# A Network Selection Strategy in Resources Mobility Environment

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*Abstract*—**Various wireless networks have emerged and constituted a complex radio access network environment. In cognitive environment, network resources are always varying with time and space. When a mobile cognitive user with a multi-mode terminal generates a call request, how to select the best network? Considering that the traffic load varying with time, we introduce back propagation (BP) neural network to predict its changing trend. At the same time, because parameters obtained through measurement or prediction are imprecise and uncertain, we introduce fuzzy logic to deal with such uncertainty. Then synthesizing technology preference, operator preference and user demand, we propose a multi-attribute decision making (MADM) network strategy based on BP neural network and fuzzy logic. Finally, we evaluate the performance of our strategy through simulations. The results show that our strategy can effectively increase users' utility-price and reduce their dropping probability.**

***Keywords-network selection; BP neural network; fuzzy logic; cost function; MADM***

## I. INTRODUCTION

Recent years, wireless communication industry has experienced great development. Various wireless networks have emerged and constituted a complex radio access network environment. In cognitive environment, network resources (such as traffic load, available spectrum, etc.) are always varying with time and space, which is usually called resources mobility. There are two main reasons leading resources mobility: first, resources themselves vary with time; second, user's movement causes resources mobility. When a mobile cognitive user with a multi-mode terminal generates a call request in such environment, how to select the most appropriate access network?

The problem of network selection across heterogeneous wireless networks has received much attention. In this context, [1] has proposed a network selection strategy based on traffic load and [2] has proposed a network selection strategy based on received signal strength. Two strategies combining traffic load and signal strength have been described in [3] and [4], while the former uses cost function method and the latter uses fuzzy logic method, respectively. In [5], a network selection strategy using analytic hierarchy process (AHP) and grey relational analysis (GRA) was introduced. In addition, a combination of compensatory and non-compensatory multi-attribute decision making (MADM) network selection strategy has been proposed in [6].

Although the above network selection strategies have their own advantages, they have not considered resources mobility. How to find the best access network in a dynamic environment? In this paper, we only consider the network resource of traffic load, which is always varying with time. We introduce back propagation (BP) neural network [7] to predict the future traffic load. At the same time, because the parameters needed in network selection are always obtained through measurement or prediction, we introduce fuzzy logic to deal with their uncertainty and imprecision. Then synthesizing technology preference (TP), operator preference (OP) and user demand (UD) [4], we propose a MADM network selection strategy based on BP neural network and fuzzy logic. Through simulation we find that with our proposed strategy, a mobile user can find the best network not only satisfies its quality of service (QoS), but also achieves the following benefits: reduction of blocking probability (PB), dropping probability (PD), power consumption and increment of utility-price.

The paper is organized as follows. In Section II, we introduce our proposed system model. In Section III our proposed network selection strategy is described in detail. In Section IV we introduce the BP neural network used in traffic load prediction. Section V provides the performance of our strategy through simulations. Finally, we conclude this paper in Section VI.

## II. SYSTEM MODEL

Assume that the entire service area is covered by $M$ different types of networks, as shown in Fig. 1 ($M$=3). Each cell of network $N_i$ ($1 \le i \le M$) has a circular cell shape, a base station (BS) or an access point (AP) at its center and $CH_i$ logical channels. Thus, a mobile user may have $M$ different network selection results at most in the overlapped area.

Assume that cognitive users with multi-mode terminals are uniformly distributed in the service area. In this paper we only consider stationary users, so the resources mobility is only caused by resources' variation with time. We assume that there are two types of calls: new calls and vertical handoff calls. A new call is generated by a user in this area who needs to select a connection among several candidate networks. A vertical handoff call is generated by an active user who needs to change its connection among different networks, such as handover from network $N_i$ to network $N_j$, where $i \ne j$, $1 \le i \le M$ and $1 \le j \le M$.

