HIERARCHICAL GENETIC ALGORITHM FOR DYNAMIC CHANNEL UNITS ALLOCATION IN TD-CDMA/TDD SYSTEM

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ABSTRACT

Hierarchical Genetic Algorithms (HGA) as a tool for search and optimizing methodology have now reached a mature stage. The minimum resource facility to carry user traffic, termed a channel unit (CU), is composed of a one time-slot and one code in the TD-CDMA/TDD system. The control of the number of CUs depends on the traffic load solves varied and asymmetrical traffic problems in the 3G system. In a cellular network, the call arrival rate, call duration and the communication overhead between the base stations and the control center are vague and uncertain, regardless of whether the criteria of concern are nonlinear, constrained, discrete or NP hard. In this paper, the HGA is used to tackle the neural network (NN) topology as well as the fuzzy logic controller for the dynamic CU allocation scheme in wireless cellular networks. Therefore, we propose a new efficient HGA CUs Allocation (HGACA) in cellular networks. It aims to efficiently satisfy the diverse quality-of-service (QoS) requirements of multimedia traffic. The results show our algorithm has a lower blocking rate, lower dropping rate, less update overhead, and shorter channel-acquisition delay than previous methods.

KEYWORDS

Dynamic channel unit allocation, load balancing, hierarchical genetic algorithms, neural-fuzzy controllers, TDD-CDMA/TDD, wireless networks, radio resource management.

1. INTRODUCTION

Code Division Multiple Access (CDMA) can be categorized as frequency division duplex (FDD) and time division duplex (TDD) modes. CDMA in the TDD (TDD-CDMA) mode will be based on the harmonization between UMTS Terrestrial Radio Access in the TDD mode (UTRA TDD) and Time Division-Synchronous CDMA (TD-SCDMA). There have been several proposals for supporting real-time and multimedia application services and so on [1-3]. TDD-CDMA uses a combined time division and code division multiple access schemes, therefore the signals of different users separated in both the time and code domains TDD mode can flexibly cope with the traffic asymmetry by changing the number of time-slots allocated to the downlink (DL) and uplink (UL). The minimum resource facility to carry user traffic, termed a channel unit (CU), is composed of one time-slot and one code. Multiple CUs are allocated when the traffic load exceeds one CU capability. The control of the number of CUs depending on the traffic load solves varied and asymmetrical traffic problems in the TD-CDMA system [3,4]. This is one of the fundamental problems in the wireless cellular network. In fact, increasing the bandwidth of a cell can increase the system capacity but not increase the efficiency in dealing with the time varying imbalance in traffic.

There are two strategies for allocation of channels to cells [5-10]: Fixed Channel Allocation (FCA) [10] and Dynamic Channel Allocation (DCA) [9,11-14]. The advantage of FCA is its simplicity. It does not, however, reflect real scenarios where the load may vary from cell to cell. DCA schemes can dynamically assign or reassign channels and are thus more flexible. In the centralized DCA schemes [11-12,15], all channels are placed in a pool and assigned to the new calls as required, and all the allocation jobs are performed by the control center. In the distributed DCA schemes, BSs must be involved [16].

The channel allocation for load balancing usually uses some fixed threshold values to distinguish the status of each cell [11-12]. 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 the threshold values are fixed. Since the load state may display sharp distinction state levels, series fluctuation like the 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 [11,12]. This is achieved by efficiently transferring channels from lightly loaded cells (cold status) to heavily loaded ones (hot status). While the great advantage of GAs is they find a solution through evolution [17-18], this is also the biggest disadvantage. Evolution is inductive in nature. Life does not evolve towards a good solution, rather it evolves away from bad circumstances, and search and optimizing are very slow. This can cause a species to evolve into an evolutionary dead end. Likewise, GAs risk finding a suboptimal solution, such as not always finding the exact solution but always finding the best solution. [Editor: I don't know if the previous sentence keeps your intended meaning.] The load information collection can not only estimate the time-varying traffic load for the cellular networks, but also provide useful information in making the channel-reallocation decisions.

