Adaptive Radio Resource Management in Heterogeneous Wireless Networks

Yao-Tien Wang and Chung-Ming Ou

Abstract— In this paper, adaptive channel management approach fuzzy neural networks in heterogeneous wireless 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 networks. Effective reliability and efficiently schemes are also needed to make network services more reliable and efficient. In a wireless networks for uneven traffic load 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. To keep the handoff calls in a two-tier wireless networks at an acceptable level with low mobility users should undergo handoff calls at micro cell boundaries, and hight mobility users should undergo hand off calls at macro cell. In wireless 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 allocation scheme in heterogeneous wureless 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 new calls blocking rate, lower call handoff calls dropping rate, less update messages overhead, and shorter channel acquisition delays.

Keywords— Dynamic channel allocation, dynamic load balancing, fuzzy neural networks, radio resource rmanagement, heterogeneous wireless networks.

I. INTRODUCTION

HIGH spectral efficiency and flexible data rate access are main focus for future wireless networks, 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.

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Traditional channel-allocation approaches can be classified into *update* and *search* [8]. The fundamental idea is that a cell must consult all the interference cells (*IN(C)*) within the minimum reuse distance before it can acquire a channel. Both approaches have advantages and disadvantages. The update approach has a short acquisition delay but a higher message complexity, while the search approach has a lower message complexity but a longer acquisition delay. The dynamic channel allocation (borrowing/ lending) problem is an important topic in a wireless networks [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-pang 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 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 wireless networks, but also provide useful information for making the channels reallocation decisions. Due to this nature, using fuzzy neural networks is 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) fuzzification, (2) fuzzy rule base, (3) fuzzy inference engine,

(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. Fig. 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 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 wireless networks model and channel allocation 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.

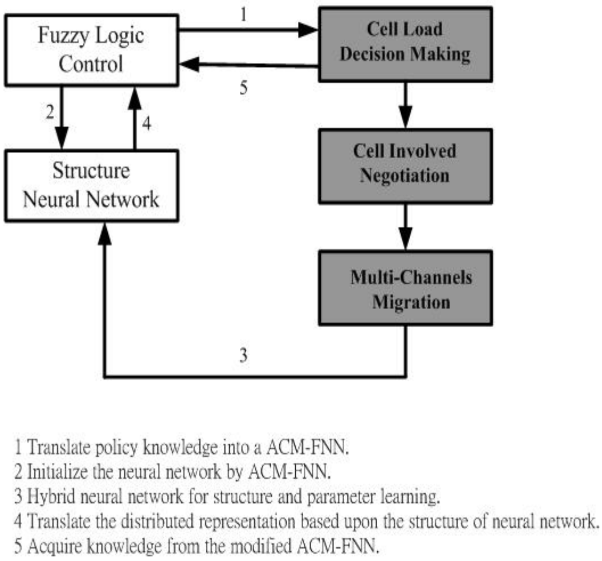

Figure 1: Block diagram of ACM-FNN.

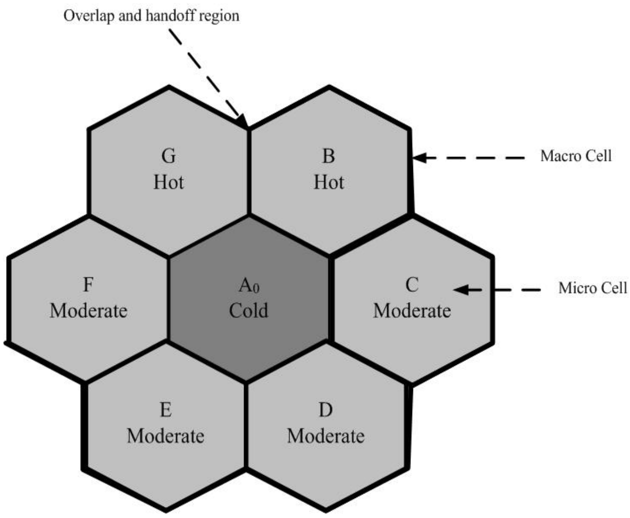

Figure 2: The two-tier cellular system.

