Fuzzy Neural Networks for Channel Management in Heterogeneous Wireless Cellular Networks

Yao-Tien Wang[1], Ay-Hwa Andy Liou[2], Yu-Cheng Lin[3] and Yu-Luen Chen[4]

[1]Department of Information Management Kainan University, Lu jhu, Taoyuan County, Taiwan

[2]Department of Information Management, Tamkang University, Taiwan

[3]Department of Information & Electronic Commerce, Kainan University, Lu jhu, Taoyuan County, Taiwan

[4]Department of Digital Content Design, National Taipei University of Education, Ho-Ping E.Rd, Sec. 2, Taipei, Taiwan

Abstract: - In this paper, adaptive channel management approach fuzzy neural networks in heterogeneous wireless cellular networks (ACM-FNN) is presented to efficient resource allocation, and admission control schemes are needed to guarantee quality-of-service (QoS) for differentiated services. The channel management in a two-tier such as micro cell or macro cell wireless cellular networks. Effective reliability and efficiently schemes are also needed to make network services more reliable and efficient. In a wireless cellular networks for uneven traffic load in a cellular system may occur creating a hot spots. So the two-tier wireless cellular system should be able to cope with such traffic load in certain cells. In a cellular network, the calls arrival rate, the call duration , the mobility speed and the communication overhead between the base station and the mobile switch center are vague and uncertain. Therefore, we propose a new efficient channel-borrowing scheme in heterogeneous distributed cellular networks based on ACM-FNN. The proposed scheme exhibits better learning abilities, optimization abilities, robustness, and fault-tolerant capability thus yielding better performance compared with other algorithms. The results show that our algorithm has lower call blocking rate, lower call dropping rate, less update messages overhead, and shorter channel acquisition delays.

Key-Words: - Dynamic channel borrowing, dynamic load balancing, fuzzy neural networks, channel management, heterogeneous wireless cellular networks.

1 Introduction

High spectral efficiency and flexible data rate access are main focus for future wireless cellular network, and the increasing demand for communication service is encouraging the addition multimedia access for their users. In the service delivery aspect, the main challenges include service convergence and (QoS) provisioning for differentiated services requirements. The microcells provide strategic radio coverage to areas with low elevation antennas, low transmit power, and low mobility users should undergo hand-off calls at micro cell. In such an architecture, a lower tier of micro cells is coverd by upper tier of macro cell, and high mobility users should undergo hand off calls at macro cell.

The channel assignment (allocation) problem is an important topic in a cellular system [1, 3, 4, 5]. The objective of the channel assignment of existing results is mainly to exploit the channel reuse factor under the constraint of *co-channel reuse distance* [4, 6]. Existing results for the channel assignment can be classified into Fixed Channel Assignment (FCA) [3, 6], and Dynamic Channel Assignment (DCA) [1, 5, 8]. The advantage of FCA is its simplicity. However, it does not reflect real scenarios where load may fluctuate and may vary from cell to cell. DCA schemes can dynamically assign/reassign channels and thus are more flexible. To be more specific, the channel borrowing for load balancing usually use some fixed threshold values to distinguish the status of each cells [1, 2]. A cell load is marked as “hot”, if the ratio of the number of available channels to the total number of channels allocated to that cell is less than or equal to some threshold value. Otherwise it is "cold". The drawback is that threshold values are fixed. Since load state may exhibit sharp distinction state level, series fluctuation like ping-pong effect may occur when loads are around the threshold. This results in wasting a significant amount of efforts in borrowing channels back and forth form micro cells to micro cells or micro cells to macro cells in heterogeneous wireless cellular networks. This is achieved by efficiently transferring channels from lightly loaded cells to heavily loaded ones. The cells load information collection can not only estimate the time-varying traffic load about the cellular networks, but also provide useful information for making the channels reallocation decisions. Due to this nature, using fuzzy neural networks the best way to approach the problem. The concept of fuzzy number plays a fundamental role in formulating quantitative fuzzy variables. The fuzzy numbers represent the linguistic concepts, such as *very hot*, *hot*, *moderate*, and so on [5]. Traditional channel allocation of the negotiation approaches can be classified into *update* and *search* [4]. The fundamental idea is that a cell must consult all the interference cells within the minimum reuse distance before it can acquire a channel. The fuzzy neural networks consist of five modules: (1) fuzzy rule base, (2) a fuzzy inference engine, (3) fuzzification, (4) defuzzification modules, and (5) neural networks. The ACM-FNN consists of (1) cell load decision-making, (2) cell involved negotiation, and (3) multi-channels migration phases. The structure of a dynamic channel borrowing for wireless cellular network is composed of three design phases by applying artificial fuzzy neural networks to them. Figure 1 shows the block diagram of our ACM-FNN. The cell load decision-making indicates the amount of information regarding the cell as well as the information gathering rules used while making the load redistribution decisions. The goal is to obtain sufficient information in order to make a decision whether the cell load is very hot, hot, moderate, cold or very cold. The cell involves in negotiation, selects the cells to or from which channels will be migrated when the load reallocation event takes place. In our channel management strategy both micro cells to micro cells and micro cells to macro cells. We adopt the number of available channels and cell traffic load as the input variables for fuzzy sets and define a set of membership functions. In addition, our scheme allows a requesting cell to borrow multiple channels at a time, based on the traffic loads of the cells and channels availability, thereby reduce the borrowing overhead further. The performance of our ACM-FNN is compared with the conventional

