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Adaptive channel borrowing for quality of service in wireless cellular networks

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SUMMARY

In the third generation of wireless cellular system, adaptive dynamic channel borrowing is presented to maximize the number of served calls in wireless cellular networks. This has led to an intensive research in mobile computing to provide mobile users access to the Internet. In this paper, a neural-fuzzy controller for the dynamic channel-borrowing scheme (NFDCBS) is presented to provide multimedia services and to support increasing number of users. In a cellular network, the call-arrival rate, the call duration and the communication overhead between the base stations and the control centre are vague and uncertain. Therefore, we propose a new efficient dynamic channel borrowing for load balancing in distributed cellular networks based on NFDCBS. The proposed scheme exhibits better learning abilities, optimization abilities, robustness, and fault-tolerant capability, thus yielding a better performance than other algorithms. It aims to efficiently satisfy their diverse quality-of-service (QoS) requirements of multimedia traffic. The results show that our algorithm has lower blocking rate, lower dropping rate, less update overhead, and shorter channel-acquisition delays than previous methods. Copyright © 2006 John Wiley & Sons, Ltd.

KEY WORDS: dynamic channel borrowing; load balancing; neural-fuzzy controllers; channel allocation; wireless cellular networks; radio resource management

1. INTRODUCTION

In an integrated services packet network (ISPN), there have been several proposals for supporting real-time service: mobile resource reservation set-up protocol (MRSVP), hierarchical MRSVP (HMRSVP) and so on [1, 2]. Efficient use of limited radio channels with a simultaneous increase in traffic capacity requires proper channel assignment. This is one of the fundamental problems in wireless cellular network. There are three strategies for the allocation of channels to cells [3–8]: fixed channel assignment (FCA) [8], dynamic channel assignment (DCA) [7, 9, 10],

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and hybrid channel allocation (HCA) [9, 11, 12]. The advantage of FCA is its simplicity. It does not, however, reflect real scenarios where load may fluctuate and vary from cell to cell. DCA schemes can dynamically assign/reassign channels, and thus are more flexible. In the centralized DCA schemes [9, 10, 13], all channels are placed in a pool and are assigned to the new calls as needed, and all the allocation jobs are done by control centre. In the distributed DCA schemes [14], base stations (BSs) must be involved. HCA techniques are designed by combining the FCA and DCA schemes. In HCA, channels are divided into two disjoint sets: one set of channels is assigned to each cell on an FCA basis, while the others are kept in a central pool for a dynamic assignment. In fact, increasing the bandwidth of a cell can increase the system capacity but not the efficiency to deal with the time-varying imbalance traffic.

To be more specific, the channel borrowing for load balancing usually use some fixed threshold values to distinguish the status of each cell [9, 10]. 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 the threshold values are fixed. Since load state may exhibit sharp distinction state levels, series fluctuation like ping-pong effect may occur when loads are around the threshold. This results in wasting a significant amount of effort in transferring channels back and forth [9, 10]. In fact, because the locations of hot spots vary from time to time, increasing the bandwidth of a cell can increase the system capacity but not the efficiency to deal with the time-varying imbalance traffic. This is achieved by efficiently transferring channels from lightly loaded cells (cold status) to heavily loaded ones (hot status). The load information collection cannot only estimate the time-varying traffic load about the cellular networks, but also provide useful information for making the channel-reallocation decisions.

Traditional channel-allocation approaches can be classified into *update* and *search* [15]. 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. Due to this nature, using neural-fuzzy controllers 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*, etc. [16, 17]. The fuzzy expert-system approach has also been applied to forecasting where the advantage of an operator's expert knowledge is used. 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 reducing the borrowing overhead further. Figure 1 shows the block diagram of our neural-fuzzy controller for the dynamic channel-borrowing scheme (NFDCBS).

Our neural-fuzzy controllers consist of five modules: a fuzzy rule base, a fuzzy inference engine, fuzzification, defuzzification modules, and neural networks. The NFDCBS consists of cell load decision-making, cell-involved negotiation, and multi-channels migration phases. The structure of a dynamic channel borrowing for a wireless cellular network is composed of three design phases by applying artificial neural networks and fuzzy logic control to them. The main purpose of a neural-fuzzy controller is to apply neural learning techniques to find and tune the parameters. In this parameter-learning phase, the possible parameters to be tuned include those associated with membership functions such as centre, widths, and slope; the parameters of the

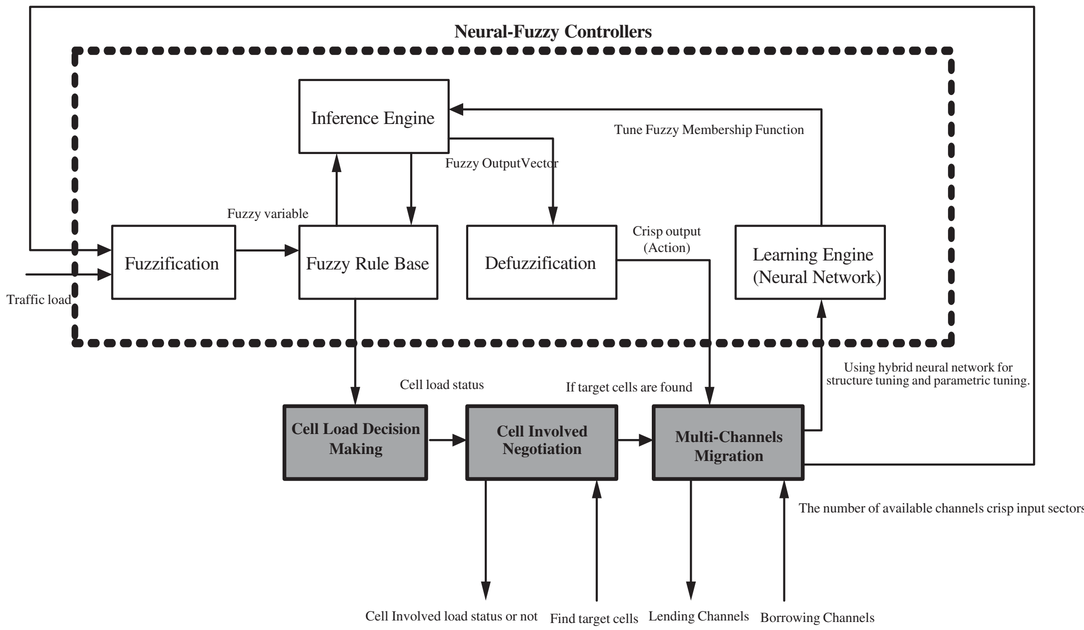

Figure 1. Block diagram of NFDCBS.

