the fuzzy neural network structure proposed in this paper are described in detail below.

The first layer (Layer 1) is the input layer where each node is directly connected to each component $x_{i,j}$ of the input vector. Since there are seven input linguistic variables, there

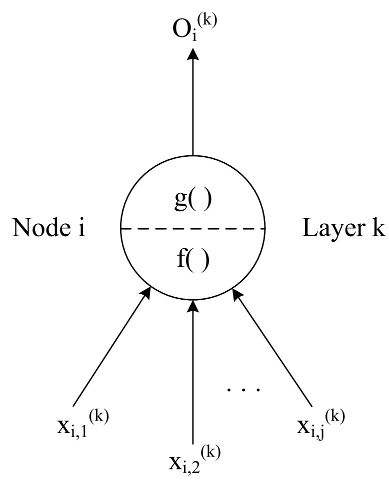

FIGURE 3. Fuzzy neural network structure.

are seven nodes in this layer. Moreover, each node has only one input, which acts to transfer the input value to the next layer, so the input and output of the Layer 1 node i are as follows:

$$I_i^{(1)} = f_i^{(1)}\left(x_{i,j}^{(1)}\right) = x_{i,j}^{(1)}, \quad (i = 1, 2, \cdots, 7, j = 1) \tag{13}$$

$$O_i^{(1)} = g_i^{(1)}\left(I_i^{(1)}\right) = x_{i,j}^{(1)}, \quad (i = 1, 2, \cdots, 7, j = 1) \tag{14}$$

The second layer (Layer 2) is the fuzzification layer, and each node represents the term of the linguistic variable (i.e. low, medium, and high). Since there are seven input linguistic variables, each variable contains three fuzzy sets, so the layer has 21 nodes, each having only one input. The function of this layer is to calculate the membership function of each input value belonging to the corresponding fuzzy set.

Since this paper use the Gaussian function as the membership function of the algorithm, the input and output of the Layer 2 node i are as follows:

$$I_i^{(2)} = f_i^{(2)}\left(x_{i,j}^{(2)}\right) = -\frac{\left(x_{i,j}^{(2)} - c_i^{(2)}\right)^2}{\left(\sigma_i^{(2)}\right)^2}, \quad (i = 1, 2, \cdots, 21, j = 1) \tag{15}$$

$$O_i^{(2)} = g_i^{(2)}\left(I_i^{(2)}\right) = e^{I_i^{(2)}} = e^{-\frac{\left(x_{i,j}^{(2)} - c_i^{(2)}\right)^2}{\left(\sigma_i^{(2)}\right)^2}}, \quad (i = 1, 2, \cdots, 21, j = 1) \tag{16}$$

The $c_i^{(2)}$ and $\sigma_i^{(2)}$ in the above formula is the mean and the variance of the Gaussian membership function of the Layer 2 node i, respectively.

The third layer (Layer 3) is a fuzzy rule layer, in which each node is connected with the seven nodes on the Layer 2, thereby corresponding to the seven input linguistic variables on the first layer. Since each input linguistic variable in this paper contains three fuzzy sets and each node in this layer corresponds to a combination of different fuzzy sets, this layer has a total of 2,187 nodes (or 3^7). In addition, each node corresponds to a fuzzy rule, which is used to match the predecessor of the fuzzy rule while adopting the fuzzy AND operation on all input data at the nodes. The output activation function of the layer nodes only transmits the equivalent value of the input function, so the input and output of the Layer 3 nodes i are as follows:

$$I_i^{(3)} = f_i^{(3)}\left(x_{i,j}^{(3)}\right) = \min\left(x_{i,j}^{(3)}\right), \quad (i = 1, 2, \cdots, 2187, j = 1, 2, \cdots, 7) \tag{17}$$

$$O_i^{(3)} = g_i^{(3)}\left(I_i^{(3)}\right) = \min\left(x_{i,j}^{(3)}\right), \quad (i = 1, 2, \cdots, 2187, j = 1, 2, \cdots, 7) \tag{18}$$

The $x_{i,j}^{(3)}$ in the above formula represents the j input data of node i on Layer 3, which is equal to the output data of node j on Layer 2 to which node i is connected.

The fourth layer (Layer 4) is a fuzzy rule inference layer. Since there are six output linguistic variables in this paper, and each linguistic variable contains three fuzzy sets, the layer has 18 nodes, each node corresponds to a fuzzy set, and each node performs a fuzzy OR operation on the input data with the same consequence in Layer 3. Then, it directly passes the data to the next layer, so the input and output of the Layer 4 node i can be expressed as follows:

$$I_i^{(4)} = f_i^{(4)}\left(x_{i,j}^{(4)}\right) = \sum_{j\in C_i} x_{i,j}^{(4)}, \quad (i = 1, 2, \cdots, 18) \tag{19}$$

$$O_i^{(4)} = g_i^{(4)}\left(I_i^{(4)}\right) = \min\left(1, I_i^{(4)}\right), \quad (i = 1, 2, \cdots, 18) \tag{20}$$

The C_i in the above formula represents the set of nodes on Layer 3 connected with the node i on Layer 4.

The fifth layer (Layer 5) is the output layer, which acts to achieve defuzzification calculation. This layer has a total of six nodes corresponding to the scores and bandwidth allocation values of the candidate networks. In this paper, the COA approach for defuzzification is used.

$$I_i^{(5)} = f_i^{(5)}\left(x_{i,j}^{(5)}\right) = \sum_{j\in T_i} c_j^{(5)}\sigma_j^{(5)}x_{i,j}^{(5)}, \quad (i = 1, 2, \cdots, 6) \tag{21}$$

$$O_i^{(5)} = g_i^{(5)}\left(I_i^{(5)}\right) = \frac{I_i^{(5)}}{\sum_{j\in T_i}\sigma_j^{(5)}x_{i,j}^{(5)}} = \frac{\sum_{j\in T_i} c_j^{(5)}\sigma_j^{(5)}x_{i,j}^{(5)}}{\sum_{j\in T_i}\sigma_j^{(5)}x_{i,j}^{(5)}}, \quad (i = 1, 2, \cdots, 6) \tag{22}$$

The $c_j^{(5)}$ and $\sigma_j^{(5)}$ in the above formula is the mean and the variance of the Gaussian membership function of node j on Layer 5, respectively, and T_i is the set of nodes on Layer 4 connected with node i on Layer 5.

D. LEARNING MODULE

The structure of the fuzzy neural network (Fig. 2) is essentially a multilayer feedforward network, so the parameters can be adjusted using the error back propagation (BP) learning algorithm similar to a BP neural network. In this paper, the parameters needing adjustments are the parameters of the membership functions of Layers 2 and 5, that is, the values of $c_i^{(2)}$, $\sigma_i^{(2)}$, $c_j^{(5)}$, and $\sigma_j^{(5)}$ of the membership functions in the fuzzification and defuzzification steps.

Suppose t_i and y_i represent the desired output value and the actual output value respectively, and the error can be defined as:

$$e_i = t_i - y_i \tag{23}$$

The ultimate goal of error correction learning is to minimize the e_i based objective function so that the actual output value of each output unit in the network approaches the desired output value. The error objective function used in this paper is the mean-square error (MSE) function, namely:

$$E = \frac{1}{2}\sum_{i=1}^{r}(t_i - y_i)^2 \tag{24}$$

The r in the above formula is the number of network outputs. In this paper, $r = 6$, and y_i is the actual output value after defuzzification, namely: $y_i = O_i^{(5)}$ In order to minimize the error objective function value, the gradient descent method is used to obtained the adjusted value of $c_i^{(5)}$,$\sigma_i^{(5)}$, $c_i^{(2)}$ and $\sigma_i^{(2)}$.