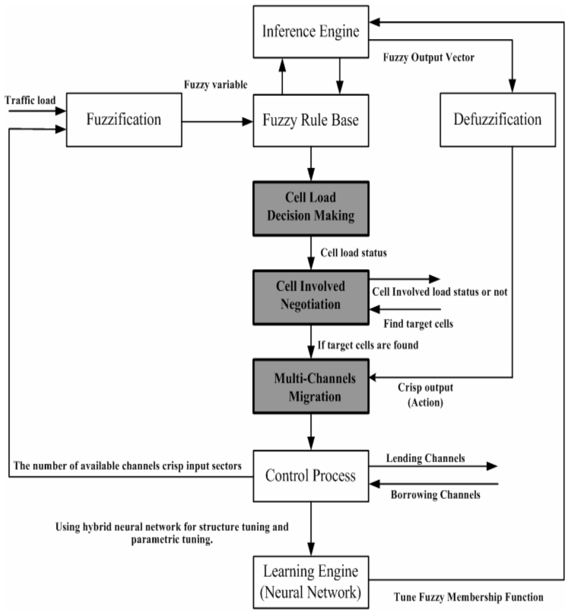


Figure 1: Block diagram of ACM-FNN.

schemes, and not only effectively reduces the blocking rate and the dropping rate but also provides considerable improvement in overall performance such as less update messages, and short channel acquisition delays. The remainder of this paper is organized as follows. In Section 2, we provide the structure of the cellular system model and channel borrowing strategy. The design issues of our proposed cell load decision making is in Section3. In Section 4, we propose the cell involved negotiation. The adaptive channel borrowing multi channel transferring scheme is presented in Section 5. Experimental results are given in Section 6. Finally, concluding remarks are made in Section 7.
structure of the cellular system model. The design issues of our proposed cell load decision making is in Section3. In Section 4, we propose the cell involved negotiation. The adaptive channel borrowing multi channel transferring scheme is presented in Section 5. Experimental results are given in Section 6. Finally, concluding remarks are made in Section 7.

2 Cellular System Model

The cellular system model in this paper is assumed as follows. A given geographical area consists of a number of hexagonal cells, each served by the BS. The BS MSs communicate through the wireless links using channel. Each cell is allocated with a fixed set of channels *CH* and the same set of channels is reused by those identical cells which are sufficiently far away from each other in order to avoid interference. A group of cells using distinct channels form a compact pattern of radius *R*. Given a cell *c*, the interference neighborhood of c', denoted by $IN(c) = \{c' \mid dist(c, c') < D_{min}\}$, where $D_{min}=3\sqrt{3}R$ [3], which macro cells overlaid on top of micro cells as shown in

Fig. 2. The many mobile users are serviced in macro cells becase traffic not heavy and there are many fast mobile users. In rush-hour, the mobile users are support in micro cells because traffic load is heavy and the speed of mobiles is slow. For example, when rush-hour traffic load conditions occur, channel are borrowed to micro cells accroding to the traffic load.