II. WIRELESS NETWORKS MODEL AND CHANNEL ALLOCATION STRATEGY

The universal mobile telecommunication system (UMTS) consists of the radio network controller (RNC) owns and controls the radio resources in its domain the base stations (BSs) connected to it. RNC is the service access point for all services UMTS Terrestrial RAN (UTRAN) provides the core network (CN), and management of connection to the user equipment (UE). The concept also applies to radio network controller in next generation of wireless networks, and a BS directly communicates with all mobile stations (MSs) or mobile equipment (ME) within its wireless transmission radius. 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 base station (BS). The BS and the 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. Partition the set of all cells into a number of disjoint subsets, $G_0, G_1, \ldots, G_{k-1}$, and such that any two cells in the same subset are apart from each other by at least a distance of $D_{\min}$ partition the set of all channels into *K* disjoint subsets, $P_0, P_1, \ldots, P_{k-1}$ The channels in P_i $(i = 0,1,\ldots, k-1)$ are called the primary (nominal) channels for the cells in G_i , it is arranged in an ordered list. A channel i either used (U_i) *i*or available (V_i)depending on whether it is assigned to a MS. For convenience, a cell C_i is a primary cell of a channel CH if and only if CH is a primary channel of C_i. Thus, the cells in G_i are primary cells of the channels in and secondary cells of the channels in $P_j\,(j \neq i)$. 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 $D_{\min} = 3\sqrt{3}R$, 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. A channel available for c becomes interfered if some cell in uses it $IN(c)$. If N_i denotes the number of cell in the ring i, then for the hexagonal geometry $N_i = 1$ if $i = 0$, and $N_i = 6i$ if $i > 0$, as shown in Fig. 2. While the motivation behind all basic channel borrowing strategies is the better utilization of the available channels with the consequent reduction of call blocking probability in each cell, very few of the schemes deal with the problem of non-uniformity traffic demand in different cells which may lead to a gross imbalance in the system performance.

In simple borrowing strategy [12] this variant of the fixed assignment scheme proposes to borrow a channel from neighboring cells provided it does not interfere with the existing calls and locked in those co-channel cells of the lending one. In the directed retry with load sharing scheme [19], it is assumed that the neighboring cells and the users overlap region and the main drawback of this scheme include increased number of hand-offs and co-channel interference, and also the load sharing is dependent upon the number of users in the overlap region. The channel borrowing without locking (CBWL) scheme [10] proposes channel borrowing when the set of channels in a cell gets exhausted; but it uses the borrowed channels under reduced transmission power to avoid co-channel interference. Additionally, the facts that only a fraction of the channels in all neighboring cells are available for borrowing. In the load balancing with selective borrowing (LBSB) [6], a cell is classified as "hot", if its degrees of coldness defined as the ratio of the number of available channel to the total number of channel channels allocated to that cell is less than or equal to some threshold value. Otherwise the cell is "cold". Aided by a channel allocation strategy within each cell, it has been presented in that the centralized LBSB achieves almost perfect load balancing and lead to a significant improvement over FCA, simple borrowing, directories and CBWL schemes in case of an overloaded cellular system. LBSB has two disadvantages. First too much dependency on the central server maintenance of continuous status information of the cells in an environment. The traffic load changes dynamically, leading to enormous amount of updating traffic, consumption of bandwidth and message delays. Second, the strategy of the channel borrowing for load balancing usually uses fixed threshold values to distinguish the status of each cell. Threshold values, however, are fixed and cannot indicate the degree of the load. Since load status may exhibit a sharp distinction state level, the channel borrowing or lending action will be made frequently around the threshold, possibly resulting in ping-pong series fluctuation. This results in wasting a significant amount of efforts in transferring channels back and forth. In this paper, the performance of a DCA strategy will depend on how the state information has been decided at the BSs. An efficient channel-assignment strategy should consider not only the present load but also the load distributed in the recent past. Based on this information, it should also to project the load distribution for the near future. To be able to get a good decision, the dependencies between a decision and the objective must be calculated. Achieving this estimation, however, is difficult and time consuming. The relationship between the communication resources is too complex to define a good rule for estimating the cell load. Borrowing of channels in cellular networks may increase the served cells of the system significantly. When the load of a cell increases, some of the channels may have to borrow from a cold cell.

III. CELL LOAD DECISION-MAKING

This section addresses our strategy of estimating of load status for micro and macro cell in heterogeneous wireless networks. This measure is vital for us to determine the most suitable site for migrating channels in order to share the load in the system. This information shall indicate not only the amount of information about the system but also the information gathering rules used in making the load redistribution decisions. This decision indicates the various load information, which regards with the wireless networks. In the initial stage, we can construct different available channels membership function, traffic load membership function, and center value for linguistic labels around through fuzzy c-means clustering algorithm [21] according to various cells' characteristics of system behavior data.