According to the gradient descent method, assume that the parameter to be adjusted is ω, which should be adjusted in the opposite direction of the gradient change of the objective function, namely:

$$\omega(t+1) = \omega(t) - \eta\frac{\partial E}{\partial\omega} \tag{25}$$

The η in the above formula represents the learning rate, so the increment by which the parameter ω needs to be adjusted is as follows:

$$\Delta\omega = -\eta \frac{\partial E}{\partial \omega} \tag{26}$$

According to (26), (21), and (22), the learning rules of the parameters $c_j^{(5)}$ and $\sigma_j^{(5)}$ of the Layer 5 membership function are as below.

$$\Delta c_j^{(5)} = \eta \left(t_i - y_i\right) \frac{\sigma_j^{(5)} x_{i,j}^{(5)}}{\sum_{j\in T_i} \sigma_j^{(5)} x_{i,j}^{(5)}} \tag{27}$$

$$\Delta \sigma_j^{(5)} = \eta \left(t_i - y_i\right) \times \frac{c_j^{(5)} x_{i,j}^{(5)} \left(\sum_{j\in T_i} \sigma_j^{(5)} x_{i,j}^{(5)}\right) - \left(\sum_{j\in T_i} c_j^{(5)} \sigma_j^{(5)} x_{i,j}^{(5)}\right) x_{i,j}^{(5)}}{\left(\sum_{j\in T_i} \sigma_j^{(5)} x_{i,j}^{(5)}\right)^2} \tag{28}$$

The detailed derivation process of (27) and (28) is shown in Appendix A and B, respectively.

Similarly, according to (15)-(20), the learning rule of the parameters $c_i^{(2)}$ and $\sigma_i^{(2)}$ of the Layer 2 membership function is as follows:

$$\Delta c_i^{(2)} = -\eta \frac{\partial E}{\partial O_i^{(2)}} e^{I_i^{(2)}} \frac{2\left(x_{i,j}^{(2)} - c_i^{(2)}\right)}{\left(\sigma_i^{(2)}\right)^2} \tag{29}$$

$$\Delta \sigma_i^{(2)} = -\eta \frac{\partial E}{\partial O_i^{(2)}} e^{I_i^{(2)}} \frac{2\left(x_{i,j}^{(2)} - c_i^{(2)}\right)^2}{\left(\sigma_i^{(2)}\right)^3} \tag{30}$$

The detailed derivation process of (29) and (30) is shown in Appendix C and D, respectively.

When correcting the parameter $\omega(k)$, the standard BP network learning algorithm adjusts the parameter only in the negative gradient direction at the time of k, without considering the gradient direction for the previous time. Thus, the oscillation often occurs during the learning process, and the convergence speed is slow. To speed up the convergence and reduce the oscillation, this paper proposes a variable step size learning method for the mixed momentum term based on [37]. This method introduces the momentum factor and changes the step size of the learning rate based on the increase in number of iterations, which is as follows:

$$\omega(k+1) = \omega(k) + \eta[(1-\alpha)D(k) + \alpha D(k-1)] \tag{31}$$

$$\eta = \lg\left(1 + \frac{1}{\beta * epoch}\right) \tag{32}$$

In the above formula, $\omega(k)$ represents the parameter to be adjusted, α is the momentum factor, and $0 \leq \alpha < 1$. In this paper, α has a value of 0.5, $D(k) = -\frac{\partial E}{\partial \omega(k)}$ is the negative gradient at time k, and $D(k-1)$ is the negative gradient at time $k-1$. η is the learning rate, which is a function of the number of training epoch. In this paper, the value of β is 3.

The complexity of the algorithm is mainly determined by the number of input and output parameters, the number of membership functions, and the number of fuzzy rules in the fuzzy neural network structure. The more these parameters, the higher the complexity of the algorithm.

IV. SIMULATION AND RESULT ANALYSIS

A. SETTING OF EXPERIMENTAL PARAMETERS

To evaluate the HWN access selection and bandwidth allocation algorithm based on the fuzzy neural network proposed in this paper, the experiment uses Matlab for calculation. The simulation experiment of this scenario includes a WiMAX base station, a LTE base station, and a WLAN access point, whose transmit powers are 1,000 mW, 1,000 mW, and 100 mW, respectively (i.e. 30 dBm, 30 dBm, and 20 dBm, respectively), and the users randomly move within the overlapped coverage of the wireless signals of these networks, and this paper assumes that the distance from the WiMAX base station when users move is 50-1,000 m, 50-800 m from the LTE base station, and 50-200 m from the WLAN access point.

To calculate the RSS between the access point and the user, the experiment uses an improved model based on the COST-231 Hata model to calculate the path loss PL_{dB}. According to [38], the COST-231 Hata model is defined as (33)-(35), as shown at the bottom of this page.

The f, h_b, h_M, and d in the above formula represent frequency (MHz), height of the access point from the ground (m), height of the user from the ground (m), and distance between the access point and the user (km), respectively. This paper set $f = 2,000$ MHz, $h_b = 15$ m and $h_M = 1.5$ m, and both F(h_M) and C are medium-sized cities. Lastly, the streamlined path loss model is as follows:

$$PL_{dB} = 144 + 38\lg d \tag{36}$$

In addition, this paper sets the total bandwidth of WiMAX, LTE, and WLAN networks to 10 MHz, 25 MHz, and

$$PL_{dB} = 46.3 + 33.9\lg f - 13.82\lg h_b + (44.9 - 6.55\lg h_b)\lg d - F\left(h_M\right) + C \tag{33}$$

in which

$$F\left(h_M\right) = \begin{cases} (1.1\lg f - 0.7 \times h_M - (1.56 \times \lg f - 0.8)) & \text{for medium and small size cities} \\ 3.2 \times (\lg(1.75 \times h_M))^2 & \text{for large cities} \end{cases} \tag{34}$$

$$C = \begin{cases} 0dB & \text{for medium - size cities and suburban areas} \\ 3dB & \text{for large cities} \end{cases} \tag{35}$$

TABLE 2. Comparison of membership function parameter values before and after learning.