3 Cell Load Decision-Making

This section addresses our strategy of estimating of load status for micro and macro cell in a wireless cellular network. We employ the used available channel and traffic load as the input variables for the fuzzy sets. *Fuzzification* function is introduced for each input variable to express the associated measurement uncertainty. We consider an interval of real number and the notation $e^* = \int_u u_e(a_i)/a_i$, and $e = \int_u u_e(b_i)/b_i$, where e is denoted available channel and e^* is denoted as traffic load, a_i and b_i are actual input values, respectively. Let a_i present the center value for linguistic labels of available channel membership function and let b_i present the center value for linguistic labels of traffic load membership function. The status of e may be very cold, cold, moderate, hot or very hot for different value of available channels (x) and the status of e^* may be low, moderate or high for different value of traffic load (y). Fig. 3(a) shows membership function for the number of available channel; Fig. 3(b) is the example for the fuzzification of the system parameter traffic load. These functions are defined on the interval [a_0, a_6], [b_0, b_2].

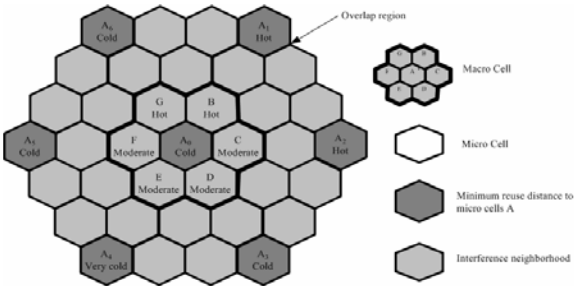
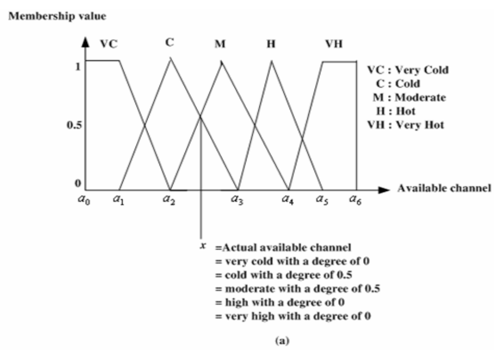


Figure 2: The two-tier cellular system.



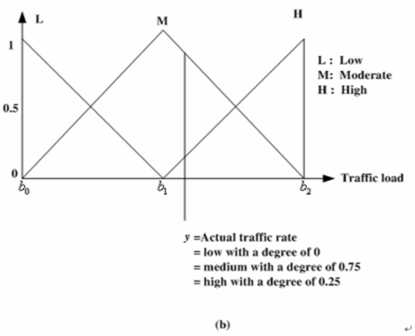


Figure 3: Example for the fuzzification of the system parameter (a) the number of available channel and (b) traffic loads.

4 Cell Involved Negotiation

After the cell load level of each BS has been decided by the load information, the objective of the cell negotiation is to select the cell to or from which channels will be borrowed when the cell load reallocation event takes place. The traditional channel allocation algorithm in negotiation can be classified into *update* and *search* methods [8]. In the search approach, a cell does not inform its neighbors of its channel acquisitions or releases. When a cell needs a channel, it searches all neighboring cells to compute the set of currently available channels, and then acquires one according to the underlying DCA strategy. In the update approach, a cell always informs its neighbors whenever it acquires/releases a channel so that each cell knows the set of channel available for its use and underlying DCA strategy. Both approaches have advantages and disadvantages. The update approach has short acquisition delay and good channel reuse, but it also has a higher message complexity. In other word, the search approach has lower message complexity, but it has longer acquisition delay and ineffective channel reuse [8].