parameterized fuzzy connectives; and the weights of the fuzzy logic control rules. The performance of our NFDCBS is compared with the FCA [18], simple borrowing [8], directed retry [19], channel borrowing without locking (CBWL) [20], and load balancing with selective borrowing (LBSB) [9]. The experimental results reveal that our proposed scheme performs better than conventional schemes. Our adaptive neural-fuzzy controllers for load-balancing algorithm not only effectively reduces the blocking rate and the dropping rate, but also provides considerable improvement in the overall performance, such as with fewer 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 neural-fuzzy controller wireless cellular system are given in Section 3. Experimental results are given in Section 4. Finally, concluding remarks are made in Section 5.

2. CELLULAR SYSTEM MODEL AND CHANNEL-BORROWING STRATEGY

The universal mobile telecommunication system (UMTS) consists of the radio network controller (RNC), which owns and controls the radio resources in its domain, and the 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 RNC in next generation of wireless cellular system, and a BS directly communicates with all mobile stations (MSs) or mobile equipment (ME) within its wireless transmission radius. The cellular system model proposed in this paper is assumed to be as follows. A given geographical area consists of a number of hexagonal cells, each served by the 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 are reused by those identical cells, which channels are sufficiently far away from each other in order to avoid interference [15].

The set of all cells is partitioned into a number of disjoint subsets, $G_0, G_1, \ldots, G_{k-1}$ such that any two cells in the same subset are apart from each other by at least a distance of $D_{\min}$, partitioning 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) 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 P_i and secondary cells of the channels in $P_j (j \neq i)$. A group of cells using distinct channels forms a compact pattern of radius R.

Given a cell c, the interference neighbourhood of c, denoted by $\mathrm{IN}(c) = \{c' | \mathrm{dist}(c, c') < D_{\min}\}$, where $D_{\min} = 3\sqrt{3R}$. A channel available for c becomes interfered if some cell in uses it $\mathrm{IN}(c)$. 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 $i > 0$, the collection of cells in the coverage of the group of the BSs is called a *cluster*, as shown in Figure 2. While the motivation behind all basic channel-borrowing strategies is the better utilization of the available channels with the consequent reduction in 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 [8] this variant of the fixed assignment scheme proposes to borrow a channel from neighbouring cells provided it does not interfere with the existing calls

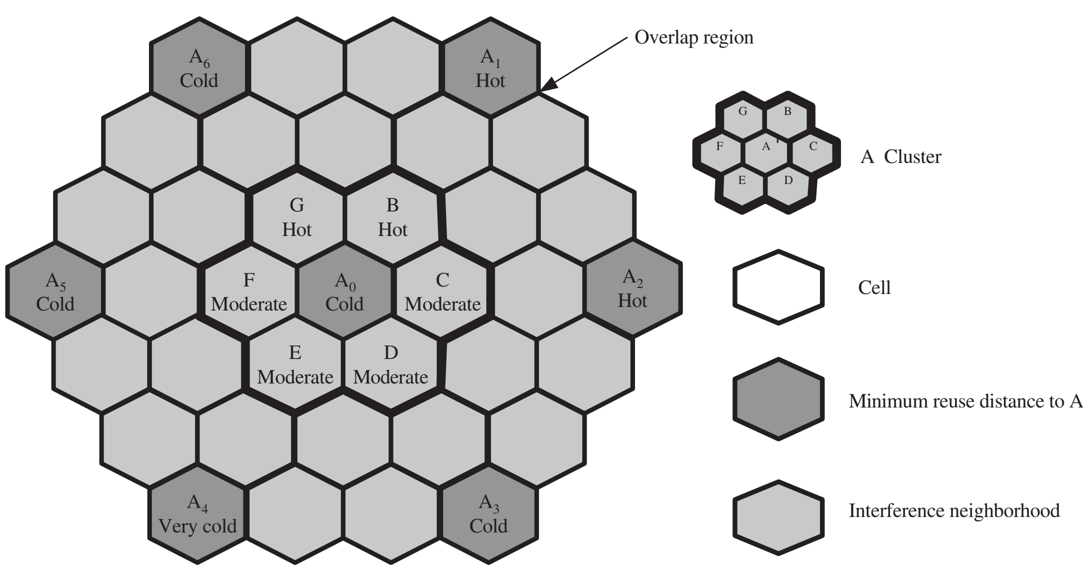

Figure 2. Hexagonal cellular networks.

and locked in the co-channel cells of the lending one. In the directed retry with load-sharing scheme [19], it is assumed that the neighbouring cells and the users overlap the region and the main drawback of this scheme include increased number of handoffs and co-channel interference, and also the load sharing is dependent upon the number of users in the overlap region. The CBWL scheme [20] 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, only a fraction of the channels in all neighbouring cells are available for borrowing. In the LBSB [9], 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 that the centralized LBSB achieves almost perfect load balancing and leads 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, the load distribution for the near future should also be projected. To be able to get a good decision, the dependencies between the decision and 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.

