A Semi-distributed Network Selection Scheme in Heterogeneous Wireless Networks

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Abstract. Joint radio resource management (JRRM) mechanism helps to optimize the radio resource usage of heterogeneous wireless networks but the introduction of central new entity which manages the information of all networks in JRRM may require unbearable change to current network architecture. Aiming at easily integrating with existing and forthcoming heterogeneous wireless networks, this paper proposes a semi-distributed scheme without centralized entity, in which user terminal make decision on network selection through fuzzy neural network method based on local information and the selected network finishes the admission control to user terminal according to its actual resource condition. Our scheme is verified by the simulation in the UMTS/WLAN scenario and can effectively balance the load between the UMTS/WLAN networks while maintaining the level of blocking probability compared to traditional distributed WLAN-prefer algorithm.

Keywords: heterogeneous wireless networks, semi-distributed, access network selection, fuzzy neural network.

1 Introduction

In the last decade, wireless mobile communication system has a significant development, leading to the deployment of a series of radio access technologies (RATs). At present, global system for mobile communications (GSM) technology co-exist with general packet radio service (GPRS) and universal mobile telecommunications system (UMTS) technologies. In addition, there are many other interface technologies: high-speed downlink packet access (HSDPA), IEEE 802.11 standards, long-term evolution (LTE) system, etc. Therefore, these different wireless technologies constitute heterogeneous wireless access environment.

With the availability of multi-mode user terminals capable of accessing different technologies, the introduction of heterogeneous wireless access environment raises a new challenge for the study of radio resource management. In heterogeneous scenarios, the joint radio resource management (JRRM) is considered a

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appropriate method to manage dynamically allocation and deallocation of radio resources among different radio access networks, and has been widely studied (e.g.[1] -[4]). In particular, selecting a radio access network for users, while improving the whole heterogeneous networks radio resource utilization, has become a hot topic in radio resource management of heterogeneous networks.

Considering the problem of access network selection, the concept of ABC (always best connected) allows a user terminal connectivity to applications and access technologies that best suit the user's needs[5]. However, how to define "the best" is not much accurate because it depends on many different aspects, such as user preferences, terminal capabilities, service QoS, network coverage, network load, price and many other factors. The decision making of access network has been considered[3][4][6] -[9]. However, most schemes published are based on JRRM mechanism, and need a new entity above all of radio access technologies (RATs). The entity has to acquire global information to make a centralized decision. So that, because of requiring unbearable change, these schemes are difficult to implement in current network structure.

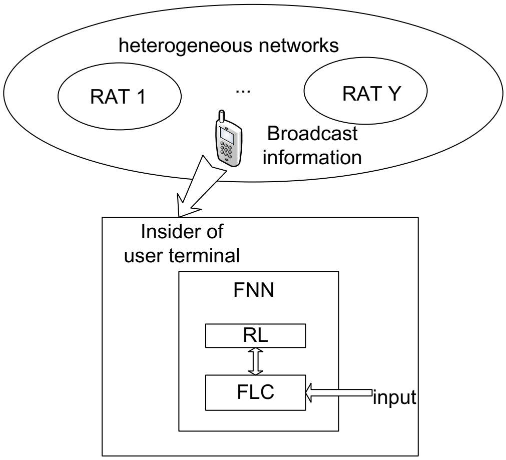

Fig. 1. This figure shows the architecture of the semi-distributed access network selection scheme we proposed. It is user-based and network-assisted. After collecting all the information for decision, user terminal intelligently selects the access network based on fuzzy neural network which consists of FLC and RL. The selected network just does the admission control.

In this paper, we present a semi-distributed access network selection scheme in which the user terminal decides which network to access. This scheme can be implemented in current networks because of no need of central entity. After collecting the information for decision, user terminal intelligently selects the access network based on fuzzy neural network, and then sends an access request message to the selected network. The selected network may refuse this request, because the information at the user terminal may not be exactly up-to-date which is cased by the delay of broadcast message. If being refused, the user terminal should do the selection process again based on the latest information, and then apply for access until receiving the reply. Otherwise, the user terminal should realize that the coverage of the current location is not good enough, and then change its own location. The architecture of the scheme we proposed is shown in Fig.1.

The innovation of this paper can be summarized as follows: first of all, the scheme we proposed is semi-distributed, and the user terminal selects the access network, while the selected network just do the admission control. Secondly, the decision made by user terminal adopts fuzzy neural mechanism with load balance reinforcement learning techniques to achieve the intelligent access network selection.