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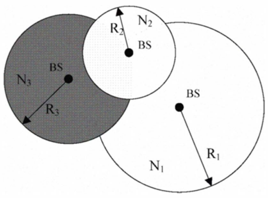

Figure 1. System model

## III. NETWORK SELECTION STRATEGY

The network selection strategy we proposed is network controlled and user assisted. It can work in resources mobility environment and achieve a tradeoff among TP, OP and UD. Here, we define the value of synthesizing TP, OP and UD as the network's appropriate access value (AAV), which will be described later. In the following, we introduce how our network selection strategy works.

### *A. When a new call is generated, the strategy works as follows,as shown in Fig. 2.*

- Each BS collects current traffic load and predicts future traffic load. User sends the signal strength it received and UD information to each BS through radio enabler (RE).
- BS treats traffic load and signal strength with normalization and fuzzy logic, and then calculates each candidate network's TP value by cost function.
- BS synthesizes TP, OP and UD through MADM to calculate each network's AAV and sends it to user through RE.
- Finally user compares these AAVs and selects the best network to access.

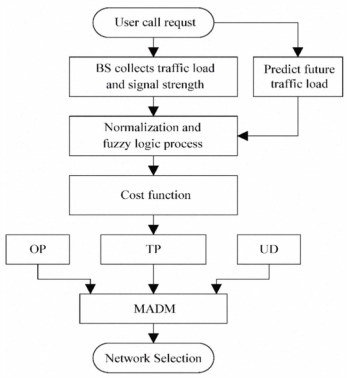

Figure 2. Network selection strategy flow chart

### *B. When a vertical handoff call is generated, the strategy works as follows.*

- User detects whether other networks are available in its location. If exists, continue to the next step; otherwise, terminate handoff request and return back to the current connection.
- User evaluates the available networks' performance and compares with the current ones. Then user selects the best network and handovers to it. If the best network is just the current one, no handover is needed.

When a user initiates a call request and finds that there are several available networks. Each BS starts to collect its traffic load and corresponding signal strength user received from it. Then, BS uses current traffic load to predict future traffic load with integration of BP neural networks, which will be described in detail in Section IV. Because traffic load and signal strength have different physical meanings and units, they cannot be directly compared or added. Therefore, we normalize them like in [3].

Traffic Load: $L_i = \frac{CH_i^{use}}{CH_i}$ , where $CH_i^{use}$ is the number of logic channels being occupied in network $N_i$, $CH_i$ is the total number of logic channels in network $N_i$.

Signal Strength: $S_i = \frac{P_i^{\max} - P_i^{re}}{P_i^{\max} - P_i^{th}}$ , where $P_i^{\max}$ is the maximum signal strength sent by the BS of network $N_i$, $P_i^{th}$ is the receiver threshold in network $N_i$ , $P_i^{re}$ is the current received signal strength in network $N_i$.

The traffic load and signal strength are obtained through estimation or prediction. They are uncertain and imprecise. So we introduce fuzzy logic to deal with such uncertainty. Fuzzy logic decision is based on fuzzy logic controller (FLC) which consists of three modules: fuzzifier, fuzzy inference engine and defuzzifier [8]. The membership function we used in fuzzification is a triangle function, and the method we used in defuzzification is the center of area. Considering that the rule base needed in fuzzy inference engine requires lots of prior knowledge, we use a cost function to instead fuzzy inference, as follows.

$$C_i = w_l L_i + w_s S_i \tag{1}$$

where, the subscript $i$ represents the $i$th network; $w_l$ and $w_s$ are weight factors of $L_i$ and $S_i$, respectively; they subject to $0 \le w_l \le 1$ , $0 \le w_s \le 1$ and $w_l + w_s = 1$ . Furthermore, $C_i$ is just the TP decision value of network $N_i$.

Finally, the network selection strategy synthesizes the following three decision elements:

- TP — contains traffic load and signal strength;
- OP — contains operator's business model;
- UD — contains power consumption and user cost.

Note the decision values of TP, OP and UD as $D^{TP}$ , $D^{OP}$ and $D^{UD}$ , respectively. This is a typical MADM problem which can be solved by using AHP method [5]:

*1) Creat the relative importance matrix of the three decision elemens.*

The relative importance between each two decision elements is estimated through comparison based on prior knowledge. When the $i$th decision element is compared to the $j$th decision element, the result is presented at the $i$th row and $j$th column. The whole comparison results are presented in a square matrix, noted as $A$, which is shown in (2), where the first row is TP, the second row is OP, and the third row is UD.

$$A = \begin{pmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{pmatrix} \tag{2}$$

It should be noticed that $a_{ij}$ satisfies: $a_{ii} = 1$, $a_{ij} = 1/a_{ji}$, $1 \le i, j \le 3$.