Traditional channel allocation approaches can be classified into update and search [19]. The fundamental idea is 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 HGACA is the best way to approach the problem. The concept of the fuzzy number plays a fundamental role in formulating quantitative fuzzy variables. The fuzzy numbers represent the linguistic concepts, such as very hot, hot, and moderate etc [20-21]. 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 CUs at a time, based on the traffic loads of the cells and channel availability, thereby further reducing the channel allocation overhead. Fig. 1 shows the block diagram of our HGACA.

Our HGACA consist of six modules: a fuzzy rule base, a fuzzy inference engine, fuzzification, defuzzification modules, genetic algorithm, and neural networks. The HGACA consists of cell load decision making, cell involved negotiation, and multi-CUs migration phases. The structure of a dynamic channel borrowing for a wireless cellular network is composed of three design phases by applying HGACA to them. The main purpose of a HGACA is to obtain an optimal neural network topology, and neural network 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 the center, widths, and slope; the parameters of the parameterized fuzzy connectives; and the weights of the fuzzy logic control rules. The performance of our HGACA is compared with the simple borrowing [10,22], directed retry [23], CBWL [24], and LBSB [11]. The experimental results reveal our proposed scheme performs better than conventional dynamic channel allocation schemes. Our HGACA for CUs algorithm not only effectively reduces the blocking rate and the dropping rate but also provides significant improvement in overall performance, such as fewer update messages and shorter CUs acquisition delay. The rest of this paper is organized as follows. In Section 2, we provide the structure of the cellular system model and channel allocation strategy. The design issues of our proposed HGACA wireless cellular system are in Section 3. The experimental results are given in Section 4, and concluding remarks are given in Section 5.

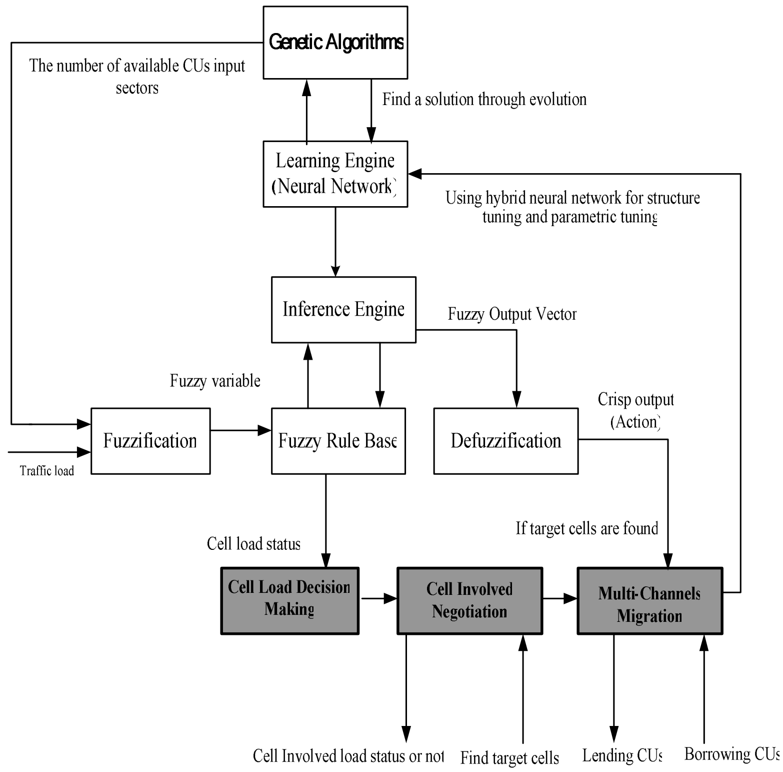

Fig. 1: Block diagram of HGACA.

2. System Model and Channel Allocation Strategy

The universal mobile telecommunication system (UMTS) consists of the radio network controller (RNC) that owns and controls the radio resources in its domain and the base stations (BSs) connected to it. The RNC is the service access point for all services. The UMTS Terrestrial RAN provides the core network (CN) and management of the connection to the user equipment (UE). The concept also applies to the radio network controller in the next generation of wireless cellular systems, and a BS directly communicating 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 base station and the mobile stations communicate through the wireless links using the channel. Each cell is allocated a fixed set of CUs and the same set of channels are reused by those identical cells, which channels are sufficiently far from one another to avoid interference, such as inter-cell and intra-cell interference [4,19].