The rest of this paper is organized as follows. In Section 2, the system model of radio resource management (RRM) is described. The details of the proposed semi-distributed scheme are described in Section 3. Section 4 gives simulation results of the UMTS/WLAN scenario and related discussions, and the conclusion is made in Section 5.

2 System Model

We define the heterogeneous wireless networks system as: $y = \{1, 2, ...Y\}$, and each subsystem has its own cellular structure and access points, such as, BSs in UMTS subsystem, APs in WLAN system and ground stations in satellite system.

We define the set of service as: $s = \{1, 2, ...S\}$, and each type of service demands different QoS: date rate, bandwidth, delay and so on. For the simplicity, we only consider date rate here. Let $N_s = \{N_1, N_2, ...N_S\}$, $R_s = \{R_1, R_2, ...R_S\}$ represent the number of users of each service and the average date rate of each service respectively. R denotes the total heterogeneous networks system capacity constraints.

We define $U_s(R_s)$ as the utility function on behalf of the service. In general, the utility function of user i is expressed as $U_i(R_i)$.

Therefore, radio resource management (RRM) comes down to the optimization problem of the overall heterogeneous networks utility, as follows:

$$\begin{gathered} \max_{R_s} \textstyle\sum_{s=1}^{S} N_s U_s(R_s), \\ s.t. \textstyle\sum_{s=1}^{S} N_s R_s \le R \end{gathered} \tag{1}$$

Because the utility functions are assumed to be strictly concave, there must exist a unique optimal solution Rs^*. However, it is a essentially global optimization and NP-hard problem. So that the optimal solution is so hard to compute. In this paper, taking into account the feasibility with the existing network architecture, we propose a semi-distributed network selection scheme that will be described in part 3.

3 The Semi-distributed Scheme

3.1 The Access Selection-Admission Process

The semi-distributed scheme we proposed is user-based and network-assisted. The user terminal does the access selection process, and after that the selected network does the admission control. The flowchart is shown in Fig.2.

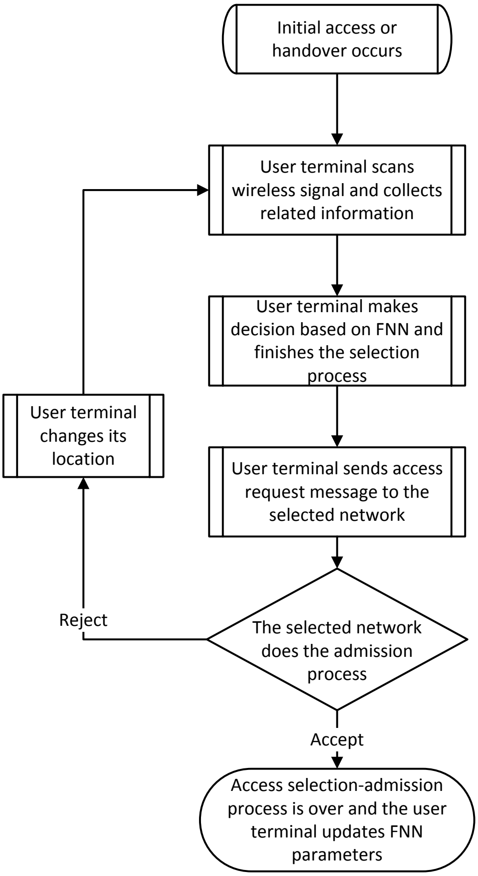

Fig. 2. Flowchart of the access selection-admission process of the semi-distributed scheme we proposed

When initial access or handover occurs, the access selection process in user terminal is triggered.

As access selection is triggered, the user terminal can detect the set of available networks by scanning the wireless signals. At the same time, the user can also acquires the load indicator of each available network which is assumed to broadcast periodically.

Then, after network coverage indicator, load indicator and terminal mobility rate have been collected, the user terminal input these parameters to the fuzzy neural network to get an output of the most suitable network to access. At this point, the user terminal completes the selection process.

The user terminal sends an access request message to the selected network, along with the user's QoS requirement (service type, rate requirements, etc). The selected network starts the process of admission. If the user's QoS could be satisfied, this request will be accepted. Otherwise, the network will reply a reject message. And then, the process of admission is over.