Then we verify the consistency of matrix $A$. If satisfies, continue to the next step; otherwise readjust the matrix.

*2) Calculate the relative weight factors of decision elements.*

Calculate the eigenvector corresponding to the maximum eigenvalue of matrix $A$ and normalize it. Thus we obtain the weight factors of TP, OP and UD, noted as $w_{TP}$, $w_{OP}$ and $w_{UD}$. They subject to $0 \le w_{TP} \le 1$, $0 \le w_{OP} \le 1$, $0 \le w_{UD} \le 1$ and $w_{TP} + w_{OP} + w_{UD} = 1$.

*3) Calculate each network's AAV through the following cost function:*

$$AAV_i = w_{TP} D_i^{TP} + w_{OP} D_i^{OP} + w_{UD} D_i^{UD} \tag{3}$$

where the subscript $i$ represents the $i$th network. It should be noticed that $D_i^{TP} = C_i$. Furthermore, $D_i^{OP}$ and $D_i^{UD}$ are subjective values which will be described in Section V.

*4) User chooses the network with the largest AAV as its access network.*

## IV. BP Neural Network

Due to time-varying traffic load, the network user selected at the access moment maybe just temporarily best. User may even endure a call drop during service caused by traffic load's sudden increase. Therefore, predicting the future traffic load of each candidate network is necessary. Generally, the traffic load in a particular area can be modeled as a periodic non-stationary random process [9]. Obviously, it is a nonlinear system.

From [7], we know that neural network has the ability to model and predict any nonlinear system. So we introduce BP neural network to predict the future traffic load. BP algorithm is a gradient descent algorithm. Its main idea is dividing the learning process into a signal forward propagation process and an error signal backward propagation process. For computation simplicity, we only use a three-layer BP neural network, as shown in Fig. 3. The input layer, hidden layer and output layer contains $m$, $q$ and $n$ nodes, respectively. The vector $X = (x_1, x_2 \ldots, x_m)$ is the input data and the vector $Y = (y_1, y_2 \ldots, y_n)$ is the output data. We assume that the BP network is fully connected, where $V$ and $W$ are the connection weight factors.

The definition of mean square error ($MSE$) is:

$$MSE = \frac{1}{nP} \sum_{k=1}^{P} \sum_{j=1}^{n} \left( t_j^k - y_j^k \right)^2 \tag{4}$$

where, $P$ is the number of sample sets, $n$ is the number of nodes in output layer, $t_j^k$ is the $j$th real value in the $k$th sample set, $y_j^k$ is the corresponding predicted value.

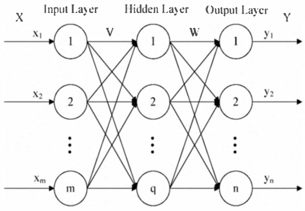


Figure 3. BP neural network

BP algorithm is a weak learning algorithm. It will get a poor prediction performance when there is short of training data sets. The integration of multiple BP neural networks is usually more accurate than only one BP neural network in prediction. In this paper, we introduce Bagging algorithm [10] to generate individual training sets and use average method to integrate 10 BP neural networks' predicting results, as shown in Fig.4.

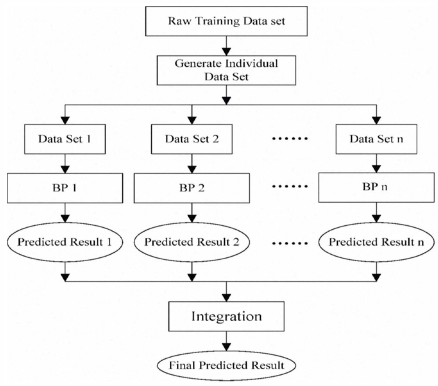


Figure 4. Integration method

Assume that the BP neural network's hidden and output layers contain 10 and 3 nodes respectively. First we use last 10 days' traffic load information to train BP neural networks, then input current traffic load values to predict future traffic load. Finally we have the prediction $MSE$ with input layer containing 5, 6, 7, 8, 9 and 10 nodes respectively, as shown in Fig. 5.