3. NEURAL-FUZZY CONTROLLER WIRELESS CELLULAR SYSTEM

Some of the techniques used to load balancing in heuristic techniques, are usually a threshold used to determine where the load is cold or hot. This binary state makes the system load state to fluctuate between hot and cold loads when the cell load is near the threshold value. It will cause channel reallocation frequently because of the load change. Simulation techniques have widely been used by the researchers. Although it provides more flexibility and freedom, it has its own limitations and drawbacks. For example, the load is usually artificial and predetermined. Some methods use a simple queuing model of a mobile cellular system [8–11, 13, 15, 19, 20]. Those proposed schemes completely ignore other resources than traffic load. Therefore, while it may be reasonable to detect the performance of purely available channels, the utility of this is questionable for channels that use the other resources of contention. We recognize that it is difficult, perhaps impossible, to find the cell load information that satisfies all of the above requirements. Moreover, they may be contradictory. But the cell load information may be judged by the degree to which it meets the above criteria. The problem with such methods is that many unrealistic assumptions must be made to make the study feasible. For example, most models use exponential distributions for arrival and service times. NFDCBS, based on a fusion of ideas from fuzzy control and neural networks, possesses the advantages of both neural networks such as learning abilities, optimization abilities, and fuzzy control systems such as human-like IF–THEN rule thinking and ease of incorporating expert knowledge. In this way, we can bring the low-level learning and computational power of neural networks to fuzzy control systems and also provide the high level, human-like IF–THEN rule thinking and reasoning of fuzzy control systems to neural network. Neural networks can improve their transparency, making it closer to fuzzy logic control, while fuzzy logic controls can self-adapt, making them closer to neural networks.

3.1. Structure and operation of neural-fuzzy controllers

The typical architecture of fuzzy logic control includes four principal components: fuzzifier, fuzzy rule base, inference engine and defuzzifier. The fuzzifier has the effect of transforming crisp measured data into suitable linguistic values. The fuzzy rule base stores the empirical knowledge of the operation of the process of the domain experts. The inference engine is the kernel of fuzzy logic control: it also has the capability of simulating human decision-making by performing approximated reasoning to achieve a desired control strategy. Finally, the defuzzifier is utilized to yield a non-fuzzy decision of control action from an inferred fuzzy control action by the inference engine [15].

3.1.1. 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, $\mathrm{Supp}(A) = \{x \in U | u_A(x) > 0\}$. The definitions of *complementation*, *intersection*, and *union* proposed by Zadeh [21] are as follows:

1. The complementation of a fuzzy set A is denoted by $\bar{A}$ and the membership function of $\bar{A}$ is given by $\bar{A}(x) = 1 - u_A(x)\ \forall x \in X$.
2. The intersection of fuzzy sets A and B is denoted by $A \cap B$ and the membership function of $A \cap B$ is given by $A \cap B(x) = \min\{u_A(x), u_B(x)\}\ \forall x \in X$.
3. The union of fuzzy sets A and B is denoted by $A \cup B$ and membership function of $A \cup B$ is given by $A \cup B(x) = \max\{u_A(x), u_B(x)\}\ \forall x \in X$.

3.1.2. Fuzzy rule base. *Fuzzy rule base* is characterized as collection of fuzzy IF–THEN rules in which the preconditions and consequent involve linguistic variables. This collection of fuzzy control rules characterizes the simple input–output relation of the system. The general form of the fuzzy control rules in case of multi-input–single-output systems (MISO) is

$$R_i : \text{IF } X \text{ is } A_i \text{ AND } Y \text{ is } B_i, \text{ THEN } Z \text{ is } C_i \quad i = 1, 2, \ldots, n$$

where x, y, and z are linguistic variables representing the control variable, respectively, and A_i, B_i, and C_i are the linguistic values of the linguistic variables x, y, and z, respectively.

3.1.3. 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.

$$\begin{aligned} u_{c'}(w) &= \bigcup_{u,v} \{[u_{A'}(u) \wedge u_{B'}(v)] \wedge [u_{Ai}(u) \wedge u_{Bi}(v) \wedge u_{ci}(w)]\} \\ &= \bigcup_{u} \left\{ [u_{A'}(u) \wedge u_{Ai}(u) \wedge u_{ci}(w)] \wedge \left[\bigcup_{v} \{u_{B'}(v) \wedge u_{Bi}(v) \wedge u_{ci}(w)\} \right] \right\} \\ &= \bigcup_{u} \{u_{A'}(u) \wedge u_{Ai}(u) \wedge u_{ci}(w) u_{B' \circ R_c(B_i;C_i)}(w)\} \end{aligned}$$

where $R_c(A_i, B_i; C_i) = (A_i \;\; AND \;\; B_i) \to C_i$.

That is,

$$C' = (A', B') \circ R_c(A_i, B_i, C_i) = [A' \circ R_c(A_i; C_i)] \cap [B' \circ R_c(B_i; C_i)]$$

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

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

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

where α_i denotes the weighting factor of the ith rule, which is a measure of the contribution of the ith 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.

3.1.4. Defuzzifier. Defuzzification is a mapping form 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 actual control. A defuzzification strategy is aimed at producing a non-fuzzy control action that best represents the possibility distribution of an inferred fuzzy control action. Unfortunately, there is no systematic procedure for choosing a defuzzification strategy. Two commonly used methods of defuzzification are the centre of area (COA) method and the mean of maximum (MOM) method [16, 17, 21].

3.1.5. Hybrid structure parameter learning. We discussed system models of neural-fuzzy controllers that can be built from a set of input–output training pairs through hybrid structure-parameter learning. In parameter learning, we mean the tuning of membership functions and other parameters in a neural-fuzzy control wireless cellular network. The network architecture has been fixed or determined previously by expert knowledge or some structural-learning techniques.

The parameter learning problems considered in this section are considered supervised learning problems, and we are given a set of input–output training data and neural-fuzzy network architecture such as fuzzy rules from which proper network parameters are to be determined. Figure 3 shows the hybrid structure parameter learning of the NFDCBS. The system has a total of four layers. The nodes in layer1 are linguistic nodes that represent input linguistic variables; layer 4 is the output layer. There are two linguistic nodes for each output variable. One is for desired output to feed into the network; the other is for actual output to be pumped out of the network. Nodes in layers 2 and 3 are term nodes, which act as membership functions