A. fuzzifier

A fuzzifier performs the function of fuzzification, which is a subjective valuation to transform measurement data into valuation of a subjective value. Hence, it can be defined as a mapping from an observed input space to labels of fuzzy sets in a specified input universe of discourse. Since the data manipulation in a fuzzy logic control is based on fuzzy set theory, fuzzification is necessary and desirable at an early stage. In fuzzy control applications, the observed data are usually crisp. These membership grades are represented by real-number values ranging between 0 and 1 through an action and the value 1 is the largest possible support. The grades of membership basically reflect an ordering of the objects in fuzzy set A: another way of representing a fuzzy set is through the use of the *support* of a fuzzy set. The support of a fuzzy set A is the crisp set of all $x \in U$ such that $u_x(x) > 0$. That is, $Supp(A) = \{x \in U \mid u_A(x) > 0\}$.

The channel assignment schemes have received considerable attention because of their reliability and solvability. The decision-making indicates the significance of various loading, which is regarded with the cellular system. Many researchers use available channel as the single load index for BS in cellular system [6], [11]. Although the number of available channels is the obvious factors having an impact on the system load, other factors are also influential, including system load, call arrival rate and call duration. For the accuracy of evaluating the load state of a cell, we employ the used available channel and traffic load as the input variables for the fuzzy sets. The fuzzification function is introduced for each input variable to express the associated measurement uncertainty. We consider an interval of real number and the notation $x = \int_u u_e(a_i)/a_i$, and $y = \int_u u_e(b_i)/b_i$, where x is denoted as available channel and y 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 for $0 \le i \le 2$, and let b_i present the center value for linguistic labels of traffic load membership function for $0 \le i \le 4$. The status of very cold (VC), cold (C), moderate (M), hot (H) or very hot (VH) for different value of traffic load and the status of low (L), moderate (M) or high (H) for different values of available channels. The fuzzified information is then passed on to the fuzzy inference engine. Fig. 3 shows membership function for the number of available channels and the system parameter traffic load. These functions are defined on the interval $[a_{0,} a_4]$, $[b_0, b_2]$.

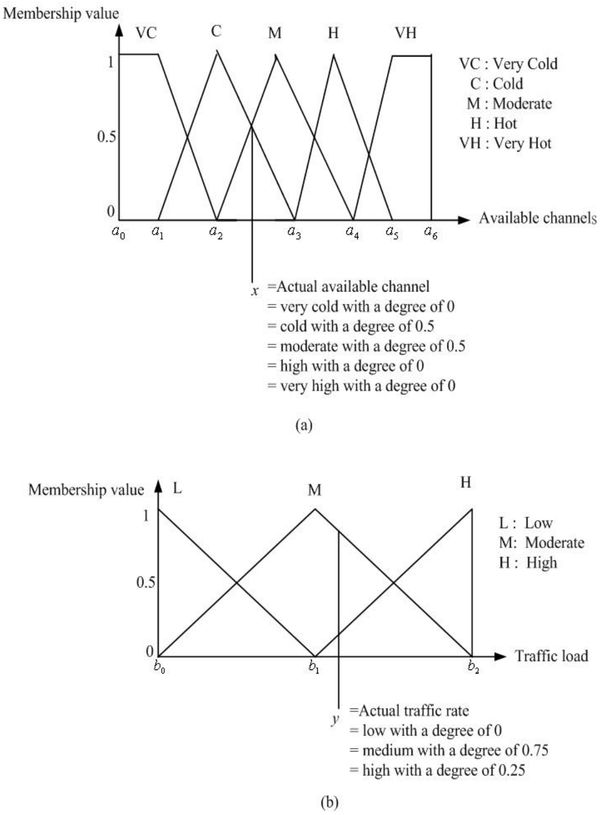

Figure 3 Example for the fuzzification of the system parameter (a) the number of available channel and (b) traffic loads.

x \ y	Low	Moderate	High
Very Cold	(Lending) NL	(Lending) NM	(Lending) NS
Cold	(Lending) NM (4)	(Lending) NS	(Stable) AZ
Moderate	(Lending) NS	(Stable) AZ	(Borrowing) PS
Hot	(Stable) AZ	(Borrowing) PS	(Borrowing) PM
Very Hot	(Borrowing) PS	(Borrowing) PM	(Borrowing) PL

Figure 4 Fuzzy rules for channel borrowing/lending control.