When a new call arrives at a hot cell, the ACM-FNN is activated requesting its cluster or macro cell for help, and attempts to borrow sufficient free channels to satisfy its demand. Our researchers study takes advantage of ACM-FNN and presented an enhanced version of the negotiation scheme, called cell involved negotiation. When the load state is hot, it plays the role of the borrowing channel action; in contrast, it plays the role of the lending channel action when its load state is cold. It is observed that a fuzzy enhanced algorithm can enhance the overall system performance effectively. At each BS, the load state table is maintained. The entries of the table are the current load status of every cluster cells or macro cells as well as the co-channel cells. The cell operation types of load state information exchanges among cells, and each BSs keeps the state information of the cells and runs the channel borrowing algorithm to update load state.

4.1 *Fuzzy Rule Base*

Fuzzy Rule Base is characterized as collection of fuzzy IF–THEN rules in which the preconditions and consequent involve linguistic variables. Next, the degree of truth through the input membership functions is obtained and the same method applies to the membership functions for available channes and traffic load fuzzy set and multi-channel migrate output fuzzy set [5]. The BS keeps the load-state information of the cells and runs the fuzzy based channel-borrowing algorithm to borrow free channels from the very cold or cold cells for the very hot or hot cells whenever it finds any very hot cells or hot cells.

4.2 Inference Engine

In an *inference engine* the knowledge pertaining to the given control problem is formulated in terms of a set of fuzzy inference rules. There are two principal ways in which relevant inference rules can be determined. In the above rules, the connectives AND and ALSO may be interpreted as either intersection $\cap$ or union $\cup$ for different definition of fuzzy implication. Denote the $\max(\vee)$ - $\min(\wedge)$ composition operators. Then we have the following theorem governing the connective AND with one fuzzy control rule to obtain the conclusion. Let us assume that there is one rule R_i with fuzzy implication R_c, the conclusion C' can be expressed as the intersection of the individual conclusions of input linguistic state variables

$$u_{c'}(w) = \bigcup_{u,v} \{[\ u_{A'}(u) \wedge u_{B'}(v)\ ] \wedge [u_{Ai}(u) \wedge u_{Bi}(v) \wedge u_{ci}(w)]\}$$

$$= \bigcup_{u} \left\{ [u_{A'}(u) \wedge u_{Ai}(u) \wedge u_{ci}(w)] \wedge \left[\bigcup_{v} \{\ u_{B'}(v) \wedge u_{Bi}(v) \wedge u_{ci}(w)\ \} \right] \right\}$$

$$= \bigcup_{u} \{u_{A'}(u) \wedge u_{Ai}(u) \wedge u_{ci}(w) u_{B' \circ R_c (B_i ; C_i)}(w)\}$$

Where $R_c(A_i, B_i; C_i) = (A_i \quad AND \quad B_i) \rightarrow C_i$.

If the system inputs are fuzzy singletons, $A' = u_0$ and $B' = v_0$ then the results C' derived employing minimum operation rule R_c and product operation rule R_p, respectively, may be expressed simply as

$$R_c : u_{c'}(w) = \bigcup_{i=1}^{n} \alpha_i \wedge u_{ci}(w) = \bigcup_{i=1}^{n} [u_{Ai}(u_0) \wedge u_{Bi}(v_0)] \wedge u_{ci}(w)$$

$$R_p : u_{c'}(w) = \bigcup_{i=1}^{n} \alpha_i \wedge u_{ci}(w) = \bigcup_{i=1}^{n} [u_{Ai}(u_0) \wedge u_{Bi}(v_0)] \bullet u_{ci}(w)$$

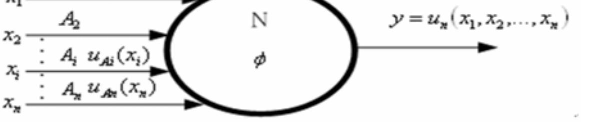


Figure 4: Fuzzy neural structure of the ACM-FNN.