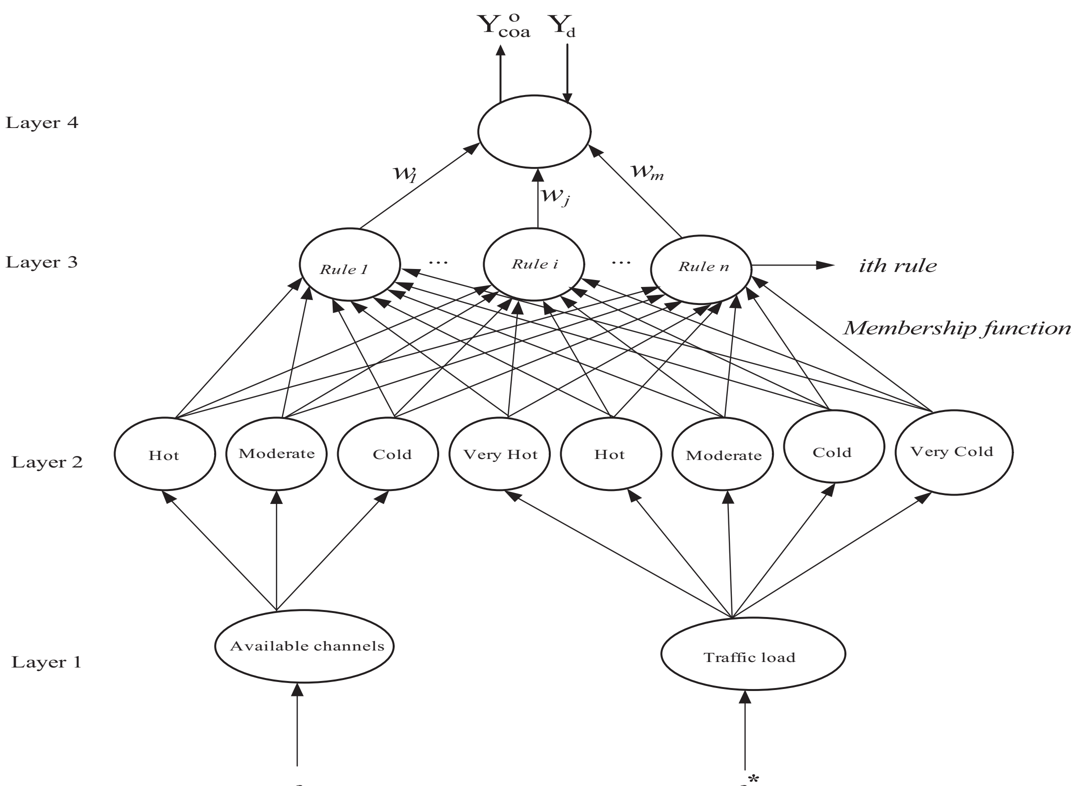

Figure 3. Hybrid structure parameter learning of the NFDCBS.

representing the terms of the respective linguistic variables. Actually, layer 2 nodes can be either a single node that performs a triangle-shaped membership function or one that performs a complex membership function. Each node in layer 3 is a rule node that represents one fuzzy rule. Additionally, the links between the rule nodes and the output term nodes are initially fully connected. Only a suitable term in each output linguistic variable's term set will be chosen after the learning process, where Y^0_{coa} represents the number of migrate channels, and y_{d} is our desired output.

3.2. Cell load decision-making

This section addresses our strategy of estimating of load status in a wireless cellular network. 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. We recognize that it is difficult, perhaps impossible, to find an information policy that satisfies all of the above requirements. Moreover, they may be contradictory. But information may be judged by the degree to which it meets the above criteria. This decision indicates the various load informations regarding the cellular system. In the initial stage, we can construct different available channels membership function, traffic load membership function, and centre value for linguistic labels around through fuzzy c-means clustering algorithm [22] according to various cells' characteristics of system-behaviour data. The distributed 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 the cellular system [9, 12]. Although the number of available channels is the obvious factor 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 $e^* = \int_u u_e(a_i)/a_i$ and $e = \int_u u_e(b_i)/b_i$, where e is denoted as available channel and e^* is denoted as traffic load, a_i and b_i are actual input values, respectively. Let a_i present the centre value for linguistic labels of available channel membership function for $0 \leqslant i \leqslant 2$, and let b_i present the centre value for linguistic labels of traffic load membership function for $0 \leqslant i \leqslant 4$. The status of e^* may be very cold (VC), cold (C), moderate (M), hot (H) or very hot (VH) for different value of traffic load and the status of e may be low (L), moderate (M) or high (H) for different value of available channels. The fuzzified information is then passed on to the fuzzy inference engine. Figure 4 shows membership function for the number of available channels and the system parameter traffic load. These functions are defined on the interval $[a_0, a_4]$, $[b_0, b_2]$.

3.3. 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 [15]. In the search approach, a cell does not inform its neighbours of its channel acquisitions or releases. When a cell needs a channel, it searches all neighbouring cells to compute the set of currently available channels, and then acquires one