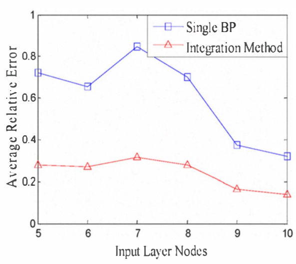


Figure 5. Integration performance

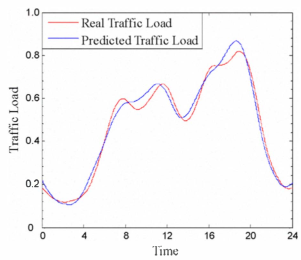


Figure 6. Predicted result

From Fig. 5, we know that the integration method has a much better performance than only one BP neural network prediction. The whole traffic load prediction result with the input layer contains 10 nodes is shown in Fig. 6.

## V. SIMULATION AND ANALYSIS

We only consider stationary users in this paper. Assume that the whole service area has three types of networks— $N_1$, $N_2$ and $N_3$. The radii of networks $N_1$, $N_2$ and $N_3$ are 1000, 500 and 700 meters, respectively. The total number of logic channels in each network are set to $CH_1 = 50$, $CH_2 = 20$ and $CH_3 = 30$, respectively. Assume that a mobile user occupies only one logic channel during connection. We set the decision values of OP and UD as follows: $D_1^{OP} = 0.5$, $D_2^{OP} = 0.2$, $D_3^{OP} = 0.3$ and $D_1^{UD} = 0.5$, $D_2^{UD} = 0.2$, $D_3^{UD} = 0.3$, where the subscript number represents different networks. The relative importance matrix of TP, OP and UD is set as (5).

$$A = \begin{pmatrix} 1 & 2 & 2 \\ 1/2 & 1 & 2/3 \\ 1/2 & 3/2 & 1 \end{pmatrix} \tag{5}$$

According to (5) the TP is twice more important than OP and UD, and UD is a bit more important than OP. As stated before, we obtain the weight factors of TP, OP and UD as $w_{TP} = 0.5$, $w_{OP} = 0.2$ and $w_{UD} = 0.3$.

We define that the utility-price is the ratio of the network's AAV to the cost user pays, which is a transient value. So the overall utility-price is the total utility-price user obtained in its whole service time.

### A. *Fuzzy logic*

#### 1) *Different fuzzy logic levels' comparison*

Treat traffic load and signal strength with fuzzy logic, 2, 4 and 8 levels of granularity, respectively. Then we examine the blocking probability of new calls generated in the area. It is obviously shown in Fig. 7, the blocking probability with a higher fuzzy logic level of granularity is slightly smaller than that with a lower level of granularity. This is because that the parameters treated by a higher fuzzy logic level are much closer to their real values.

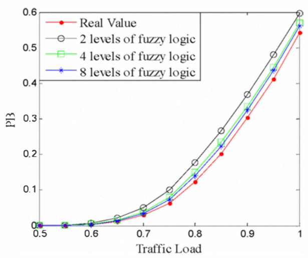


Figure 7. Different fuzzy logic levels' comparison

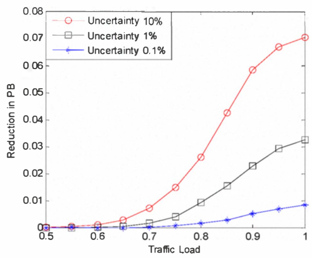


Figure 8. Fuzzy logic against uncertainty

#### 2) *Against parameters' uncertainty*

We define the parameter's uncertainty as the variance of the parameter we obtained through measurement or prediction. Fix fuzzy logic level at 4, and assume that the uncertainties of traffic load and signal strength are set to 10%, 1%, 0.1%, respectively. Fig. 8 shows the reduction in PB after the introduction of fuzzy logic. As shown in this figure, we benefit more from fuzzy logic when the parameters have a large uncertainty.