Where α_i denotes the weighting factor of the *i*th rule, which is a measure of the contribution of the *i*th rule to the fuzzy control action. If the max-product compositions operator $(\bullet)$ is considered, then the corresponding R_c and R_p are the same. The rules $(R)_{i=1\rightarrow 5,\ j=1\rightarrow 3})$ for driving the system input x and **y**, are then coded in the following manner:

Rule 1: **IF** (x is *very hot)* **AND** (y is *Very high)*
THEN (*Δu* is *PVL).*

....

*R*ule n : **IF** (x is *Very cold)* **AND** (y is *Very low)*
THEN (*Δu* is *NVL)*

5 Multi-Channels Migration

The ACM-FNN, when a requesting cell and a probed cell are decided, the number of reallocated channels is just one channel in each iteration. It is very inefficient if the cell load of these two cells differ very much. For example, in the next generation multi-media mobile network, a call may need multiple channels at a time, and a cell in handoff needs a new channel in the new cell within a very short period. If the new channel is not acquired in time, the call is dropped. In this idea, we could make the cell load between two cells more balanced. The purpose of *defuzzification* is to convert each result obtained from the inference engine, which is expressed in terms of fuzzy sets, to a single real number [5]. This process is necessary because in many practical application crisp controls action is required for the actual control. This value is calculated by the formula:

$$Y^{o}_{coa} = \left[\left[\frac{\sum_{i=1}^{n} w_i \times B_i}{\sum_{i=1}^{n} w_i} \right] \right] - IN(c)$$

Where Y^{o}_{coa} represent the number of migrate channels, W_i = the antecedent degree of *i*th control rule, and B_i = the consequent center value of *i*th control rule. Consequently, the Y^{o}_{coa} obtained by the formula can be interpreted as an expected value of variable. Finally, we obtain**:**

Migrate Channels = Min [Borrowing cell (Y^{o}_{coa}), Lending cells (Y^{o}_{coa})].

After multi-channels are reallocated, we using hybrid neural network to tune the fuzzy membership function. The ACM-FNN, this type of fuzzy neuron, denoted by N, is show in figure 4 and has n nonfuzzy inputs $x_1, x_2, \ldots, x_n$. The weights for N are fuzzy sets A_i, $1 \le i \le n$; That is, the weighting operations are relpaced by input and output membership functions The result of each weighting operation is the membership value $u_{A_i}(x_i)$ of the corresponding input x_i in the fuzzy set weight A_i. The aggregation operation repreaentd by ϕ use any aggregation operator such as min or max . A mathematical representation of such a fuzzy neural N is:

$$u_N(x_1,x_2,\ldots,x_n = u_{A_1}(x_1)\phi u_{A_2}(x_2)\phi..\phi u_{A_i}(x_i)\phi..\phi u_{A_n}(x_n),$$

where x_i is the ith (nonfuzzy) input to the neural, $u_{A_i}(\bullet)$ is the membership function of the ith fuzzy weight, $u_N(\bullet)$, and ϕ is an aggregation operator.Where Y^0_{coa} represents the number of migrate channels, and y_d is our desired output. We define the isosceles triangular membership function of load status, and the antecedent degree of ith control rule is dependent upon the membership function center value a_i, the membership function width b_i. $U_i(x) = \frac{1-2|X_i - a_i|}{b_i}$. According to the number of migrate channels Y^0_{coa} and the objective error function E, This value is calculated by the formula:

$$E = \frac{1}{2}\left[\left(\left\lfloor \frac{\sum_{i=1}^{n} w_i \times B_i}{\sum_{i=1}^{n} w_i} \right\rfloor\right) - Y_d\right]^2 .$$

Since the shape of the membership function $U_i(x)$ is defined by the center value a_i and the width b_i, the objective error function E consists of the tuning parameter a_i, b_i, w_i, and η is the learning rate, for $i = 1,\ldots,n.$ Hence the learning rules can be derived as follows

$$a_i(t+1) = a_i(t) - \eta a \cdot dE/da_i$$
$$b_i(t+1) = b_i(t) - \eta b \cdot dE/db_i$$
$$w_i(t+1) = w_i(t) - \eta w \cdot dE/dw_i .$$