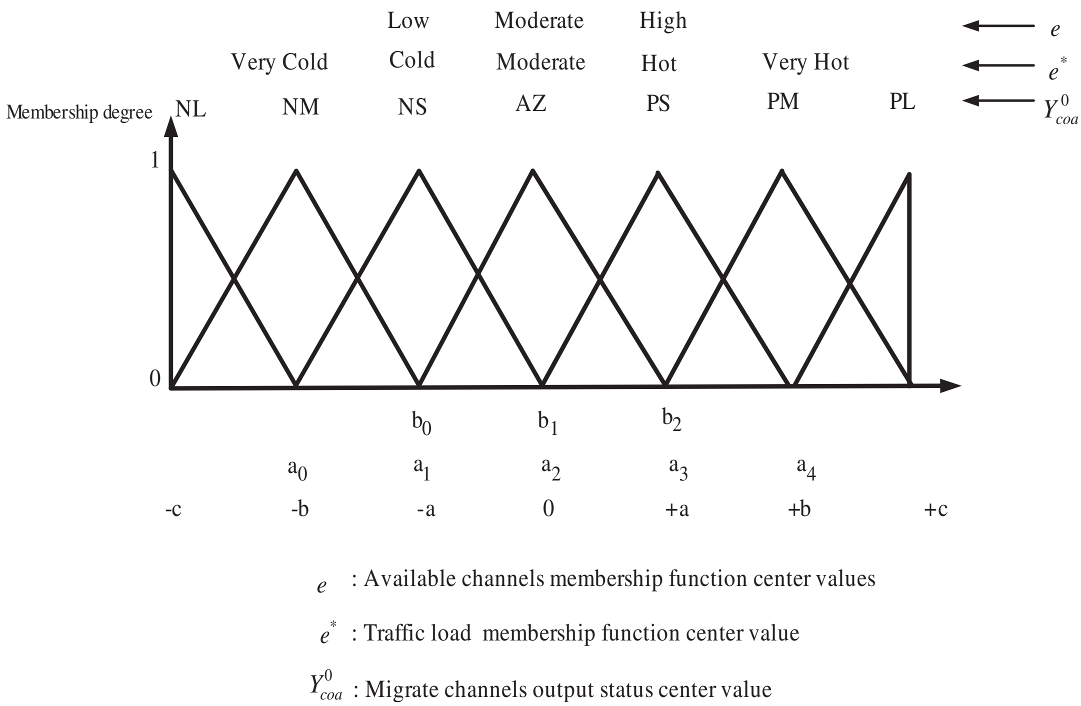

Figure 4. Membership functions of the fuzzy input and output.

according to the underlying DCA strategy. In the update approach, a cell always informs its neighbours 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, and it also has a higher message complexity. In other words, the search approach not only has lower message complexity, but also has longer acquisition delay and ineffective channel reuse [15]. The fundamental idea of the basic schemes is that a cell must consult co-channel cells, and its cluster cells, before it can acquire channels. When a new call arrives at a hot cell, the NFDCBS algorithm is activated requesting its cluster for help, and attempts to borrow sufficient free channels to satisfy its demand.

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 or hot cells. The moderate cells are neither allowed reallocation any channels from or to any other cells nor updated interfering neighbourhood cells. To conclude this section, let us introduce a special notation that is often used in the literature for defining fuzzy sets with a finite support. Assume further that the following seven linguistic states are selected for migrating channels of the variables: negative large (NL), negative medium (NM), negative small (NS:), approximately zero (AZ), positive large (PL:), positive medium (PM), and positive small (PS). This paper has 15 rules as shown in Figure 5.

3.4. Multi-channels migration. Multi-channel migration, the new channel borrowing with multi-channel 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 these two values. The number of available channels and traffic load are the values, which represent the average during the recent minutes. The NFDCBS, we have discussed in the last section, has 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 these two cells differ greatly. The idea we propose is as follows: why not borrow several channels instead of only one between two cells whose BS load differ greatly. Furthermore, we propose borrowing several channels between two cells whose serviced load

e^* \ e	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 5. Fuzzy rules for channel borrowing/lending control.

differs greatly. For example, 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. The difference is that we reallocate several channels instead of only one channel borrowed while making load balancing in each iteration. For example, in the next generation multimedia mobile network, a call may need multiple channels at a time. Under our proposal, the cell load between two cells could be made more balanced. Let us return to the beginning of the problem, that is, after the requested and selected cells are decided. According to our observation the number of available channels is the main factor affecting the computing time; it can be divided into two aspects: the available channel and traffic load. Our borrowing mechanism for multi-channel transfers calculates the amount of transferred channels by these two values.

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 distinguish the difference of cell load on two cells. If one cell is in the 'very hot' state (PL), it will borrow several channels from the cell with 'very cold' state (NL). If there are no 'very cold' cells, then it would choose several cells with 'cold' (NM/NS). The numbers of available channels and the traffic load are the values, which represent the average during the recent minutes. 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 controls action is required for the actual control. Figure 4 shows the membership function for channel borrowing/lending a quantity control number of the channels range $[-c, +c]$ of the fuzzy output. The function is defined on the interval $[0, +c]$ for borrowing action, and on the interval $[0, -c]$ for lending action.

We have used the COA method because it supports software real-time fuzzy controls to distinguish the difference of load on two cells. This value is calculated by the formula

$$Y^0_{\text{coa}} = \left[\left\lfloor \frac{\sum_{i=1}^{n} w_i \times B_i}{\sum_{i=1}^{n} w_i} \right\rfloor \right] - \text{IN}(c)$$

where Y^0_{coa} represent the number of migrate channels, W_i is the antecedent degree of ith control rule and B_i is the consequent centre value of ith control rule.

Consequently, the defuzzified value Y^0_{coa} obtained by the formula can be interpreted as an expected value of variable. Finally, we obtain

$$\text{Migrate channels} = \text{Min}[\text{Borrowing cell } (Y^0_{\text{coa}}),\ \text{Lending cell } (Y^0_{\text{coa}})]$$

After multi-channels are reallocated, we use hybrid neural network to tune the fuzzy membership function. We define the isosceles triangular membership function of load status as shown in Figure 6, and the antecedent degree of ith control rule is dependent upon the membership function centre value a_i, the membership function width b_i.

$$U_i(x) = \frac{1 - 2|X_i - a_i|}{b_i}$$

Assume Y_d is our desired output, the objective error function E can be defined by

$$E = \tfrac{1}{2}\,[Y^0_{\text{coa}} - Y_\text{d}]^2$$

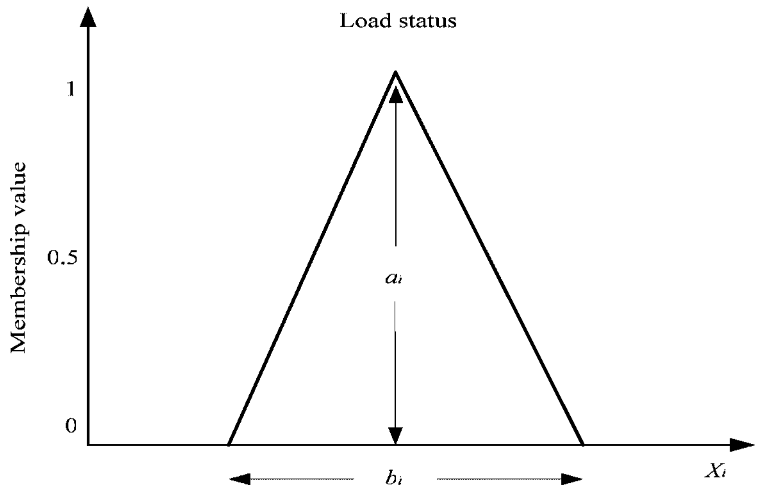

Figure 6. Isosceles triangular membership functions of load status.