When the user terminal receives the accept message from the selected network, it means that the whole access selection-admission process is over, and the user terminal should use the updated load indicator to adjust the parameters of fuzzy neural network. Otherwise, the user terminal should change the location and start the access selection-admission process again.

3.2 Decision-Making Based on FNN

The fuzzy neural network (FNN) method we takes presented in literatures[10]. FNN is a type of neural network, and takes the advantage of fuzzy logic and neural network methods together.

The reason that we use fuzzy neural network (FNN) is twofold. On the one hand, we can take advantage of the ability of fuzzy logic controller (FLC) to make effective decisions in situations where the available sources of information are qualitatively interpreted and heterogeneous in nature. On the other hand, by using of neural networks to enhance the learning ability of fuzzy logic controller (FLC), which called reinforcement learning (RL) techniques, the scheme we proposed has the ability to interact with the surrounding environment and accordingly, self-tuning and acting.

The FNN used in this paper consists of fuzzy logic control (FLC) and reinforcement learning (RL). Fuzzy logic control (FLC) implements the fuzzifier, the inference engine, and the defuzzifier. The FNN works in two phases. The first one is the decision-making process, through which the FLC based on the selected input linguistic variables, generates the corresponding output linguistic variables, and then access selection decision is made. The second phase is the parameters-tuning process, during which the reinforcement signal is propagated to adjust the FNN parameters.

For the simplify, we take two RATs for example, and the structure of FNN is shown in Fig.3.

Fuzzy Logic Controller. The FNN can be represented by the five-layered structure described in Fig.3.

The first layer nodes are input nodes. We consider five input linguistic variables here: receive signal strength (SS), resource available (RA) with both of the considered RATs and user mobile speed.

The second layer nodes execute the fuzzification operation. They calculate the degree of membership for the input received by the input nodes to the particular

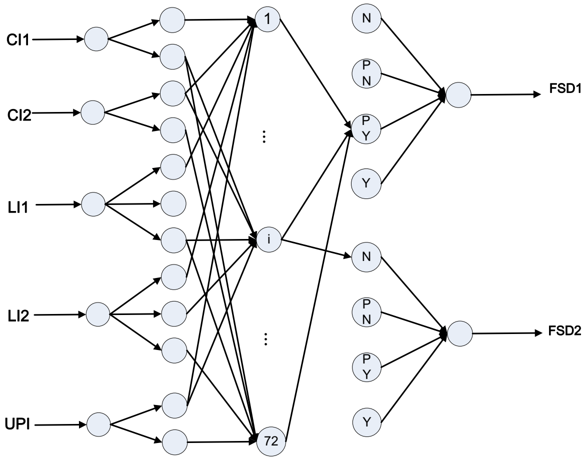

Fig. 3. The five-layer structure of fuzzy neural network

fuzzy set associated with the second layer node, which is defined by a membership function. The term sets defined for each input linguistic variable are as follows.

- $\mathrm{T}(SS_n) = \mathrm{T}\{low, high\}$,
- $\mathrm{T}(RA_n) = \mathrm{T}\{low, medium, high\}$,
- $\mathrm{T}(UPI) = \mathrm{T}\{low, high\}$,

where $n = 1, 2$. So that the second layer consists of 12 nodes. In case of Gaussian membership functions, the degree of membership μ_{ij} for the input variable i, the fuzzy set j is calculated by

$$\mu_{ij}(x_i) = \exp(-\frac{(x_i - m_{ij})^2}{2\sigma_{ij}^2}), \tag{2}$$

where x_i $(i = 1, 2, ...5)$ is one of the input linguistic variables, m_{ij} and σ_{ij} $(i = 1, 2, ...5;\ j = 1, 2$ or $j = 1, 2, 3)$ are mean and variance of the related Gaussian membership function at the second layer.

The third layer nodes calculate the degree of membership of the precondition of the fuzzy logic rule corresponding to the specific node by means of the AND operator, so that the rule node takes the minimum among the received inputs from the second layer. Considering the term sets defined in the second layer, the number of the third layer nodes is $2 \times 2 \times 3 \times 3 \times 2 = 72$. Therefore, the degree of the third layer node is calculated by

$$a_{j_1 j_2 j_3 j_4 j_5} = \min\left(\mu_{1j_1}, \mu_{2j_2}, \mu_{3j_3}, \mu_{4j_4}, \mu_{5j_5}\right), \tag{3}$$

where $a_{j_1 j_2 j_3 j_4 j_5}$ $(j_i \in [1, 72]\ , i = 1, 2, 3, 4, 5)$.