In the simple allocation strategy [10], 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 locks in the co-channel cells of the lending one. In the directed retry with the load sharing scheme [23], it is assumed the neighboring cells and the users overlap the region. The main drawback of this scheme includes the increased number of hand-offs and co-channel interference, as well as the load sharing depending on the number of users in the overlap region. The channel borrowing without locking (CBWL) scheme [24] proposes channel borrowing when the set of channels in a cell is exhausted; but it uses the borrowed channels under reduced transmission power to avoid co-channel interference. Also, only a fraction of the channels in all neighboring cells are available for borrowing. In the load balancing with selective borrowing

(LBSB) [11], a cell is classified as “hot”, if its degree of coldness defined as 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 the cell is “cold”. Aided by a channel allocation strategy within each cell, it has been presented in that the centralized LBSB achieves has 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. The LBSB scheme has two disadvantages: (1) 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 an enormous amount of updating traffic, consumption of bandwidth and message delays. (2) The strategy of the channel allocation for load balancing usually uses fixed threshold values to distinguish the status of each cell. However, the [insert noun] are fixed and cannot indicate the degree of the load. Since the load status may display 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 effort 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. 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.

3. HGACA Wireless Cellular System

Some of the techniques used to load balancing in heuristic techniques involve a threshold used to determine where the load is cold or hot. This binary-state makes the system load state fluctuate between the hot and cold load when the cell load is near the threshold value. It will cause frequent channel reallocation because of the load change. Simulation techniques have been widely used by 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 [10-13,15,19,23-24]. Those proposed schemes completely ignore resources other than the 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 it is difficult, perhaps impossible, to find the cell load information that satisfies all 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 many unrealistic assumptions must be made to make the study feasible. For example, most models use exponential distributions for the arrival and service times.

The typical architecture of fuzzy logic control includes four principal components: fuzzifier, fuzzy rule base, inference engine and defuzzifer. 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 ability to simulate 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 [19,21,25-26].

HGACA is based on the optimum size of a neural network to reduce the enormous search spaces in learning and using mathematical methods to determine the architecture and parameters of the neural network [27]. The advantage of this approach is genes of the chromosome are classified into categories in a hierarchical form. The HGA differs from the standard GA with a structure where each chromosome consists of multiple levels of genes. Each consists of two types of genes, and the control genes and connection genes. The control genes in the form of a bit are the genes for layers and neurons for activation. The connection genes, a real value representation, are the genes for connection weightings and neuron bias. A neuron consists of an activity level, a set of input and output connections with a basic value associated to each connection.

Fig. 2 shows a typical neuron with n-input connections and a single output connection. The output of the neuron is determined as: $y = f(\sum_{i=1}^{n} \omega_i x_i + \eta)$, where $x_1, x_2, ..., x_n$ are input signals, $\omega_1, \omega_2, ..., \omega_n$ are connection weightings, η is the basic value, and f is output function.

The GA processes imitate natural evolution, and therefore include biomimetic operation such as reproduction, crossover, and mutation.

(1) Population: The choice of an appropriate population size is a fundamental decision to be taken in all GA implementations. If the population sizing is too small, the GA will usually converge too quickly. If the population size is too large, a population will take a very long time to evaluate. In the study, the population of at k-th generation, $p^{(k)}$, is divided into several connection subgroups, $G_1^{(k)} \cup G_2^{(k)} ... \cup_M^{(k)} = P^{(k)}$ and $G_i^{(k)} \cap G_j^{(k)} = \phi, \forall i \neq j$, where M is the maximum number of possible connections represented by HGACA, and $G_i^{(k)}$ is the subgroup of chromosomes representing those networks with i active connection at k-th generation.

(2)Objective functions: The objective of training the network is to minimize two different parameters, the accuracy of the network (f1) and the complexity of the network (f2). The accuracy of the network (f1) is defined as: $f_1 = \frac{1}{N} \sum_{i=1}^{N} (y_i^T - y_i)^2$, where N is the size of the testing vector, y_i^T and y_i are the network output and desired output for the i-th pattern of the test vector respectively.

(3) Selection process: Parent selection is a routine to emulate the survival of the fittest mechanism of nature. Chromosomes in the population are selected for the generation of new chromosomes using certain selection schemes. There are two different objective functions, (f1) and (f2) of the problem optimization process.