		mean		variance	
		before learning	after learning	before learning	after learning
RSS_{WiMAX}	L	-114.00	-113.9787	9.00	9.2943
	M	-89.00	-89.0644	9.00	10.5078
	H	-64.00	-64.0257	9.00	9.3363
NL_{WiMAX}	L	0.00	-0.0049	0.15	0.1441
	M	0.50	0.4676	0.15	0.2048
	H	1.00	0.9817	0.15	0.1917
RSS_{LTE}	L	-110.00	-109.7529	8.00	8.3689
	M	-87.00	-87.0222	8.00	9.2569
	H	-64.00	-64.1250	8.00	8.3513
NL_{LTE}	L	0.00	-0.0077	0.15	0.1405
	M	0.50	0.4769	0.15	0.1987
	H	1.00	0.9849	0.15	0.1857
RSS_{WLAN}	L	-97.00	-96.7771	4.00	4.4616
	M	85.50	-84.8415	4.00	5.3717
	H	-74.00	-73.8975	4.00	3.8121
NL_{WLAN}	L	0.00	0.0169	0.15	0.1891
	M	0.50	0.5386	0.15	0.2081
	H	1.00	1.0173	0.15	0.1218
REQ_{user}	L	0.00	-0.2283	2.00	1.5619
	M	5.00	4.7694	2.00	2.6119
	H	10.00	9.9523	2.00	2.1837
SC_{WiMAX}	L	0.00	-0.0073	0.15	0.1646
	M	0.50	0.4310	0.15	0.1518
	H	1.00	0.9896	0.15	0.1320
BW_{WiMAX}	L	0.00	0.0005	0.15	0.1507
	M	0.50	0.4630	0.15	0.1709
	H	1.00	0.9846	0.15	0.1250
SC_{LTE}	L	0.00	-0.0031	0.15	0.1620
	M	0.50	0.4776	0.15	0.1436
	H	1.00	0.9947	0.15	0.1437
BW_{LTE}	L	0.00	0.0028	0.15	0.1468
	M	0.50	0.4823	0.15	0.1700
	H	1.00	0.9864	0.15	0.1308
SC_{WLAN}	L	0.00	0.0023	0.15	0.1472
	M	0.50	0.5214	0.15	0.1461
	H	1.00	0.9991	0.15	0.1565
BW_{WLAN}	L	0.00	0.0370	0.15	0.0895
	M	0.50	0.5857	0.15	0.1897
	H	1.00	1.0018	0.15	0.1553

20 MHz, respectively. The network load represents the ratio of allocated bandwidth resources to total bandwidth resources. Finally, the user rate requirement REQ_{user} is set to a range of 0 – 10 Mbps.

To test the outcome of the algorithm, the simulation experiment is divided into three parts. The first part is to adjust the parameters of the membership functions through supervised learning according to the training data. Then, compare the difference between membership functions before and after learning, as well as the influences of membership functions on the evaluation scores and the bandwidth allocation of candidate networks before and after the change. The second part is to change the inference rules according to user preferences. Then, compare the influences of such change on the number of selections and the utilization of bandwidth resources of candidate networks. Finally, the third part is to compare the algorithm proposed in this paper with other algorithms.

B. ADJUSTMENT OF MEMBERSHIP FUNCTION PARAMETERS

To analyze the impact of the learning process on the results of network selection, compare and analyze the changes in the membership functions of Layers 2 and 5 first. In the experiment, the adjustment of the mean and variance of the membership functions of Layers 2 and 5 is made using the learning rules described in Section 3.4, so that the adjusted membership function is more in line with the characteristics of the training data. In the learning process, the change to the mean will cause the applicable membership function to shift to the left or right. The change to the variance will change the width of the applicable membership function. The change to the values of both parameters changes the position and shape of the membership function, thus affecting the evaluation score and bandwidth allocation of each candidate network.

Changes in the membership function parameter values of the inputs (i.e. RSS, load, and user rate requirements of candidate networks) and outputs (i.e. evaluation scores of candidate networks and bandwidth values assigned to users by each candidate network) are shown (Table 2). In respect of the change in the parameter values of the membership functions given (Table 2), the changes in shape of the membership functions of the inputs and outputs are shown (Fig. 4(a)-(g) and Fig. 5(a)-(f), respectively). The solid line in the figures indicates the shape of the membership function before learning,

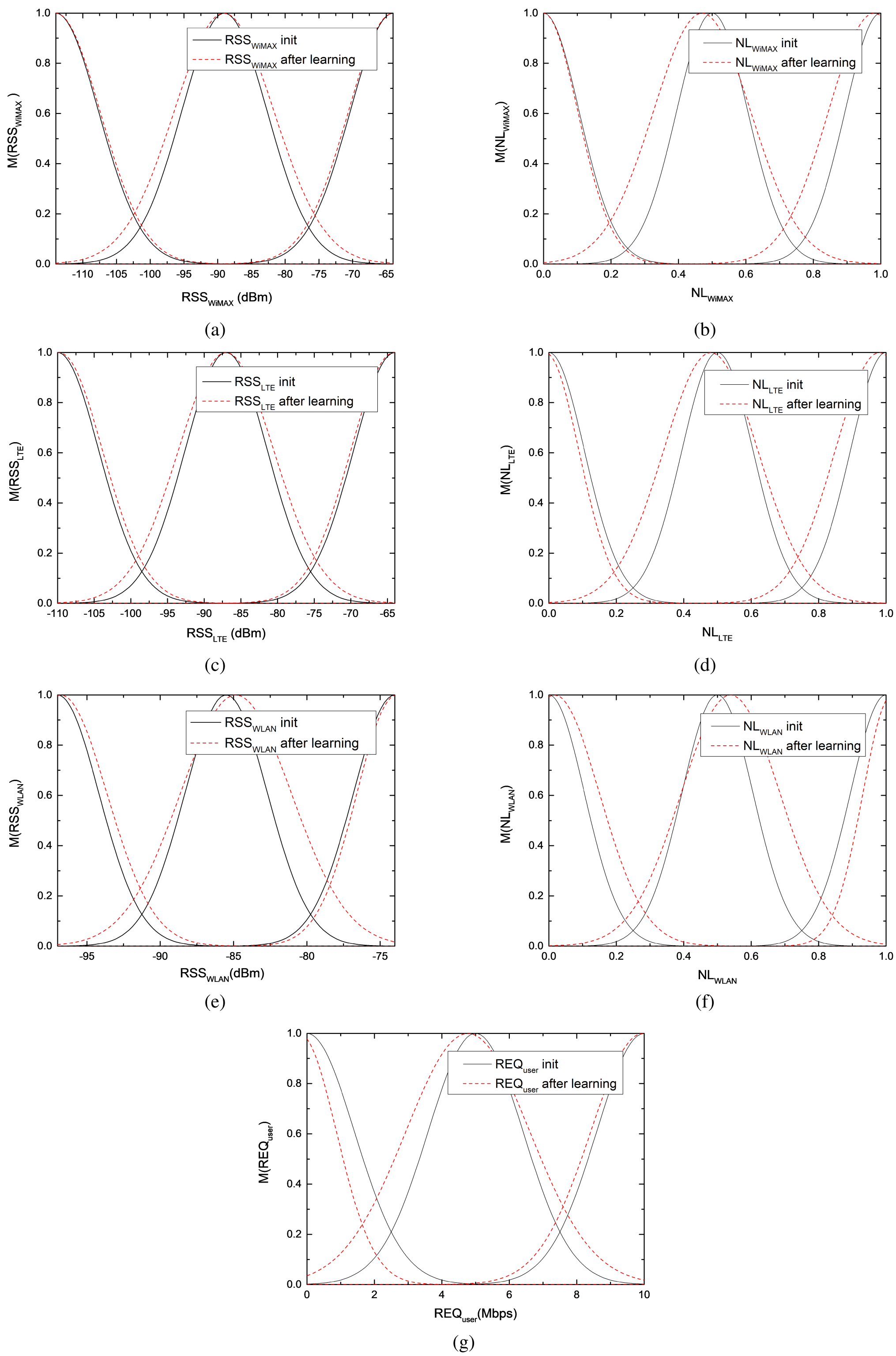

FIGURE 4. Changes in membership functions of Layer 2 before and after learning.

and the dotted line indicates the shape of the membership function after learning.