The fourth layer nodes calculate the degree of membership of the consequence of the fuzzy logic rule. The number of this layer nodes depends on the output linguistic variable of the fifth layer. The term sets defined for each output linguistic variable are as follows.

– $\mathrm{T}(FSD_j) = \mathrm{T}\{N(not), PN(probabily\,not), PY(probabily\,yes), Y(yes)\}$,

where $j = 1, 2$. FSD denotes fuzzy selection decision. So that, the fourth layer consists of 8 nodes.

The fourth layer nodes sum the degree of membership of the third layer nodes, which related to the specific fourth layer node as a consequence of the fuzzy logic rule. So,

$$b_i = \min(\sum a_{j_1 j_2 j_3 j_4 j_5}, 1), \tag{4}$$

where $a_{j_1 j_2 j_3 j_4 j_5}$ denote the third layer nodes that related to specific node i in fourth layer.

The fifth layer nodes finally perform the defuzzication process, and compute the output of fuzzy selection decision (FSD) by the center of area method.

$$FSD_i = \frac{\sum_{j \in T_i} m_j \sigma_j b_j}{\sum_{j \in T_i} \sigma_j \ b_j}, i = 1, 2 \tag{5}$$

m_j and σ_j ($j = 1, 2$) are mean and variance of the related Gaussian membership function at the fourth layar. T_i is the set of the fourth layer nodes that related to node i of the fifth layer.

Reinforcement Learning. The reinforcement learning procedure is executed after the access selection-admission process is over, and then activate an error backpropagation learning algorithm that minimizes a quadratic error function. The quadratic error function for minimization is defined as

$$E_t = \frac{1}{2}(y_t - y^*)^2, \tag{6}$$

where y_t denotes the current networks load balance indicator, which we use the difference between the highest network and the lowest network. Meantime, y^* denotes the expected value of load balance indicator, which we choose as 0.

Parameters of fuzzy neural network modified by the method of negative gradient descent. The parameter x_t according to E gradient in the opposite direction to adjust. Formula is as follows, where γ is the learning speed.

$$x_{t+1} = x_t + \gamma(-\frac{E_t - E_{t-1}}{x_t - x_{t-1}}), \tag{7}$$

According to the error propagation, fuzzy neural network updates the mean m and standard deviation σ of the fuzzification and defuzzification membership function.

In our proposed scheme, the adjustment of parameters divides into two phases. The first phase is initial offline training. We can use software simulation to adjust the parameters until E_t less than the predetermined threshold. The second phase is online training. By using the FNN already trained offline, the scheme we proposed can adjust the parameters after the each access selection-admission process. Therefore, our scheme can dynamically adapt to the heterogeneous networks condition.

Making Decision. In accordance with the fuzzy neural network output parameters FSD_i, $(i = 1, 2)$, the user terminal selects the network with greater FSD value. However, if FSD_1 and FSD_2 are both lower than 0.5, which means the available networks both are not suitable for access. Then the user terminal should change the location, and start a new access selection process.

4 Numerical Result and Discussion

In this paper, we choose wireless local area network (WLAN) as a high-bandwidth, low coverage wireless access technology, as well as universal mobile telecommunications system (UMTS) as a low-bandwidth, high coverage access technology. So that, simulation scenario of heterogeneous wireless networks HWN = {UMTS, WLAN}.

According to Part 3, the input of FNN are SS, RA and UPI that described in detail as follow.

- SS(dbm): Signal strength received by the user terminals from UMTS and WLAN.
- RA: Resource available that the user terminals can get from broadcast message. For UMTS, $RA_{UMTS}(100\%) = 1 - \mu$, where μ denotes the uplink load factor. For WLAN, $RA_{WLAN}(units)$ = Maximum number of users (28 in simulation) − number of users allocated in the WLAN cell.
- UPI(m/s): User preference indicator, and we use the speed of the user terminals here.