6 Experimental Results

The simulated model consists of 12 macro cells with 7 micro cells each. This experiment has used the number of channels CH = 30 in a cell, total of N = 96 cells in the system. The amount of requested channel specified of minimum basic channel units (CU) is 30*Kbps* of multi-channels migration. We assume λo = 100 *calls/per hour*~ 2000 *calls/per hour* be the call originating rate per cell and $\lambda_h = (\lambda o \times 0.01 \sim \lambda o \times 1)$ is the high mobility hand-off traffic density per cell, and d = 1 sec communication delay between cells, and each handoff and new calls request delay constraint (DC=10) seconds. Let the density of simulation be 500-*people/per cell*. The assumptions of four performance metrics for our simulation study are as follows:

(1)***Blocking calls*:** If all the servers are busy, the cell does not succeed to borrow a channel from its cluster cells and its *DC* is over then the calls must be blocked, otherwise they get service.

(2) ***Dropping calls*:** When an MS moves into a neighboring cell, the call must be transferred to the neighboring BS. This procedure is a hand-off. If a channel can not be assigned at the new BS and the particular cell does not to borrow a channel from its cluster cells, then the call generated at this particular cell are stored in the queue, and its waiting time (delay constraint) is over then the calls must be dropped, otherwise they get service.

(3) ***Update-message complexity*:** Each cell needs to communicate with co-channel and macro cells in order to exchange the set of load state information.

(4) ***Channel-acquisition delays*:** The values it acquires before the selected channels, the cell must ensure that the selected channels will not be acquired by any of its cluster cells and interference cells, simultaneously. When a cell receives a channel request from an MS, it assigns a free channel, if any, to the request. Otherwise, the cell will need to acquire a new channel from its cluster cells and then assign channels to the request.

The performance of our ACM-FNN is compared with the fixed channel assignment (Fixed) [3], simple borrowing (SB) [8], and existing strategies like channel borrowing directed retry (DR) [7], CBWL [5], and LBSB [1]. The numbers of hot cells vs. blocked calls have been observed in our scheme. Fig. 4 compares the blocking probability and traffic-arrival rate. In cell cluster, while fixed channel assignment algorithms reject all the new channel requests, the other schemes can handle the imbalance and satisfy the new channel requests by borrowing channel from BSs with cold traffic load. The hand-off call dropping probabilities for ACM-FNN and other methods are plotted in Fig. 5 against the hand-off dropping probability at different traffic loads. In every case, when the hand-off dropping probability is fixed, the ACM-FNN has a lower hand-off call dropping probability than other methods. We compared the performance of proposed method with a conventional method in this experiment**.** The experiment is to observe the change of messages required per channel acquisition (messages complexity) when the number of hot cells to be performed is 80. In the proposed algorithm, the algorithm shows the fewest updated messages complexity because the load balancing activity performs the ACM-FNN considering the load state when it determines a light-loaded cell shows in Fig. 6. The ACM-FNN scheme performs especially well when the numbers of hot cells are large, which support multi-channel migration. The channel acquisition delays are also discussed in our experiment. Fig. 7 shows that our proposed scheme has the shortest channel acquisition delays. This results in a channel-borrowing scheme with efficient channel use in all traffic conditions.

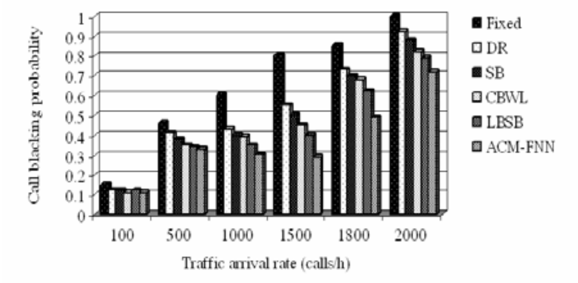


Figure 4: Compare blocking probability and traffic-arrival rate.