As can be seen (Figs. 4 and 5), when the membership function moves to the left and right, or the width of the membership function becomes wider and narrower, the values corresponding to low, middle, and high in the fuzzy set will also change. Taking Fig. 4(f) as an example (i.e. the membership function of NL_{WLAN}), the function moves to the right

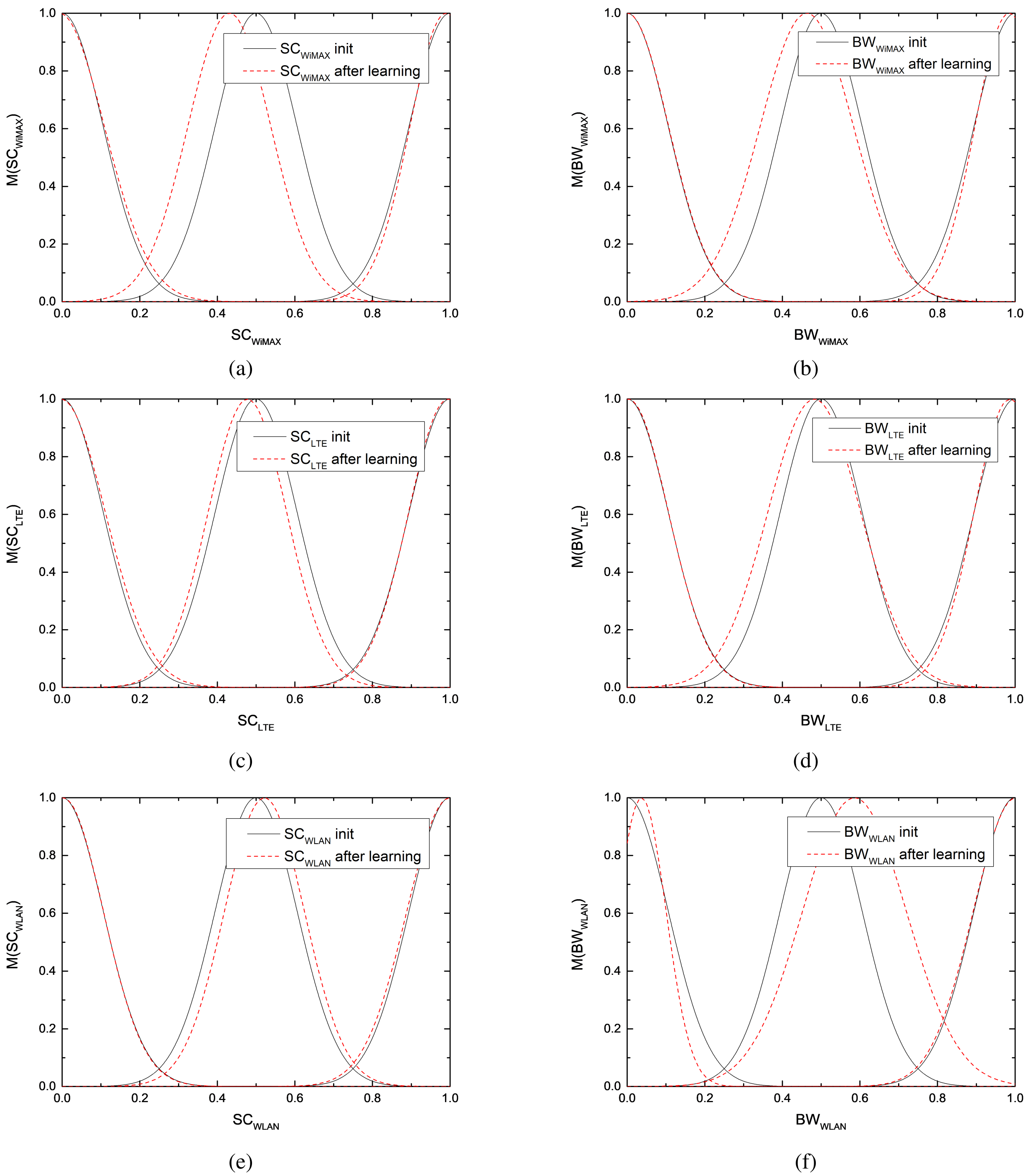

FIGURE 5. **Changes in membership functions of Layer 5 before and after learning.**

after learning and adjusting the parameter of the membership function. Given a certain value of NL_{WLAN}, the membership value in the low fuzzy set will become greater, and the evaluation score of the WLAN will increase, so the probability that the WLAN is selected will also increase. In addition, while other parameters remain unchanged, the bandwidth value allocated by the WLAN to users will also increase.

In addition, 2,000 sets of test data are put into the fuzzy neural network before and after learning, and the average values of the outputs before and after learning are shown (Table 3). As can be seen (Table 3), the average values of SC_{WiMAX}, BW_{WiMAX}, SC_{LTE}, and BW_{LTE} decreases, while the average values of SC_{WLAN} and BW_{WLAN} increases after learning, according to the characteristics of the training data.

TABLE 3. Comparison of average values of outputs before and after learning.

	SC_{WiMAX}	BW_{WiMAX}	SC_{LTE}	BW_{LTE}	SC_{WLAN}	BW_{WLAN}
before learning	0.5606	0.5459	0.4852	0.5209	0.5704	0.3779
after learning	0.4531	0.4952	0.4033	0.4981	0.6021	0.5555

TABLE 4. Example of fuzzy rules.

IF							THEN					
RSS_{WiMAX}	NL_{WiMAX}	RSS_{LTE}	NL_{LTE}	RSS_{WLAN}	NL_{WLAN}	REQ_{user}	SC_{WiMAX}	BW_{WiMAX}	SC_{LTE}	BW_{LTE}	SC_{WLAN}	BW_{WLAN}
L	H	L	M	L	H	H	L	M	L	H	M(L)	M
L	H	L	H	L	M	H	L	M	L	M	M(L)	H
L	H	M	H	M	H	H	L	M	L	M	M(L)	M
M	H	L	M	L	H	H	L	M	L	H	M(L)	M
M	H	L	H	L	H	H	L	M	L	M	M(L)	M
M	H	M	H	L	M	H	L	M	L	M	M(L)	H
L	L	M	L	M	L	H	M	H	M	H	H(M)	H
L	L	M	M	L	M	L	M	M	M	M	H(M)	M
M	L	M	L	L	M	M	M	M	M	M	H(M)	M
M	H	M	H	M	H	L	M	L	M	L	H(M)	L
H	L	H	M	H	M	H	M	M	M	M	H(M)	M
H	H	M	H	M	H	L	M	L	M	L	H(M)	L
M	L	M	L	H	L	L	M(H)	M	M(H)	M	H	M
H	L	H	L	H	L	M	M(H)	M	M(H)	M	H	M
H	M	M	L	M	L	L	M(H)	L	M(H)	M	H	M
H	M	M	L	H	M	L	M(H)	L	M(H)	M	H	L
H	M	H	L	H	L	L	M(H)	L	M(H)	M	H	M
H	M	H	M	H	M	L	M(H)	L	M(H)	L	H	L

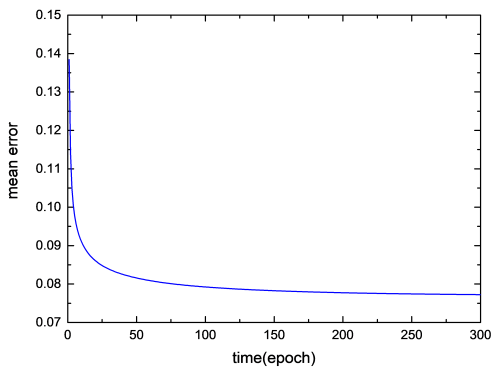

FIGURE 6. Error curve.