4.1 Single-User Performance

Fig.4 show when the SS received from UMTS and WLAN are equal, as well as RA of WLAN is enough, how the RA of UMTS effects the output of FNN. We can get that if user terminal moving high speed, FSD_{WLAN} will be always

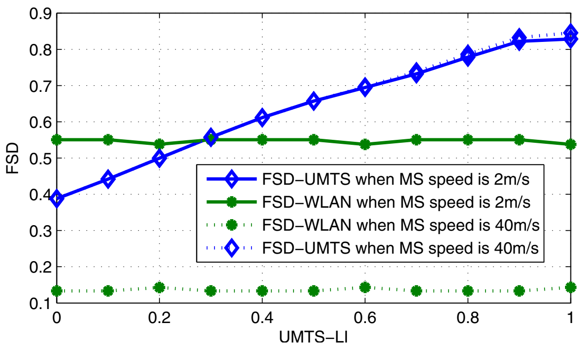

Fig. 4. Load of UMTS effects on decision when the speed of MS is $2m/s$ and $40m/s$, while $SS_{UMTS} = SS_{WLAN} = -84dbm$, $RA_{WLAN} = 10$

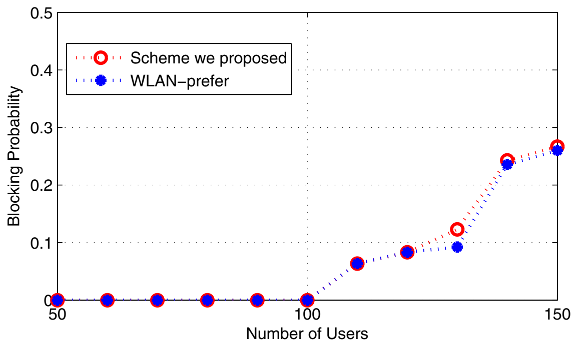

Fig. 5. This figure shows blocking probability when maximum number of users UMTS can accept is 50, and maximum number of users WLAN can accept is 28. The users initiate the call according the poisson process with arrival rate of 10 calls per hour, and the average call duration is 180 seconds.

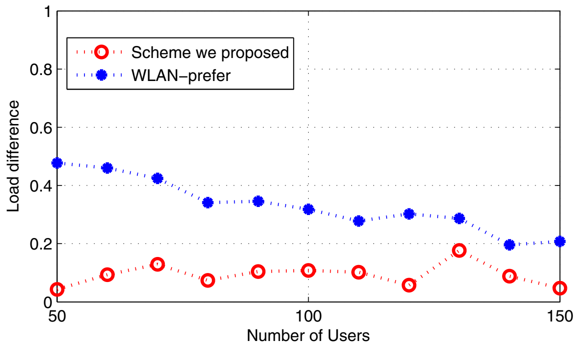

Fig. 6. This figure shows load difference when maximum number of users UMTS can accept is 50, and maximum number of users WLAN can accept is 28. The users initiate the call according the poisson process with arrival rate of 10 calls per hour, and the average call duration is 180 seconds.

below 0.5, which assistant with the fact that WLAN would be an inappropriate choice for high-speed users. However, with the condition of moving lowly, When RA of UMTS is less than 0.3, user terminal would choose WLAN, and when RA of UMTS is more than 0.3, the user terminal would attempt to choose UMTS instead. It means that, at the cross point, the load condition of both network are almost equal.

4.2 Multi-user Performance

In order to get the multi-user performance of semi-distributed scheme we proposed, we compares it with the traditional WLAN-prefer scheme. In simulation process, the users initiate the call according the poisson process with arrival rate of 10 calls per hour, and the average call duration is 180 seconds. Each user calls only once, and then leave the networks immediately after the call. Simulation results are shown in Fig.5 and Fig.6.

Fig.5 shows the blocking probability of scheme we proposed and WLAN-prefer scheme. We can clearly see that these two scheme have similar performance. Fig.6 shows the average load difference of UMTS and WLAN. Compared to WLAN-prefer scheme, the scheme we proposed gets much lower load difference. Therefore, the fuzzy neural network mechanisms of our semi-distributed scheme achieves load balancing effectively.

5 Conclusion

The heterogeneous wireless networks compose of multiple radio access technologies, and the selection of the appropriate access network for user terminal is a crucial issue for overall system performance. In this paper, we propose a semi-distributed network selection scheme based on fuzzy neural network. The proposed scheme considers the coverage and the load condition of of the available networks in addition to the mobile speed of user terminal. By simulation, we point out that our scheme can effectively achieve the load balancing and maintain the low blocking probability. As future work, we will consider more complex scenarios and evaluate the effects of more parameters of decision-making process on the performance of the access selection scheme.

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