According to the number of migrate channels Y^0_{coa} and the objective error function E, we have

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

Since the shape of the membership function $U_i(x)$ is defined by the centre 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:

$$a_i(t+1) = a_i(t) - \eta a\, \mathrm{d}E/\mathrm{d}a_i$$

$$b_i(t+1) = b_i(t) - \eta b\, \mathrm{d}E/\mathrm{d}b_i$$

$$w_i(t+1) = w_i(t) - \eta w\, \mathrm{d}E/\mathrm{d}w_i$$

4. EXPERIMENTAL RESULTS

The problem domain naturally lends itself to simulate using multiple threads since there are a lot of concurrences and global resource management issues in the system. The simulated model consists of 14 clusters with 7 homogeneous cells each. This experiment has used the number of channels CH $= 30$ in a cell, total of $N = 98$ 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 $\lambda\text{o} = 100$–2000 calls/h be the call originating rate per cell and $\lambda_{\text{h}} = (\lambda\text{o} \times 0.01 \sim \lambda\text{o} \times 1)$ is the handoff traffic density per cell, and $d = 1$ s communication delay between cells, and each handoff and new calls request delay constraint (DC) = 5 s. So, from the simulation result, the value of traffic load is chosen randomly and non-linearly. The maximum numbers of handoff calls are queued 10 for the first-class priority and new calls 10 for the second-class priority. Let the density of simulation be 500 people/cell. We define that the time of the sample interval is 3 min and the sampling time does influence previous one. The channel acquires messages transmitted between hot cell i and cold cell j, which are classified into four categories as follows.

- Request message, request (i): message sent by the hot cell i to cluster cells to request the free channels.
- 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.
- 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.
- 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. Here 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.

In order to represent various multimedia services, three different types of traffic services are assumed based on the channel requirement and QoS. In our simulation, three types of traffic services are assumed: voice service, videophone and video on demand. These types are defined on the channel requirement 30 kbps, 256 kbps and interval 1–3 Mbps, respectively. 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 waiting time (delay constraint) is over, then the calls must be blocked, otherwise they get service.
2. Dropping calls: When an MS moves into a neighbouring cell, the call must be transferred to the neighbouring BS. This procedure is a handoff. If a channel cannot be assigned at the new BS and the particular cell does not 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 cluster cells in order to exchange the set of load-state information.
4. Channel-acquisition delays: The values are acquired 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 NFDCBS is compared with the FCA (Fixed), simple borrowing (SB), and existing strategies like channel borrowing directed retry (DR), CBWL, and LBSB. The experimental results reveal that the proposed channel-borrowing scheme yields have better performance than others. The number of hot cells vs blocked calls have been observed in our

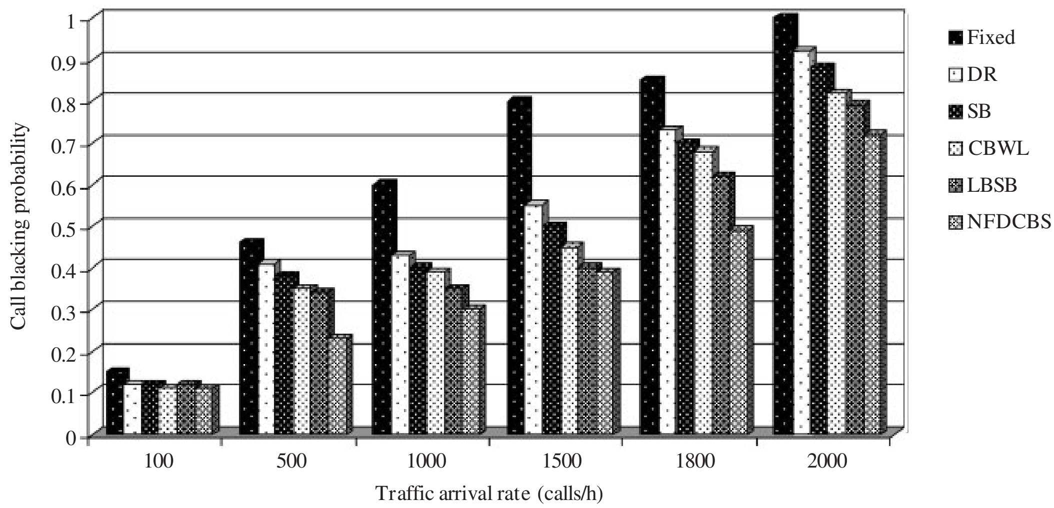

Figure 7. Compare blocking probability and traffic-arrival rate.

scheme. Figure 7 compares the blocking probability and traffic-arrival rate. Blocking probability is defined as the percentage of calls generated that can be successfully allocated to a channel. It is a key measure of the channel-assignment performance. At the base load, all the schemes have low percentage of blocked channel requests, although FCA algorithms blocks more than the other methods. When the traffic load increases, the number of blocked channel request also increases. For FCA, it increases at faster blocking rate than by using other methods. The reason for this is that a BS can only its nominal channels. When traffic load becomes hot, nominal channels are used up in many BSs. In cell cluster, while FCA algorithms reject all the new channel requests, the other schemes can handle the imbalance and satisfy the new channel requests by borrowing channels from BSs with cold traffic load. The handoff call-dropping probabilities for NFDCBS and other methods are plotted in Figure 8 against the handoff dropping probability at different traffic loads. In every case, when the handoff dropping probability is fixed, the NFDCBS has a lower handoff call-dropping probability than other methods. The improvement in the performance of the NFDCBS over other methods, however, decreases as the traffic load goes up.