During the training process, the parameters of the membership functions of Layers 2 and 5 will be reversely adjusted until the training is completed (i.e. the maximum number of trainings is reached or the error objective function value is less than the preset value). In the experiment described in this paper, the curve of error values is shown (Fig. 6). With the number of iterations increasing, the error value decreases continuously and down to 0.077 from 0.138.

C. IMPACT OF FUZZY RULES

As described in Section 3.2 above, the fuzzy rules in the fuzzy decision module determine the scores and bandwidth allocation values of candidate networks. As a fuzzy rule changes, the scores and bandwidth allocation values of candidate networks will also change. In order to verify the impact of the change in fuzzy rules on the output results, the user preferred WLAN network is taken as an example in this section to illustrate the impact of fuzzy rules on the scores of candidate network and the utilization of bandwidth resources.

In this paper, the fuzzy rule of the user preferred WLAN network is modified as follows: if SC_{WiMAX}, SC_{LTE}, and SC_{WLAN} in the fuzzy rule are "L" at the same time, then change SC_{WLAN} to "M"; if SC_{WiMAX}, SC_{LTE}, and SC_{WLAN} in the fuzzy rule are "M" at the same time, then change SC_{WLAN} to "H"; and if SC_{WiMAX}, SC_{LTE}, and SC_{WLAN} are "H" at the same time, then do not change SC_{WLAN}, and change SC_{WiMAX} and SC_{LTE} to "M".

According to the above modifications, Table 4 lists some modified rules in the fuzzy rule base. The values in the parentheses indicate the values before the modification of the fuzzy rules, and the values next to the parentheses indicate the modified values of fuzzy rules.

The fuzzy rules before modification can be referred to as the initial fuzzy rules and the modified fuzzy rules as the fuzzy rules of the user preferred WLAN. Then, the 2,000 sets of data are put into the fuzzy neural network before and after such modification. Subsequently, the number of selections of candidate networks and the utilization of network resources are counted, and the impact of changes in fuzzy rules on network selection is verified.

The effect of fuzzy rules on the number of network selections before and after modification is shown (Fig. 7), with the number of selection of WiMAX, LTE, and WLAN networks before the modification of the fuzzy rule are 667, 624, and 709, respectively. When the fuzzy rule is changed to the user preferred WLAN, the number of selections of WLAN increases to 1,085. The number of times WiMAX and LTE are selected decreases to 471 and 444, respectively. The effect of

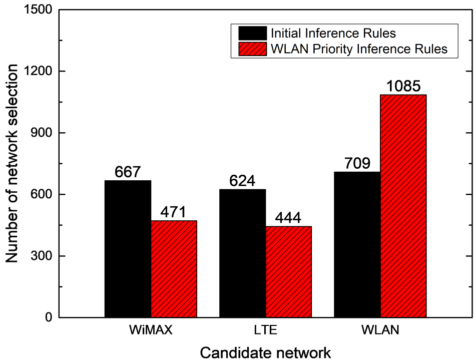

FIGURE 7. Effect of fuzzy rules on the number of network selections before and after modification.

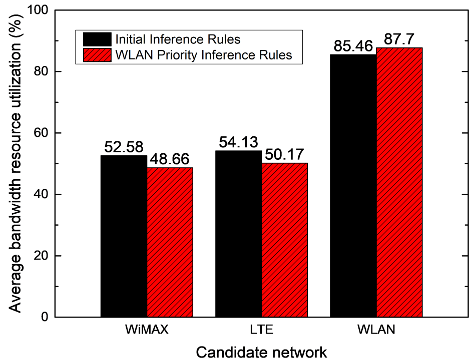

FIGURE 8. Effect of fuzzy rules on the utilization of bandwidth resources before and after modification.

fuzzy rules on the utilization of bandwidth resources before and after modification is also shown (Fig. 8). Here, when the fuzzy rule is changed to the user preferred WLAN, the average bandwidth resource utilization of WLAN increases from 85.46% to 87.7%, and the average bandwidth resource utilization of WiMAX and LTE drops by about 4% due to the increase in the number of times users select WLAN. The experiment results show that by considering multiple input parameters, the user's network selection can be adjusted through changes to the fuzzy rules, and the resource utilization of each candidate network can be adjusted in conjunction with user preferences.

D. COMPARISON OF ALGORITHMS

To evaluate the fuzzy neural network based access selection algorithm proposed in this paper, this section will compare the proposed algorithm with the RSS-based access selection algorithm and the load balancing access selection algorithm according to the decision factors for access selection as given in this paper.

The main idea of the RSS-based access selection algorithm is that the user first measures the RSS parameters of candidate networks and then selects the network with the highest RSS. Since WiMAX, LTE, and WLAN have different determination standards for signal strength, the RSS-based access selection algorithm adopts the same normalization method as the algorithm in this paper. The main idea of the load balancing-based access selection algorithm is that the user selects the network with the lowest load among all candidate networks.

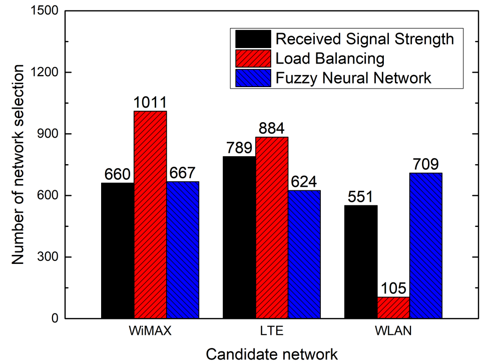

FIGURE 9. Comparison of number of network selections of candidate networks under different algorithms.

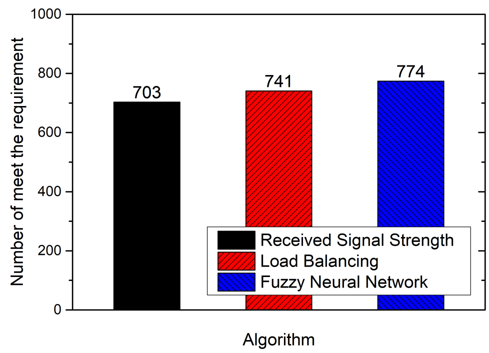

FIGURE 10. Comparison of number of meet the user rate requirement under different algorithms.