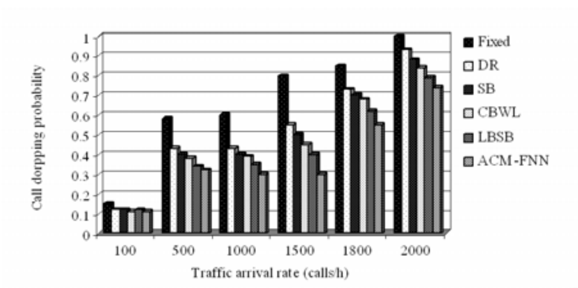


Figure 5: Compare dropping probability and traffic-arrival rate.

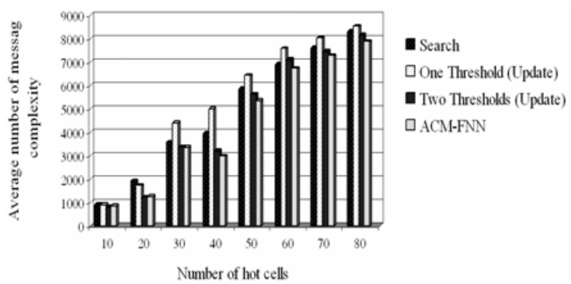


Figure 6: Average number of update message overhead in our scheme and others.

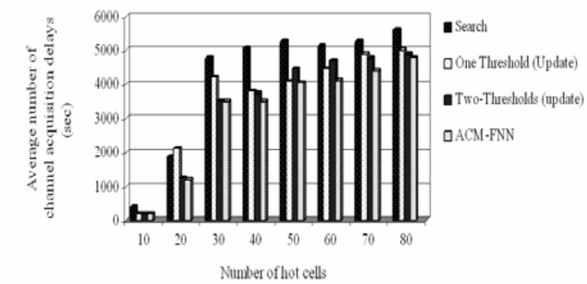


Figure 7: The channel acquisition delays of various schemes.

7 Conclusions

This is the first attempt in formulating the two-tier channel management for heterogeneous wireless cellular networks with fuzzy neural networks and with simulation for various traffic load and number of hot cell nodes. Present paper has highlighted the role of fuzzy neural networks and its application in wireless cellular networks. Neural networks are essentially low-level computational structures and algorithms that offer good performance in dealing with sensory nonlinear input data, while fuzzy logic techniques deal with reasoning on a higher level than networks. We believe that fuzzy neural networks for the control and management cellular networks are more appropriate than the conventional probabilistic models. The performance of the proposed scheme is better than that of the conventional schemes.

Reference

[1] S. K. Das, S. K. Sen and R. Jayaram, A structured channel borrowing scheme for dynamic load balancing in cellular networks, IEEE Distributed Computing Systems Conference, pp. 116-123, 1997.

[2]J. Kim, T. Lee and C. S. Hwang, A dynamic channel assignment scheme with two thresholds for load balancing in cellular networks, IEEE Radio and Wireless Conference, 141-145, 1999.

[3]X. Dong and T. H. Lai, Distributed dynamic carrier allocations in mobile cellular networks: search vs. update, IEEE Distributed Computing Systems Conference, pages 108–115, 1997.

[4]H. Jiang and S. S. Rappaport, CBWL: a new channel assignment and sharing method for cellular communication systems, IEEE Transactions on Vehicular Technology, pages 313 –322, 1994.

[5]Y. -T. Wang and J.-P. Sheu, A Dynamic Channel Borrowing Approach with Fuzzy Logic Control in Distributed Cellular Networks, the special issue of Simulation Modeling Practice and Theory, Vol. 12, pp. 287 – 303, July 2004.

[6]J. S. Engel and M. Peritsky, Statistically optimum dynamic sever assignment in systems with interfering severs, IEEE Vehicular Technology Conference, pages 1287-1293, 1973.

[7]J. Karlsson and B. Eklundh, A cellular mobile telephone system with load sharing-an enhancement of directed retry, IEEE Transactions on Communications, pages 530-535, 1989.

[8]S. Mitra and S. DasBit, A load balancing strategy using dynamic channel assignment and channel borrowing in cellular mobile environment, IEEE Personal Wireless Communications Conference, pages 278-282, 2000.