In short, the NFDCBS is more capable of achieving the goal of channel borrowing from the time when a handoff actually occurs to the time when a reservation request is sent for a possible handoff to happen. Figure 9 compares the channel-assignment algorithms according to the new call-blocking probability of channel request for the multimedia services. When the traffic load increases, the call-blocking rate of channel requests increases at a slower rate than the other schemes. Figure 10 shows the handoff call-dropping probability for various schemes at various multimedia services. The number of multimedia requirements on the horizontal axis has different meanings for voice service, videophone and video on demand. The NFDCBS scheme always has lower handoff dropping rate than the existing channel-assignment schemes with the same number of channels required. It also indicates that the NFDCBS scheme can improve performance over the other methods with the number of reserved channels by further reducing

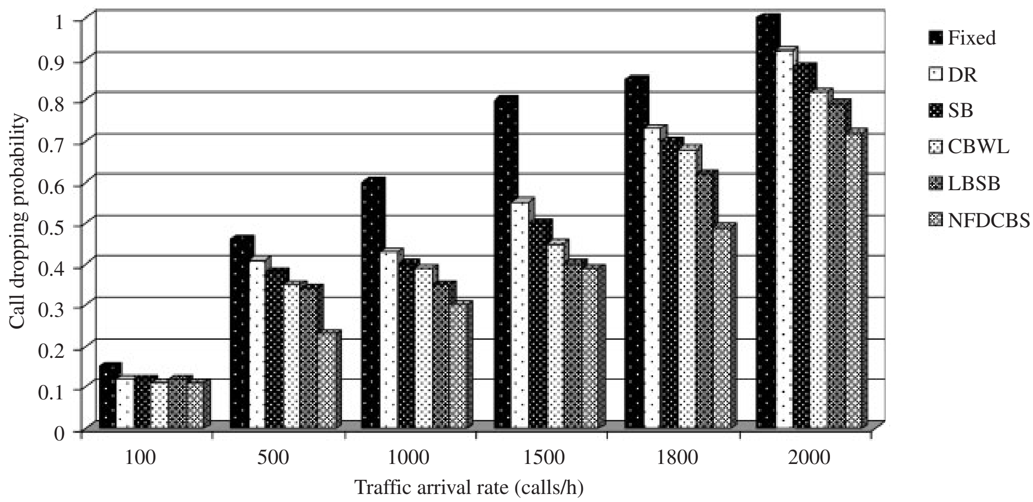

Figure 8. Compare dropping probability and traffic-arrival rate.

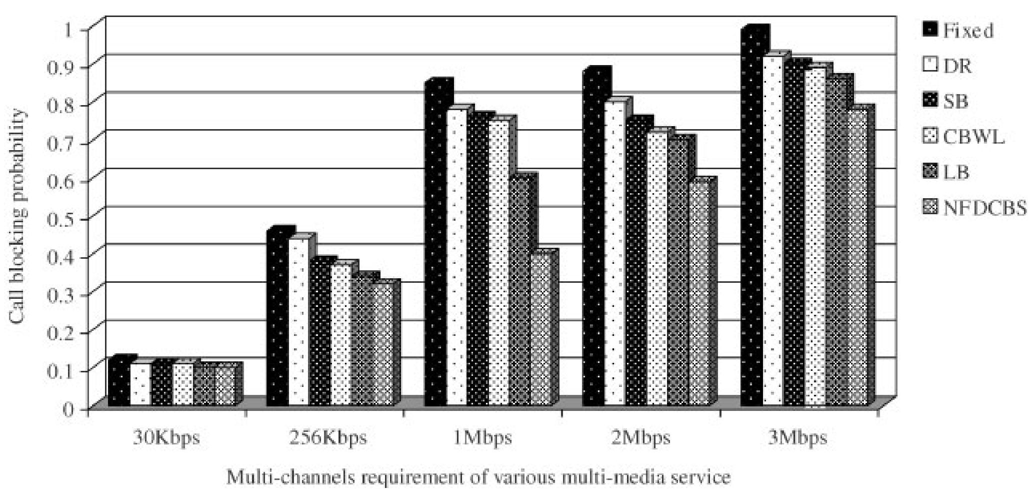

Figure 9. Blocking probability and multi-channel requirement of multimedia service.

the handoff dropping probability. Figure 11 shows the blocked calls of the six channel-assignment algorithms with the number of hot cells. We find that when there are a few hot cells in the system, our proposed scheme performs better than other schemes. In our NFDCBS, when traffic load is hot there will be a lot of channel borrowing at a time for multimedia services, although not as severe as channel-borrowing scheme. Figure 12, which depicts the messages of different channel-borrowing schemes, shows that our proposed DCA scheme has the fewest

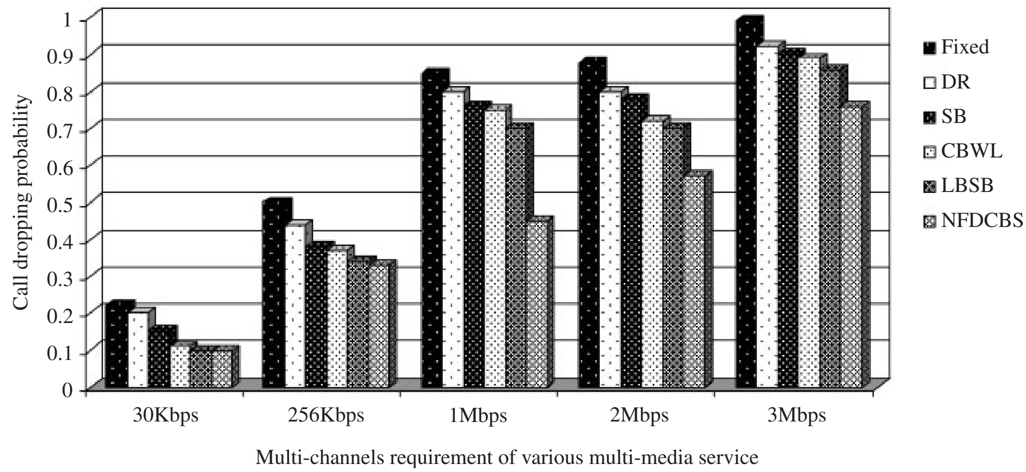

Figure 10. Dropping probability and multi-channel requirement of multimedia service.