In the experiment described in this section, the 2,000 sets of input data mentioned in the proceeding section is also used. As can be seen (Fig. 9), the most popular networks based on the RSS-based access selection algorithm are LTE, WiMAX, and WLAN. In addition, as the average load of WiMAX in the input data is low, and the load balancing-based selection algorithm only considers the load factor and does not consider factors such as signal and user requirements, the most popular network under this algorithm is WiMAX. The proposed algorithm considers signal strength, network load, and user rate requirements comprehensively, and can give reasonable scores and selection for candidate network. In addition, in order to compare the user rates in different algorithms under the same conditions, in the RSS-based access selection algorithm and the load balancing-based access selection algorithm, the bandwidth values allocated to the users are set to be the same as the algorithm in this paper. As can be seen (Fig. 10), compared with the other two algorithms, the proposed algorithm can better meet the user rate requirement and improve user satisfaction.

$$
\begin{aligned}
\Delta\sigma_j^{(5)} &= -\eta\frac{\partial E}{\partial \sigma_j^{(5)}} \\
&= -\eta\frac{\partial E}{\partial O_i^{(5)}}\frac{\partial O_i^{(5)}}{\partial \sigma_j^{(5)}} \\
&= -\eta(-e)\frac{c_j^{(5)}x_{i,j}^{(5)}\left(\sum_{j\in T_i}\sigma_j^{(5)}x_{i,j}^{(5)}\right)-\left(\sum_{j\in T_i}c_j^{(5)}\sigma_j^{(5)}x_{i,j}^{(5)}\right)x_{i,j}^{(5)}}{\left(\sum_{j\in T_i}\sigma_j^{(5)}x_{i,j}^{(5)}\right)^2} \\
&= \eta\left(t_i - y_i\right)\frac{c_j^{(5)}x_{i,j}^{(5)}\left(\sum_{j\in T_i}\sigma_j^{(5)}x_{i,j}^{(5)}\right)-\left(\sum_{j\in T_i}c_j^{(5)}\sigma_j^{(5)}x_{i,j}^{(5)}\right)x_{i,j}^{(5)}}{\left(\sum_{j\in T_i}\sigma_j^{(5)}x_{i,j}^{(5)}\right)^2}
\end{aligned} \tag{38}
$$

V. CONCLUSIONS

This paper proposes an algorithm combining access selection and bandwidth allocation in HWNs, and designs a five-layer fuzzy neural network algorithm framework, with which the scores and bandwidth allocation values of candidate networks can be obtained by inputting RSS, network load, and user rate requirements into the input module of the framework using the fuzzy logic decision module, and the learning module is used to modify the parameters of membership functions in the fuzzy neural network structure. The simulation results show that the proposed algorithm can allow users to choose the most suitable network to access and can adjust the resource utilization of different networks based on user preferences.

The next step of this paper is to further adjust and optimize the parameter values in the learning module to obtain a better algorithm in terms of convergence speed. In addition, factors such as value triggering between networks and energy consumption will be considered in order to obtain greater QoS support and a better user experience.

APPENDIX

A. THE DERIVATION PROCESS OF LEARNING RULE OF THE PARAMETER $c_j^{(5)}$ ON LAYER 5

$$
\begin{aligned}
\Delta c_j^{(5)} &= -\eta\frac{\partial E}{\partial c_j^{(5)}} \\
&= -\eta\frac{\partial E}{\partial O_i^{(5)}}\frac{\partial O_i^{(5)}}{\partial I_i^{(5)}}\frac{\partial I_i^{(5)}}{\partial c_j^{(5)}} \\
&= -\eta\left(-e_i\right)\frac{1}{\sum_{j\in T_i}\sigma_j^{(5)}x_{i,j}^{(5)}}\cdot\sigma_j^{(5)}x_{i,j}^{(5)} \\
&= \eta\left(t_i - y_i\right)\frac{\sigma_j^{(5)}x_{i,j}^{(5)}}{\sum_{j\in T_i}\sigma_j^{(5)}x_{i,j}^{(5)}}
\end{aligned} \tag{37}
$$

B. THE DERIVATION PROCESS OF LEARNING RULE OF THE PARAMETER $\sigma_j^{(5)}$ ON LAYER 5 IS AS (38):

See Equation (38).

C. THE DERIVATION PROCESS OF LEARNING RULE OF THE PARAMETER $c_i^{(2)}$ ON LAYER 2

$$
\begin{aligned}
\Delta c_i^{(2)} &= -\eta\frac{\partial E}{\partial c_i^{(2)}} \\
&= -\eta\frac{\partial E}{\partial I_i^{(2)}}\frac{\partial I_i^{(2)}}{\partial c_i^{(2)}} \\
&= -\eta\frac{\partial E}{\partial I_i^{(2)}}\frac{2\left(x_{i,j}^{(2)}-c_i^{(2)}\right)}{\left(\sigma_i^{(2)}\right)^2} \\
&= -\eta\frac{\partial E}{\partial O_i^{(2)}}\frac{\partial O_i^{(2)}}{\partial I_i^{(2)}}\frac{2\left(x_{i,j}^{(2)}-c_i^{(2)}\right)}{\left(\sigma_i^{(2)}\right)^2} \\
&= -\eta\frac{\partial E}{\partial O_i^{(2)}}e^{I_i^{(2)}}\frac{2\left(x_{i,j}^{(2)}-c_i^{(2)}\right)}{\left(\sigma_i^{(2)}\right)^2}
\end{aligned} \tag{39}
$$

Since the outputs of Layer 2 nodes affect the inputs to Layer 3 nodes to which it is connected, $\frac{\partial E}{\partial O_i^{(2)}}$ is as follows:

$$
\frac{\partial E}{\partial O_i^{(2)}} = \sum_{k=1}^{2187}\frac{\partial E}{\partial I_k^{(3)}}\frac{\partial I_k^{(3)}}{\partial O_i^{(2)}} \tag{40}
$$

The $\frac{\partial I_k^{(3)}}{\partial O_i^{(2)}}$ and $\frac{\partial E}{\partial I_k^{(3)}}$ in (40) are:

$$
\frac{\partial I_k^{(3)}}{\partial O_i^{(2)}} = \begin{cases} 1, & \text{if the layer 2 node iprovides the min} \\ & \text{among layer 3 node } k \\ 0, & \text{otherwise} \end{cases} \tag{41}
$$

$$
\begin{aligned}
\frac{\partial E}{\partial I_k^{(3)}} &= \frac{\partial E}{\partial O_k^{(3)}}\frac{\partial O_k^{(3)}}{\partial I_k^{(3)}} \\
&= \frac{\partial E}{\partial O_k^{(3)}} \\
&= \sum_{n=1}^{18}\frac{\partial E}{\partial I_n^{(4)}}\frac{\partial I_n^{(4)}}{\partial O_k^{(3)}}
\end{aligned} \tag{42}
$$

The $\frac{\partial I_n^{(4)}}{\partial O_k^{(3)}}$ and $\frac{\partial E}{\partial I_n^{(4)}}$ in (42) are as (43) and (44):

$$\frac{\partial I_n^{(4)}}{\partial O_k^{(3)}} = \begin{cases} 1, & \text{if the layer 3 node } k \text{ is connected to the layer 4 node } n \\ 0, & \text{otherwise} \end{cases} \tag{43}$$

$$\begin{aligned}\frac{\partial E}{\partial I_n^{(4)}} &= \frac{\partial E}{\partial O_n^{(4)}}\frac{\partial O_n^{(4)}}{\partial I_n^{(4)}} = \frac{\partial E}{\partial O_i^{(5)}}\frac{\partial O_i^{(5)}}{\partial O_n^{(4)}} \\ &= -(t_i - y_i)\frac{c_n^{(5)}\sigma_n^{(5)}\left(\sum_{j\in T_n}\sigma_j^{(5)}x_{i,j}^{(5)}\right) - \left(\sum_{j\in T_n}c_j^{(5)}\sigma_j^{(5)}x_{i,j}^{(5)}\right)\sigma_n^{(5)}}{\left(\sum_{j\in T_n}\sigma_j^{(5)}x_{i,j}^{(5)}\right)^2}\end{aligned} \tag{44}$$