IV. 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. Our research took advantage of fuzzy logic control 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. The moderate cells are not allowed to borrow any channels from any other cells nor lend any channels to any other cells. It is observed that a fuzzy enhanced algorithm can enhance the overall system performance effectively. At each BS, an augmented load state table is maintained. The entries of the table are the current load status of every cluster 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. The knowledge pertaining to the given control problem is formulated in terms of a set of fuzzy inference rules. We use five load actions; very cold, cold, moderate (stabilized-state), hot, and very hot. 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. The moderate cells are neither allowed reallocation any channels from or to any other cells nor updated interfering neighborhood cells., for example the rules as shown in Fig. 4.

A. *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.

B. 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

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

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

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)*

V. MULTI-CHANNEL 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 new channels migrating with multi-channels transferring can reallocate channels well especially in an unpredictable variation of cell load. Our mechanism for multi-channel transfer calculates the amount of transferred channels by the number of available channels and traffic load. The ACM-FNN, we have discussed in the last section have a common property; 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 two cells differ with a large value. Our idea is to borrow several channels once instead of only one between two cells. For example, in the next generation multi-media mobile network, a call may need multiple channels at a time. In this idea, we could make the cell load between two cells more balanced. The channel requesting messages transmitted between hot cell *i* and cold cell *j* are classified into four categories as follows. (1) Request message, *request* (*i*): Message sent by the hot cell *i* to cluster cells to request the free channels. (2) Reply message, *reply* (j,V_j,U_j): Message from cold cell *j*, $j \in cluster$ cells responding to borrow cell *i*. The message also includes the information on the reserved channels in cell *j*. (3) Inform message, *inform* (i,B_{ij}): Message sent by borrowing cell *i* to the lending and the other cells in the cluster to inform them about its channel acquisition decision, where B_{ij} is set of channels borrowed by hot cell *i* from cold cell *j* .The message also includes the requests of the reserved channels if any. (4) Confirm message, confirm (j,L_{ij}): Message sent by cold cell *j* to borrow hot cell *i* to inform it the availability of the requested channels that have been reserved at lend cold cell *j*. Where L_{ij} is the set of confirmed channels lent from cold cell *j* to hot cell *i*, and cold cell *j* can still assign the reserved channels to new arrival calls before sending the confirm message back to hot cell *i*.

According to our observation, the number of available channels is the main factor that affects the computing time mostly and it can be divided into two aspects: the available channel and traffic load. Our borrowing mechanism for multi-channel transfer calculates the amount of transferred channels by the traffic load and the number of available channels. The multi-channel allocation pertains to handle the allocation of channels from one cell to another. To accomplish this, we use five load values which are Very hot, Hot, Moderate, Cold and Very cold, to distinct the difference of cell load on two cells. If one cell is in the Very hot state; then it will borrow several channels from the cell with Very cold state. If there does not exist any Very cold cell, and then it would choose the cells with Cold status. The numbers of borrowed channels are allocated according to the value calculated by fuzzy MAX-MIN composition from the available channels and traffic load. Measurements of input variables of a fuzzy controller must be properly combined with the relevant fuzzy information rules.

A. Defuzzifier

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. Defuzzification is a mapping from a space of fuzzy control actions defined over an output universe of discourse into a space of non-fuzzy (crisp) control actions. This process is necessary because in many practical applications crisp, control action is required for the actual control. Fig. 5 shows the membership function for the channel borrowing/lending a quantity control number of the channel range [*-d,+d*] of the fuzzy output. The function is defined on the interval [*0,+d*] for borrowing action, and on the interval [*0, −d*] for lending action. Assume further that following seven linguistic states are selected for migrating channels of the variables: negative （NL）large, negative medium（NM), negative small（NS）, approximately zero （AZ） , positive large （PL） , positive medium （PM） , and positive small （PS） .We have used *center of area* (*COA*) method because it supports software real time fuzzy controls to differentiate the difference of load on two cells. 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 5 and has *n* nonfuzzy inputs $x_1, x_2, ..., x_n$. 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:

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

where x_i is the ith (nonfuzzy) input to the neural, $u_{A_i}(\bullet)$ is the membership function of the *i*th 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.