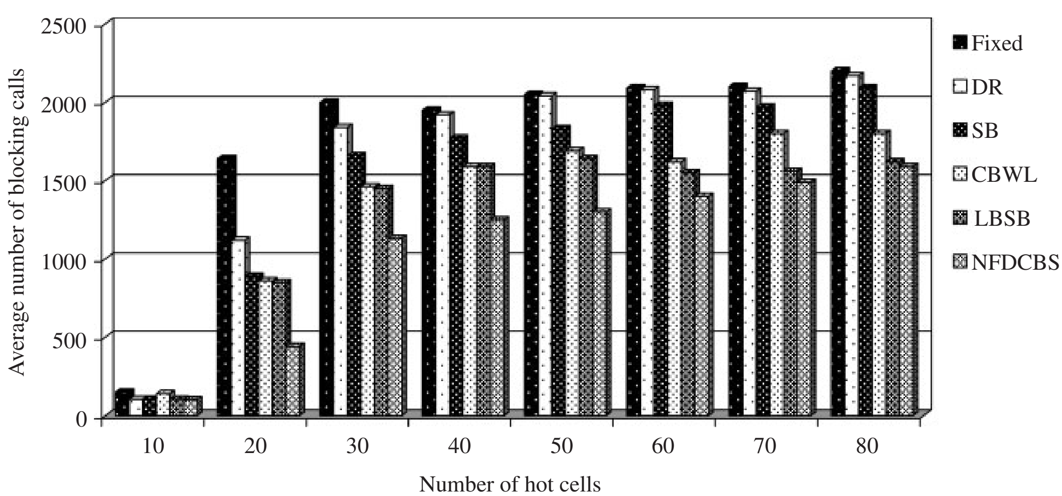

Figure 11. Number of blocked calls of our scheme with others.

updated messages. Our proposed scheme performs especially well when the numbers of hot cells are large. The channel-acquisition delays are also discussed in our experiment. Figure 13 shows that our proposed scheme has the shortest channel-acquisition delays. This results in a channel-allocation scheme with efficient channel use in all traffic conditions.

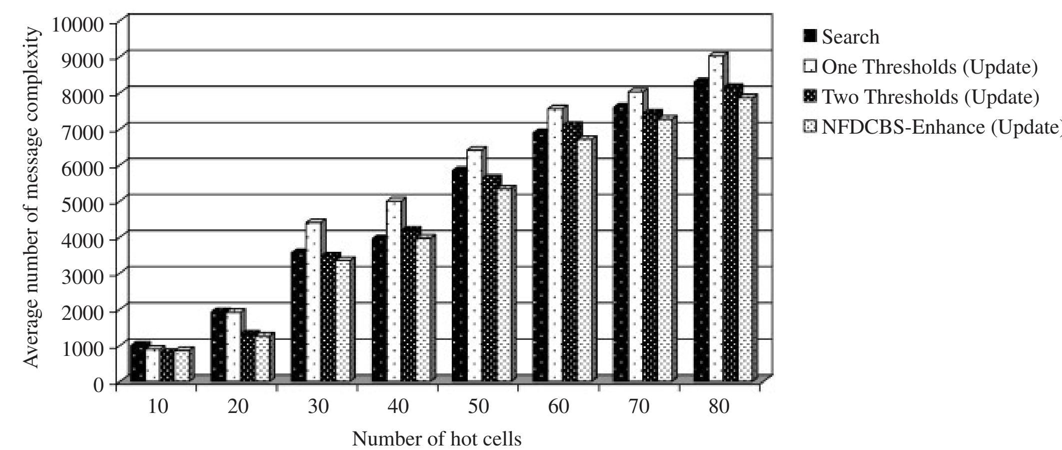

Figure 12. Average number of update message overhead in our scheme and others.

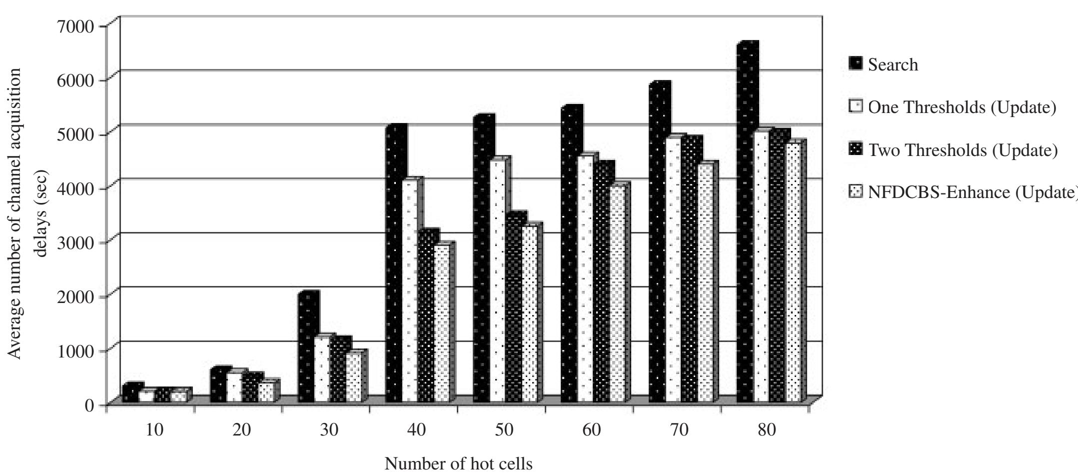

Figure 13. The channel-acquisition delays of various schemes.

5. CONCLUSION

Fuzzy logic control and neural networks are complementary technologies in the design of intelligent wireless cellular network. Neural networks are essentially low-level computational structures and algorithms that offer good performance in dealing with sensory non-linear input data, while fuzzy logic techniques deal with reasoning on a higher level than networks. This is the first attempt in formulating the dynamic channel-borrowing problem with neural-fuzzy controller and with simulation for various traffic loads and a number of hot-cell nodes. The present paper has highlighted the role of the neural-fuzzy controller and its application in wireless cellular networks. In addition, the NFDCBS has often shown a faster and smoother response than conventional systems. Based on these parameters, a set of fuzzy inference rule is established. Since fuzzy logic control rules are constructed by using linguistic variables, intuitive knowledge is easily integrated into the control system. We believe that a neural-fuzzy controller for the control and management of cellular networks is more appropriate than the conventional probabilistic models. It can also efficiently determine the suitable cell for borrowing channels. The performance of the proposed scheme is better than that of conventional schemes on the blocking rate, dropping rate, messages complexity and channel-acquisition delays.

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