Therefore, the learning rule of the parameter $c_i^{(2)}$ on Layer 2 is as (45):

$$\begin{aligned}\Delta c_i^{(2)} &= -\eta\frac{\partial E}{\partial O_i^{(2)}}e^{I_i^{(2)}}\frac{2\left(x_{i,j}^{(2)}-c_i^{(2)}\right)}{\left(\sigma_i^{(2)}\right)^2} \\ &= -\eta\sum_{n=1}^{18}\frac{\partial E}{\partial I_n^{(4)}}\sum_{k=1}^{2187}\frac{\partial I_n^{(4)}}{\partial O_k^{(3)}}\frac{\partial I_k^{(3)}}{\partial O_i^{(2)}}e^{I_i^{(2)}}\frac{2\left(x_{i,j}^{(2)}-c_i^{(2)}\right)}{\left(\sigma_i^{(2)}\right)^2}\end{aligned} \tag{45}$$

D. THE DERIVATION PROCESS OF LEARNING RULE OF THE PARAMETER $\sigma_i^{(2)}$ ON LAYER 2

$$\begin{aligned}\Delta\sigma_i^{(2)} &= -\eta\frac{\partial E}{\partial\sigma_i^{(2)}} \\ &= -\eta\frac{\partial E}{\partial I_i^{(2)}}\frac{\partial I_i^{(2)}}{\partial\sigma_i^{(2)}} \\ &= -\eta\frac{\partial E}{\partial I_i^{(2)}}\frac{2\left(x_{i,j}^{(2)}-c_i^{(2)}\right)^2}{\left(\sigma_i^{(2)}\right)^3} \\ &= -\eta\frac{\partial E}{\partial O_i^{(2)}}\frac{\partial O_i^{(2)}}{\partial I_i^{(2)}}\frac{2\left(x_{i,j}^{(2)}-c_i^{(2)}\right)^2}{\left(\sigma_i^{(2)}\right)^3} \\ &= -\eta\frac{\partial E}{\partial O_i^{(2)}}e^{I_i^{(2)}}\frac{2\left(x_{i,j}^{(2)}-c_i^{(2)}\right)^2}{\left(\sigma_i^{(2)}\right)^3}\end{aligned} \tag{46}$$

The $\frac{\partial E}{\partial I_i^{(2)}}$ in (46) has the same learning rule as the membership function parameter $c_i^{(2)}$ of Layer 2 in Appendix C, so (47) is obtained:

$$\begin{aligned}\Delta\sigma_i^{(2)} &= -\eta\frac{\partial E}{\partial O_i^{(2)}}e^{I_i^{(2)}}\frac{2\left(x_{i,j}^{(2)}-c_i^{(2)}\right)^2}{\left(\sigma_i^{(2)}\right)^3} \\ &= -\eta\sum_{n=1}^{18}\frac{\partial E}{\partial I_n^{(4)}}\sum_{k=1}^{2187}\frac{\partial I_n^{(4)}}{\partial O_k^{(3)}}\frac{\partial I_k^{(3)}}{\partial O_i^{(2)}}e^{I_i^{(2)}}\frac{2\left(x_{i,j}^{(2)}-c_i^{(2)}\right)^2}{\left(\sigma_i^{(2)}\right)^3}\end{aligned} \tag{47}$$

REFERENCES

[1] A. Damnjanovic et al., "A survey on 3GPP heterogeneous networks," *IEEE Wireless Commun.*, vol. 18, no. 3, pp. 10–21, Jun. 2011.
[2] A. Malik, J. Qadir, B. Ahmad, K.-L. A. Yau, and U. Ullah, "QoS in IEEE 802.11-based wireless networks: A contemporary review," *J. Netw. Comput. Appl.*, vol. 55, pp. 24–46, Sep. 2015.
[3] M. Jo, T. Maksymyuk, R. L. Batista, T. F. Maciel, A. L. F. D. Almeida, and M. Klymash, "A survey of converging solutions for heterogeneous mobile networks," *IEEE Wireless Commun.*, vol. 21, no. 6, pp. 54–62, Dec. 2014.
[4] A. Ghosh et al., "Heterogeneous cellular networks: From theory to practice," *IEEE Commun. Mag.*, vol. 50, no. 6, pp. 54–64, Jun. 2012.
[5] E. Gustafsson and A. Jonsson, "Always best connected," *IEEE Wireless Commun.*, vol. 10, no. 1, pp. 49–55, Feb. 2003.
[6] A. Keshavarz-Haddad, E. Aryafar, M. Wang, and M. Chiang, "HetNets selection by clients: Convergence, efficiency, and practicality," *IEEE/ACM Trans. Netw.*, vol. 25, no. 1, pp. 406–419, Feb. 2017.
[7] H. Kalbkhani, S. Yousefi, and M. G. Shayesteh, "Adaptive handover algorithm in heterogeneous femtocellular networks based on received signal strength and signal-to-interference-plus-noise ratio prediction," *IET Commun.*, vol. 8, no. 17, pp. 3061–3071, 2014.
[8] Y. Li, B. Cao, and C. Wang, "Handover schemes in heterogeneous LTE networks: Challenges and opportunities," *IEEE Wireless Commun.*, vol. 23, no. 2, pp. 112–117, Apr. 2016.
[9] E. Obayiuwana and O. E. Falowo, "Network selection in heterogeneous wireless networks using multi-criteria decision-making algorithms: A review," *Wireless Netw.*, vol. 23, pp. 2617–2649, Nov. 2017.
[10] L. Tang, S. Ji, and J. Yan, "A heterogeneous network access selection algorithm based on attribute dependence," *Wireless Pers. Commun.*, vol. 92, pp. 1163–1176, Feb. 2017.
[11] R. K. Goyal, S. Kaushal, and A. K. Sangaiah, "The utility based non-linear fuzzy AHP optimization model for network selection in heterogeneous wireless networks," *Appl. Soft Comput.*, vol. 67, pp. 800–811, Jun. 2018.
[12] X. Wu and Q. Du, "Utility-function-based radio-access-technology selection for heterogeneous wireless networks," *Comput. Electr. Eng.*, vol. 52, pp. 171–182, May 2016.
[13] Y. K. Salih, O. H. See, and R. W. Ibrahim, "An intelligent selection method based on game theory in heterogeneous wireless networks," *Trans. Emerg. Telecommun. Technol.*, vol. 27, pp. 1641–1652, Dec. 2016.
[14] R. Trestian, O. Ormond, and G.-M. Muntean, "Game theory-based network selection: Solutions and challenges," *IEEE Commun. Surveys Tut.*, vol. 14, no. 4, pp. 1212–1231, 4th Quart., 2012.
[15] D. Niyato and E. Hossain, "Dynamics of network selection in heterogeneous wireless networks: An evolutionary game approach," *IEEE Trans. Veh. Technol.*, vol. 58, no. 4, pp. 2008–2017, May 2009.
[16] S. Goudarzi, W. H. Hassan, M. H. Anisi, and S. A. Soleymani, "MDP-based network selection scheme by genetic algorithm and simulated annealing for vertical-handover in heterogeneous wireless networks," *Wireless Pers. Commun.*, vol. 92, pp. 399–436, Jan. 2017.
[17] L. Xiao, Q. Zhi-Hong, T. Hong-Liang, and W. Xue, "Markov decision model based handoff selection algorithm for heterogeneous wireless networks," *Acta Phys. Sinica*, vol. 65, no. 23, 2016, Art. no. 236402.
[18] K. Ahuja, B. Singh, and R. Khanna, "Particle swarm optimization based network selection in heterogeneous wireless environment," *Optik*, vol. 125, pp. 214–219, Jan. 2014.
[19] Y. Choi, H. Kim, S.-W. Han, and Y. Han, "Joint resource allocation for parallel multi-radio access in heterogeneous wireless networks," *IEEE Trans. Wireless Commun.*, vol. 9, no. 11, pp. 3324–3329, Nov. 2010.