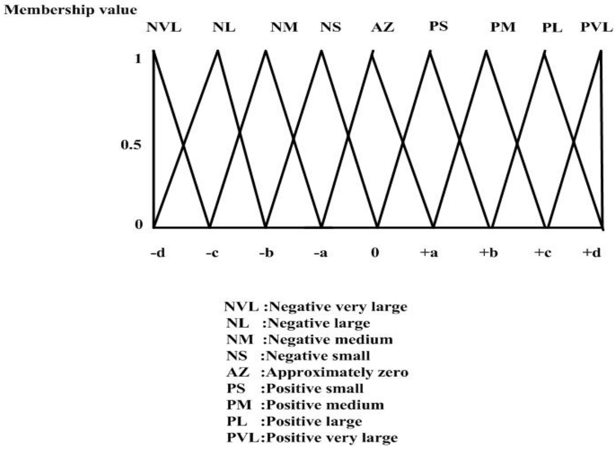

Figure 5 The membership function of the fuzzy output.

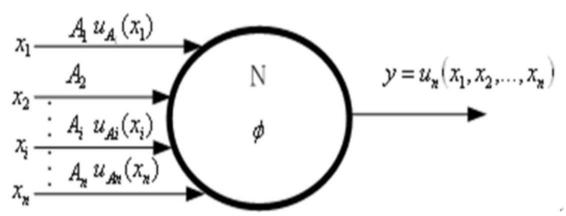

Figure 6 Fuzzy neural structure of the ACM-FNN.

We define the isosceles triangular membership function of load status, and the antecedent degree of *i*th control rule is dependent upon the membership function center value a_i, the membership function width b_i. $U_i(x) = \dfrac{1 - 2|X_i - a_i|}{b_i}$.

According to the number of migrate channels Y^{0}_{coa} and the objective error function E, This value is calculated by the formula:

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

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 $i = 1, ..., n$. Hence the learning rules can be derived as follows:

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

VI. 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. 7 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. 8 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. 9. 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. 10 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.

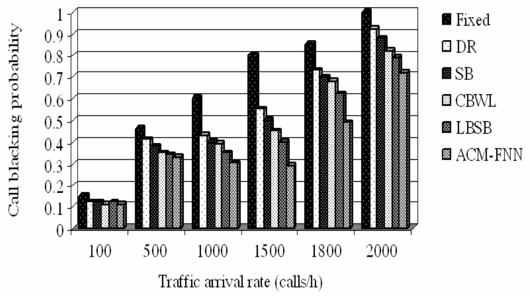

Figure 7 Compare blocking probability and traffic-arrival rate.

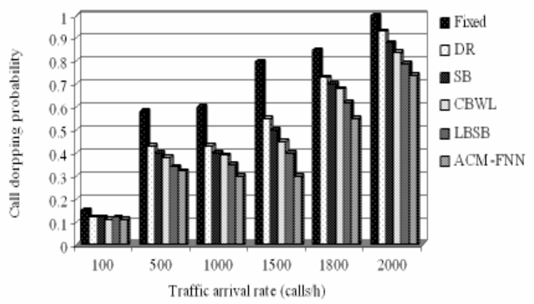

Figure 8 Compare dropping probability and traffic-arrival rate.

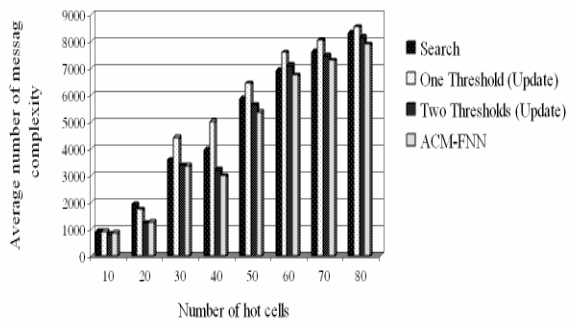

Figure 9 Average number of update message overhead in our scheme and others.

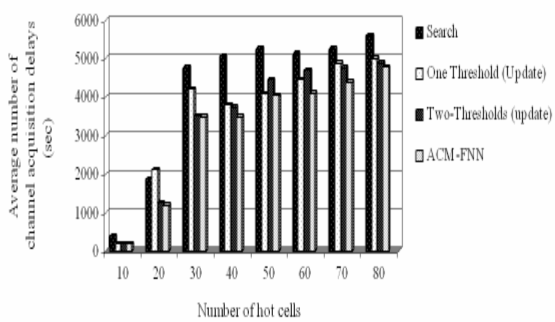

Figure 10 The channel acquisition delays of various schemes.

VII. CONCLUSION

This is the first attempt in formulating the two-tier channel management for heterogeneous wireless 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.

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