### B. *Load balance*

We only consider vertical handoff calls here. For various reasons, active users may not satisfy their QoS obtained from current networks, so they generate vertical handoff requests. Using the network selection strategy proposed in Section III, those users switch to more appropriate networks to continue their services. Through simulation, we find that the users' overall utility-price increases a lot after the execution of vertical handoffs. At the same time, the traffic load among different networks is more balanced. As shown in Fig.9 and Fig.10, respectively.

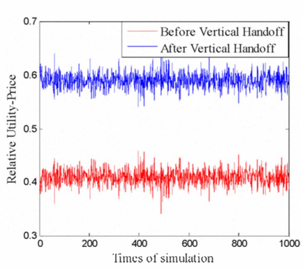


Figure 9. Utility-price

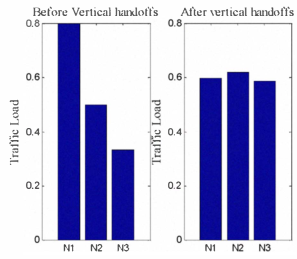


Figure 10. Load balance

### C. *Traffic load prediction*

Assume that the mean values of the traffic loads in networks $N_1$, $N_2$ and $N_3$ varying with time are shown in Fig. 11. Users' service time obey exponential distribution with mean value of 3. Assume that users randomly generate calls at any time.

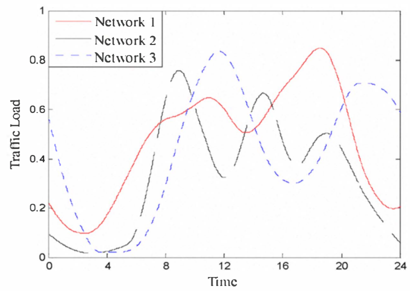


Figure 11. Mean value of traffic load

We compare the user's blocking probability (PB), dropping probability (PD), utility-price at the access moment (AUP) and overall utility-price in the whole service time (OUP) between simulations with prediction and without prediction. Finally, we have the following results: the PD reduces a lot and the OUP increases a lot after the introduction of traffic load prediction, as shown in Table 1.

Table1. User performance comparison

| | Without Prediction | With Prediction |
|---|---|---|
| PB | 0.0004 | 0.0016 |
| PD | 0.0488 | 0.0383 |
| AUP | 0.5013 | 0.4987 |
| OUP | 0.4954 | 0.5046 |

### D. *Overall performance*

In the following, we discuss the overall performance of our proposed network selection strategy. Different networks' traffic loads varying with time are shown in Fig. 11. Assume that users generate new calls at any time. We compare the following different network selection strategies in utility-price, PB, power consumption and network selection result.

*a) Our proposed strategy (PS):* A MADM network selection strategy based on BP neural network and fuzzy logic.

*b) Load strategy (LS):* The user selects the network with lightest traffic load.

*c) Signal strength strategy (SS):* The user selects the network with the strongest signal strength.

*d) Cost function strategy (CS):* Combining the traffic load and signal strength together, like proposed in [3].

From the main ideas of the LS and the SS, it can be easily understood that the LS has the smallest PB and the SS has the minimum power consumption.

Through simulation, we have the following result. Fig. 12-a is the average traffic load of each network. It is obviously shown in Fig. 12-b that: the PS obtains the highest UP with a relatively small power consumption; the SS has the minimum power consumption. Fig. 12-c shows the network selection result varies with different strategies. Though network $N_1$ has a heavy traffic load, but both user and operator prefers it, so the PS allows more users to access $N_1$. On the contrary, the LS allows more users to access $N_2$ since it has the lightest traffic load. The CS combines traffic load and signal strength, so there are not too many users accessing $N_2$. In addition, since users' locations are randomly generated in simulation, the signal strength they received is uniformly distributed in [0, 1] after normalization, which has been stated before. As a result, the ratio of selecting different networks is basically the same when using the SS.