(4) Control and Connection, Genes Crossover: Crossover operates on two solution strings and results in other two strings. A typical crossover operator exchanges the segments of selected strings across a crossover point with probability. There are two steps producing two offspring by crossover operator.(1) A given number of crossing sites are uniformly selected along the parent strings at random. (2) Two new exchanging alternate pairs of sections between the secreted forms string crossing sites.

(5) Mutation: The mutation operator prevents irreversible loss of certain patterns by introducing small random changes into chromosomes. Change each bit value with the probability.

(6) Fitness function: The intended insect uses the GA evolutionary process, and the feature of this particular chromosome must be specified. The programmed will proceed and each of the generated chromosomes will be checked according to this ideally specified chromosome. The measure of this checking mechanism represents the fitness function. This can be a combination of the genes, and the genetic algorithm is only able to optimize the characteristics explicit in the fitness function. Fig. 3 shows the hybrid structure parameter learning of the HGACA.

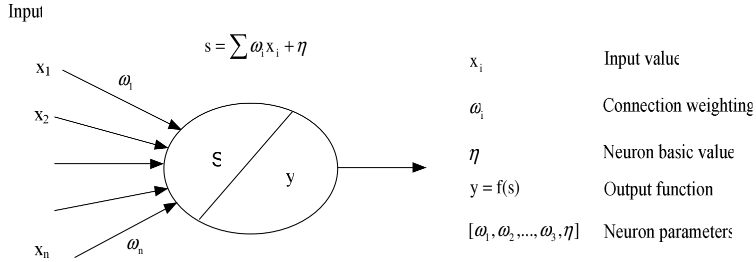

Fig. 2: A single neuron.

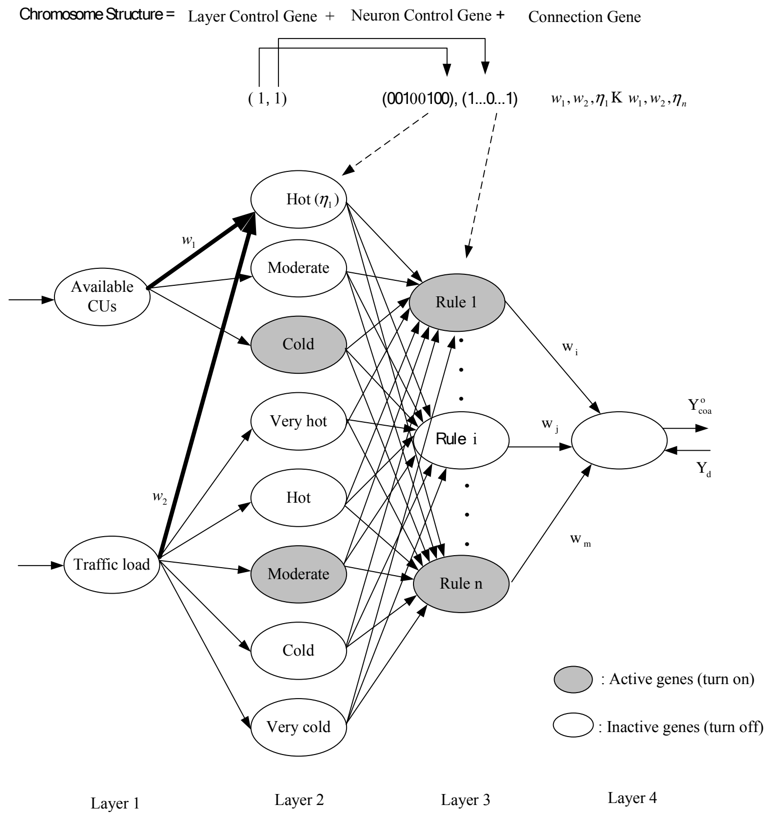

Fig. 3: Hybrid structure parameter learning of the HGACA.

