ADAPTIVE NEURAL-FUZZY CONTROLLERS FOR DYNAMIC CHANNEL BORROWING IN WIRELESS CELLULAR NETWORKS

Yao-Tien Wang
Department of Information Management
Kai-Nan University, Lu Chu, Taoyuan, Taiwan, R.O.C.
Email: tywang@mail.knu.edu.tw
Department of Computer Science and Information Engineering
National Central University, Chung-Li, Taiwan, R.O.C.
Email: ytwang@axp1.csie.ncu.edu.tw

Abstract—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 calls arrival rate, the call duration and the communication overhead between the base station and the control center are vague and uncertain. Therefore, we propose a new novel efficient dynamic channel borrowing for load balancing in distributed cellular networks based on neural-fuzzy controllers scheme. The proposed scheme exhibits better learning abilities, optimization abilities, robustness, and fault-tolerant capability thus yielding better performance compared with other algorithms. It aims to efficiently satisfy their diverse quality- of service (QoS) requirements. The results show that our algorithm has lower blocking rate, lower dropping rate, less update overhead, and shorter channel acquisition delays than the previous methods.
Keywords: Dynamic channel borrowing, load balancing, neural-fuzzy controllers, channel allocation, wireless cellular networks.

I. INTRODUCTION

Efficient use of limited radio channels with a simultaneous increase of traffic capacity requires proper channel assignment. This is one of the fundamental problems in wireless cellular network. There are three strategies for allocation of channels to cells [1][2][4]. Existing results for the channel assignment can be classified into *Fixed* Channel Assignment (FCA) [5], Dynamic Channel Assignment (DCA) [2][6], and Hybrid Channel Allocation (HCA) [3][6]. 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. In the centralized DCA schemes [1], 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 center. In the distributed DCA schemes [1], BSs are needed to 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 FCA basis, while the others are kept in a central pool for the 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. This is achieved by efficiently transferring channels from lightly loaded cells (cold status) to heavily loaded ones (hot status).

Traditional channel allocation approaches can be classified into *update* and *search* [1]. 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 short acquisition delay, but it has higher message complexity. In other word, the search approach has lower message complexity, but it has longer acquisition delay. Due to this nature, using neural-fuzzy controllers seems to be 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 [7]. 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. Fig. 1 shows the block diagram of our NFDCBS.

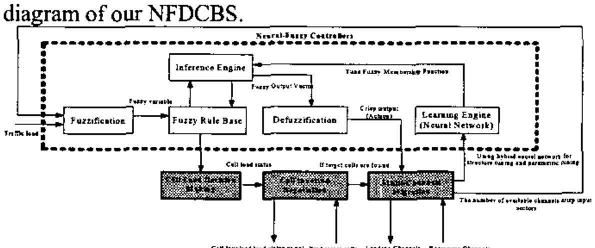

Fig. 1. Block diagram of NFDCBS.

Our neural-fuzzy controllers consist of five modules: (1) a fuzzy rule base, (2) a fuzzy inference engine, (3) fuzzification, (4) defuzzification modules, and (5) neural networks. The NFDCBS 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 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 center, widths, and slope; the parameters of the parameterized fuzzy connectives; and the weights of the fuzzy logic control rules. The performance of our NFDCBS is compared with the fixed channel assignment [4], simple borrowing [9], directed retry [5], CBWL [3], and LBSB [6]. The experimental results reveal that our proposed scheme yields better performance as compared with others 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 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 neural-fuzzy controller wireless cellular system in Section 3. Experimental results are given in Section 4. Finally, concluding remarks are made in Section 5.

II. CELLULAR SYSTEM MODEL AND CHANNEL BORROWING STRATEGY

A cellular system consists of a control center, and a set of cells, each with a fixed base station (BS). The concept also applies to radio network controller in 3G systems, and a BS directly communicates with all mobile stations (MSs) 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 base station and the mobile host 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 [1]. 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 base stations is called a cell *cluster*. 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 [9] 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 [5], 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 on the number of users in the overlap region. The channel borrowing without locking (CBWL) scheme [3] propose channel borrowing when the set of channels in a cell gets exhausted, but to use 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 over loaded cellular system. The disadvantages of LBSB are summarized as follows: (1) Too much dependency on the central server maintenance of continuous status information of the cells in an environment. The traffic load changes dynamically, lead to enormous amount of updating traffic, consumption of bandwidth and message delay. (2) The strategy of the channel borrowing for load balancing usually use some fixed threshold values to distinguish the status of each cell. 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 transferring channels back and forth. In this paper, the performance of a DCA strategy will depend on how the state information has decided at the BSs. An efficient channel assignment strategy should not only consider the present load, but also the load distributed in the recent past. Based on this information, it should also to project the load distribution in near future. To be able to get a good decision, the dependencies between a decision and the objective must be calculated. This estimation is, however, very 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. NEURAL-FUZZY CONTROLLER WIRELESS CELLULAR SYSTEM

The concept of fuzzy number plays a fundamental role in formulating quantitative fuzzy variables. Fig. 2 shows membership function for the number of available channel (e) and traffic load (e^*). These functions are defined on the interval $[b_0, b_2]$, $[a_0, a_4]$, respectively, and the range of the output variable Y^o_{coa} is [-c, +c]. Assume further that following nine linguistic states are selected for migrate channels of the variables: NVL: negative very large, NL: negative large, NM: negative medium, NS: negative small, AZ: approximately zero, PVL: positive very large, PL: positive large, PM: positive medium and PS: positive small.