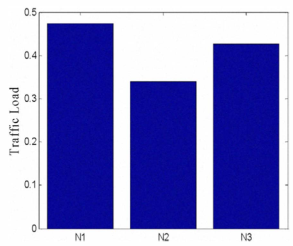


Figure 12-a. Different network traffic load

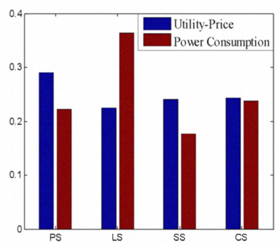


Figure 12-b. User performance

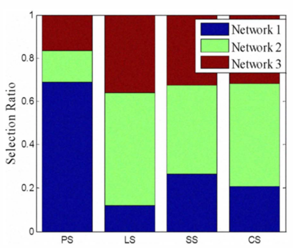


Figure 12-c. Network selection result

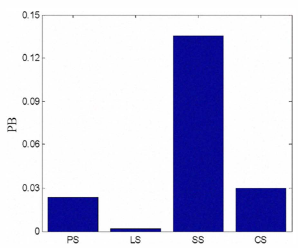


Figure 12-d. Users' PB

In the above simulation, users are rarely blocked because every network has a relatively light traffic load. So we arbitrarily set each network to have a traffic load of 0.8, then we compare different strategies' PB performance. As shown in Fig. 12-d, the PS obtains a relatively small PB, and the LS has the minimum PB.

Though the CS and PS both combine the traffic load and signal strength, but the former does not consider OP and UD, so it cannot achieve a high utility-price. On the other hand, the PS achieves the highest utility-price with a small PB and power consumption.

## VI. CONCLUSION

In this paper, considering resources mobility in cognitive network environment, we propose a MADM network selection strategy based on BP neural network and fuzzy logic. It can effectively treat against traffic load mobility and parameters uncertainty. The results have shown that the strategy we proposed can achieve great advantages for both users and networks. Resources mobility due to user's movement has not been discussed here. Future research will pay more attention to user's handover among networks in such environment.

## REFERENCES


[1] Mark Stemm, Randy H.Katz; "Vertical handoffs in wireless overlay networks," in Mobile Networks and applications, vol. 3, no. 4, Jan.1998.

[2] Nishith D. Tripathi, Jeffrey H. Reed, Hugh F. VanLandingham; "Adaptive handoff algorithm for cellular overlay systems using fuzzy logic," in Vehicular Technology Conference, vol. 2, pp. 1413-1418, 1999.

[3] Wei Shen, Qing-An Zeng; "Cost-Function-Based Network Selection Strategy in Integrated Wireless and Mobile Networks," in IEEE Transactions on vehicular technology, vol. 57, no. 6, pp. 3778-3788, Nov. 2008.

[4] Lorenza Giupponi, Ramon Agustí, Jordi Pérez-Romero, Oriol Sallent Roig; "A Novel Approach for Joint Radio Resource Management Based on Fuzzy Neural Methodology," in IEEE Transactions on vehicular technology, vol. 57, no. 3, pp. 1789-1805, May. 2008.

[5] Qingyang Song; Abbas Jamalipour; "Network selection in an integrated wireless LAN and UMTS environment using mathematical modeling and computing techniques," in IEEE wireless communications, vol. 12, no. 3, pp. 42-48, 2005.

[6] Farooq Bari and Victor C.M. Leung, "Automated Network Selection in a Heterogeneous Wireless Network Environment," in IEEE network, vol. 21, no. 1, pp. 34-40, 2007.

[7] Zhihua Zhou, Cungen Cao, Neural Network Theroy and Application, Beijing, Tsinghua University Publisher 2004.

[8] Jing Zhu, Fuzzy Control Theory and System Theory, Beijing, Machinery Industry Publisher 2005.

[9] Xiukui Li and Seyed A.Zekavat; "Traffic pattern prediction and performance investigation for cognitive radio systems," in IEEE WCNC 2008, pp. 894-899, 2008.

[10] Leo,Breman, Bagging Predictors in Machine Learning, Boston, Kluwer Academic Publishers pp.123-140, 1996.

[11] Yaonan Wang, Intelligent Control System: Fuzzy Logic, Expert System, Neural Network, Changsha, Hunan University Publisher 1996.