[20] L. Wang and G.-S. G. S. Kuo, "Mathematical modeling for network selection in heterogeneous wireless networks—A tutorial," *IEEE Commun. Surveys Tuts.*, vol. 15, no. 1, pp. 271–292, 4th Quart., 2013.
[21] A. Ahmed, L. Boulahia, and D. Gaiti, "Enabling vertical handover decisions in heterogeneous wireless networks: A state-of-the-art and a classification," *IEEE Commun. Surveys Tut.*, vol. 16, no. 2, pp. 776–811, 2nd Quart., 2014.
[22] S. Kubler, J. Robert, W. Derigent, A. Voisin, and Y. Le Traon, "A state-of the-art survey & Testbed of fuzzy AHP (FAHP) applications," *Expert Syst. Appl.*, vol. 65, pp. 398–422, Dec. 2016.
[23] T. Thumthawatworn, P. Tillapart, and P. Santiprabhob, "Adaptive multi-fuzzy engines for handover decision in heterogeneous wireless networks," *Wireless Pers. Commun.*, vol. 93, pp. 1005–1026, Apr. 2017.
[24] K. Vasu, S. Maheshwari, S. Mahapatra, and C. S. Kumar, "QoS-aware fuzzy rule-based vertical handoff decision algorithm incorporating a new evaluation model for wireless heterogeneous networks," in *EURASIP Journal on Wireless Communications and Networking*. Cham, Switzerland: Springer, 2012.
[25] L. Giupponi, R. Agusti, J. Pérez-Romero, and O. Sallent, "Fuzzy neural control for economic-driven radio resource management in beyond 3G networks," *IEEE Trans. Syst., Man, Cybern., C (Appl. Rev.)*, vol. 39, no. 2, pp. 170–189, Mar. 2009.
[26] M. Taki, M. Heshmati, and Y. Omid, "Fuzzy-based optimized QoS-constrained resource allocation in a heterogeneous wireless network," *Int. J. Fuzzy Syst.*, vol. 18, pp. 1131–1140, Dec. 2016.
[27] M. Khan, A. Ahmad, S. Khalid, S. H. Ahmed, S. Jabbar, and J. Ahmad, "Fuzzy based multi-criteria vertical handover decision modeling in heterogeneous wireless networks," *Multimedia Tools Appl.*, vol. 76, pp. 24649–24674, Dec. 2017.
[28] K. Ahuja, B. Singh, and R. Khanna, "Network selection in wireless heterogeneous environment by C-P-F hybrid algorithm," *Wireless Pers. Commun.*, vol. 98, pp. 2733–2751, Feb. 2018.
[29] X. Yan, P. Dong, T. Zheng, and H. Zhang, "Fuzzy and utility based network selection for heterogeneous networks in high-speed railway," *Wireless Commun. Mobile Comput.*, vol. 2017, Oct. 2017, Art. no. 4967438.
[30] J. Chen, Y. Wang, Y. Li, and E. Wang, "QoE-aware intelligent vertical handoff scheme over heterogeneous wireless access networks," *IEEE Access*, vol. 6, pp. 38285–38293, 2018.
[31] A. Çalhan and C. Çeken, "Artificial neural network based vertical handoff algorithm for reducing handoff latency," *Wireless Pers. Commun.*, vol. 71, pp. 2399–2415, Aug. 2013.
[32] A. G. Mahira and M. S. Subhedar, "Handover decision in wireless heterogeneous networks based on feedforward artificial neural network," in *Advances in Intelligent Systems and Computing*, vol. 556, H. S. Behera and D. Mohapatra, Eds. Berlin, Germany: Springer-Verlag, 2017, pp. 663–669.
[33] L. Giupponi, R. Agusti, J. Perez-Romero, and O. S. Roig, "A novel approach for joint radio resource management based on fuzzy neural methodology," *IEEE Trans. Veh. Technol.*, vol. 57, no. 3, pp. 1789–1805, May 2008.
[34] L. Giupponi, R. Agusti, J. Perez-Romero, and O. Sallent, "A framework for JRRM with resource reservation and multiservice provisioning in heterogeneous networks," *Mobile Netw. Appl.*, vol. 11, pp. 825–846, Dec. 2006.
[35] Y.-H. Chen, C.-J. Chang, and C. Y. Huang, "Fuzzy Q-learning admission control for WCDMA/WLAN heterogeneous networks with multimedia traffic," *IEEE Trans. Mobile Comput.*, vol. 8, no. 11, pp. 1469–1479, Nov. 2009.
[36] J. Mar, H.-C. Nien, and J.-C. Cheng, "Intelligent data rate control in cognitive mobile heterogeneous networks," *IEICE Trans. Commun.*, vol. E95-B, no. 4, pp. 1161–1169, Apr. 2012.
[37] N. Qian, "On the momentum term in gradient descent learning algorithms," *Neural Netw.*, vol. 12, no. 1, pp. 145–151, 1999.
[38] H. Wu *et al.*, "Content-aware cooperative transmission in HetNets with consideration of base station height," *IEEE Trans. Veh. Technol.*, vol. 67, no. 7, pp. 6048–6062, Jul. 2018.

GEN LIANG received the M.S. degree from Jilin University, China, in 2006. He is currently pursuing the Ph.D. degree with the School of Computer Science and Engineering, South China University of Technology, China. His current research interests include wireless communications, radio resource management, and networks' simulation.

HEWEI YU received the B.S. and M.S. degrees from Xi'an Jiaotong University, China, in 1989 and 1992, respectively, and the Ph.D. degree from the South China University of Technology, China, in 2004, where he is currently a Professor and a Doctoral Tutor. He has authored over 70 technical papers in major journals and conferences. His current research interests include the next-generation wireless networks, multi-carrier communication technology, and multimedia transmission technology.

XIAOXUE GUO received the B.S. and M.S. degrees in computer science and technology from South China Normal University, Guangzhou, China, in 2002 and 2006, respectively. She is currently an Associate Professor with the College of Science, Guangdong University of Petrochemical Technology. Her current research interests include wireless communications, wireless sensor networks, and networks' protocols.

YONG QIN received the Ph.D. degree from the South China University of Technology, China, in 2008. He is currently a Professor with the Dongguan University of Technology. His current research interests include the next-generation wireless networks and networks' protocols.