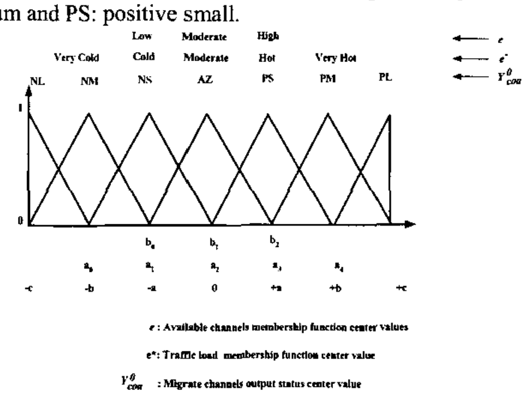

Fig.2. shows membership function of the fuzzy input and output.

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. In this step, a fuzzification is introduced for each input variable to express the associated measurement uncertainty information [7][8]. The goal is to obtain sufficient information in order to make a decision whether the cell load is hot or the others load level. The *cell involves in negotiation*, selects the cells to or from which channels will be migrated when the load reallocation event takes place by fuzzy interference rules and inference engine [7][8]. 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, thereby reduce the borrowing overhead further. The new channel borrowing with *multi-channels migration* can reallocate channels well especially in an unpredictable variation of cell load, a fuzzy controller select a suitable defuzzification method [7][8]. 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. 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 multi-media mobile network, a call may need multiple channels at a time. If the new channel is not acquired in time, the call is dropped.

Neural networks can improve their transparency, making them closer to fuzzy logic control, while fuzzy logic control can self-adapt, making them closer to neural networks. Hybrid structure parameter learning of the NFDCBS has a total of four layers. The nodes in layer 1 are linguistic nodes that represent input linguistic variables, and 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, and the other is for actual output to be pumped out of the network. Nodes in layer 2 and 3 are term nodes, which act as membership functions representing the terms of the respective linguistic variables. Actually, a layer 2 node can either be a single node that performs a triangle-shaped membership function or that performs a complex membership function. Each node in layer 3 is a rule node that represents one fuzzy rule. Also 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. Fig. 4 shows the hybrid structure parameter learning of the NFDCBS. 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 multi-channels allocation pertains to handle the allocation of channels from one cell to another. If one cell is in the "*Very hot*" state; then it will borrow several channels from the cell with "*Very cold*" state. If there do not exist any "*Very cold*" cell, then it would choose several cells with "*Cold*". 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 application crisp controls action is required for the actual control. The Fig. 2 shows the membership function for channel borrowing/lending a quantity control number of the channels range [-c, +c] of the fuzzy output.

We have used the *center of area* (COA) method because it supports software real time fuzzy controls to distinct the difference of load on two cells. This value is calculated by the formula

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

Where Y^{o}_{coa} represent the number of migrate channels,

W_i = The antecedent degree of *ith* control rule and

B_i = The consequent center value of *ith* control rule

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

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

After multi-channels are reallocated, we hybrid neural network to tune the fuzzy membership function. We define the isosceles triangular membership function of load status as shown in Fig. 3, and the antecedent degree of ith control rule is depended on the membership function center value a_i, the membership function width b_i.

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

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

$$E = \frac{1}{2}\left[Y_{coa}^0 - Y_d\right]^2$$

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

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

Since the shape of the membership function $U_i(x)$ is defined by the center value a_i and the width bi, 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:

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

IV. EXPERIMENTAL RESULTS

The simulated model consists of 14 clusters and each cluster consists of 7 homogeneous cells. This experiment has used the number of channels C = 30 in a cell, total of N = 49 cells in the system. The amount of requested channel, specified of minimum basic channel units (CU) is 30Kbps of multi-channels migration. We assume λo = 100 *calls/per hours*~ 2000 *calls/per hours* be the call originating rate per cell and $\lambda_h = (\lambda o \times 0.01 \sim \lambda o \times 1)$ be the hand-off traffic density per cell, and d = 1 sec communication delay between cells, and each handoff and new calls request delay constraint (DC=5)secs. So, from the simulation result, the value of traffic load is chosen randomly and non-linearly. Let the density of simulation be 500 peoples/per cell. We define that the time of the sample interval is 3 minutes and the sampling time does influence previous one. In order to represent various multi-media 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 30Kbps, 256Kbps and interval 1Mbps to 3Mbps, respectively. The assumptions of

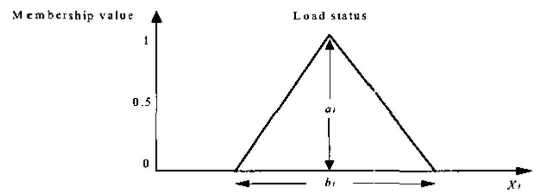

Fig. 3. shows isosceles triangular membership function of load status.

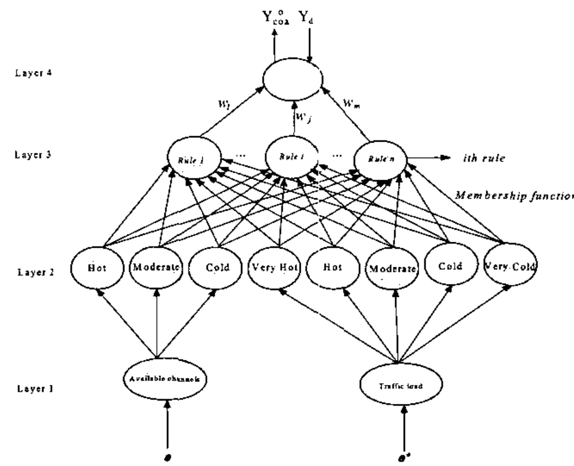

Fig. 4. Hybrid structure parameter learning of the NFDCBS.

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 neighboring cell, the call must be transferred to the neighboring BS. This procedure is 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 cluster 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 NFDCBS is compared with the previous methods; the experimental results reveal that the proposed channel borrowing scheme yields have better performance than others. Fig. 5 compares the channel assignment algorithms according to the new call blocking probability of channel request for multi-media services. When the traffic load increases, the call blocking rate of channel requests increases at a slower rate than the other schemes. Fig. 6 shows the hand-off call dropping probability for various schemes at a various multi-media service. The NFDCBS scheme always has lower hand-off dropping rate than the existing channel assignment schemes with the same number of channel requirement. It also indicates that NFDCBS scheme can improve the performance over the other methods with the number of reserved channels by further reducing the hand-off dropping probability. Fig. 7 depicts the messages of different schemes, and we found that our proposed scheme has the shortest updated messages. Especially, our proposed scheme performs well when the numbers of hot cells are large. The channel acquisition delays are also discussed in our experiment. Fig. 8 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.

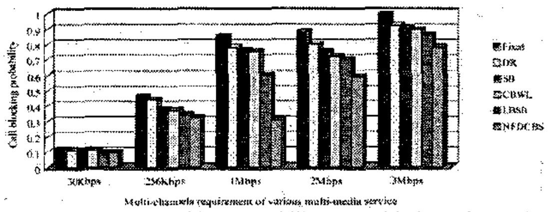

Fig. 5. Compare blocking probability vs multi-channels requirement of multimedia service.

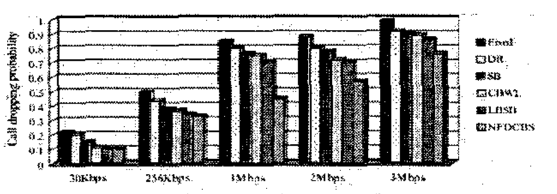

Fig. 6. Compare dropping probability vs multi-channels requirement of multimedia service.

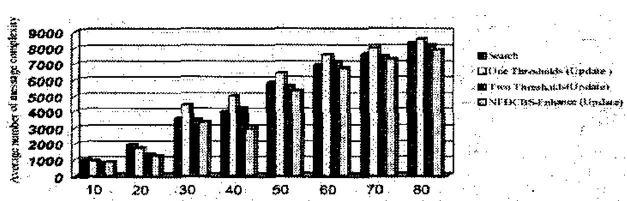

Fig. 7. Compare the average number of update messages overhead of our scheme with others.

Fig. 8. The channel acquisition delays of various schemes.

V. CONCLUSIONS

Fuzzy logic 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 nonlinear input data, while fuzzy logic techniques deal with reasoning on a higher level than networks. It also can efficiently determine the suitable cell for borrowing channels and the performance of the proposed scheme is better than that of the conventional schemes on the blocking rate, the dropping rate, the messages complexity and the channel acquisition delays.

REFERENCES

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

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

[3] 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.

[4] S. Kim and P. K. Varshney. Adaptive Load Balabcing with Preemption for Multimedia Cellular Network. IEEE Wireless Communications and Networking Conference, pages 1680–1684, 2003.

[5] T. S. Yum M. Zhang. Comparisons of channel-assignment strategies in cellular mobile telephone systems. IEEE Transactions on Vehicular Technology, pages 211–215, 1989.

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

[7] Y. T. Wang. A Fuzzy-Based Dynamic Channel Borrowing Scheme for Wireless Cellular Networks. IEEE Vehicular Technology Conference, pages 1517–1521, 2003.

[8] L. A. Zadeh. Fuzzy Algorithm. Information and Control, pages 94–102, 1968.

[9] Y. Zhang. A new adaptive channel assignment algorithm in cellular mobile systems. IEEE Systems Sciences Conference, pages 1–7, 1999.