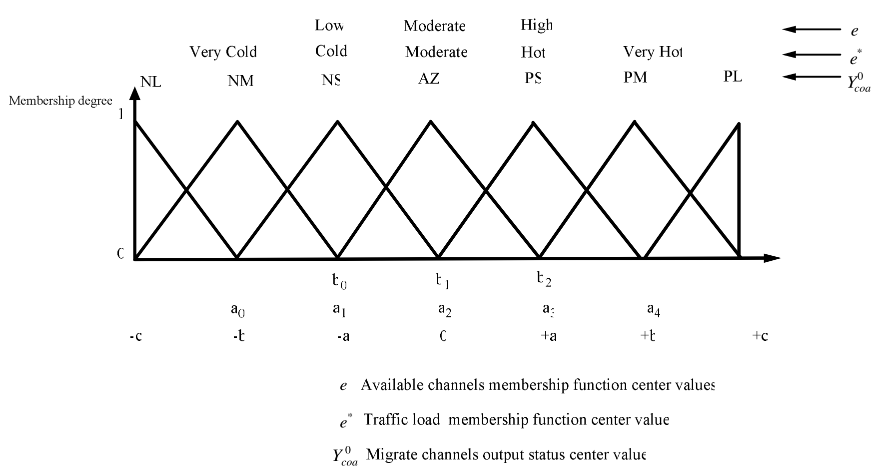

Fig.4: Membership functions of the fuzzy input and output.

The system has a total of four layers. The nodes in layer 1 are linguistic nodes representing 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. The nodes in layers 2 and 3 are term nodes, which act as membership functions representing the terms of the respective linguistic variables. Actually, layer 2 nodes can be either a single node performing a triangle-shaped membership function or one performing a complex membership function. Each node in layer 3 is a rule node representing 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, where Y_{coa}^{0} represents the number of migrating channels, and y_d is our desired output.

3.1 Cell Load Decision-Making

This section addresses our strategy of estimating load status in a wireless cellular network. This measure is vital for us to determine the most suitable site for migrating channels to share the load in the system. We can construct different available channels membership functions, and traffic load membership functions. The distributed channel assignment schemes have received considerable attention because of their reliability and solvability. Many researchers use available channels as the single load index for BS in cellular systems [11,14]. Although the number of available channels is the obvious factor affecting 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 the 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 the available channel and e^* is denoted as the traffic load, a_i and b_i are actual input values, respectively. Let a_i represent the center value of the linguistic labels of available channel membership function for $0 \le i \le 2$, and let b_i stand for the center value of the linguistic labels of traffic load membership function for $0 \le i \le 4$. 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 values of available channels. The fuzzified information is then passed on to the fuzzy inference engine. Fig. 4 shows the membership function for the number of available channels and the system parameter traffic load. These functions are defined on the interval $[a_{0,} a_4]$, $[b_0, b_2]$.

3.2 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 [19]. In the search approach, a cell does not inform its neighbors of its channel acquisitions or releases. When a cell requires a channel, it searches all neighboring cells to calculate 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 or releases a channel, so each cell knows the set of channels available for its use and the underlying DCA strategy.

Both approaches have advantages and disadvantages. The update approach has short acquisition delay and good channel reuse, but it also has higher message complexity. In other words, the search approach has lower message complexity, but it has longer acquisition delay and ineffective channel reuse [19]. Our research took advantage of HGACA and presented an enhanced version of the negotiation scheme, termed 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 cell nor lend any channels to any other cell. At each BS, an augmented load state table is maintained. The entries of the table are the current load status of every cluster cell 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 the 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 to or from any channels, nor to any other cells or update interfering neighborhood cells. [Editor: I don't know if the previous sentence keeps your intended meaning.] Further, assume 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 Table1.

Table 1 .IF-THEN rule.

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**

3.3 Multi-CUs Migration

The new channel allocation with multi-CUs transferring, can reallocate CUs well, especially in an unpredictable variation of cell load. Our mechanism for multi-CUs transfer calculates the amount of transferred channels by these two values. The number of available CUs and traffic load are the values, representing the average during the recent minutes. The HGACA we discussed in the previous 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 greatly differ. We propose the idea of allocating several CUs instead of only one between two cells whose BS load greatly differ. For example, in the next generation multimedia mobile network, a call may require multiple CUs at one time. Under our proposal, the cell load between two cells could be made more balanced. To accomplish this, we use five load values, which are very hot, hot, moderate, cold and very cold to distinguish the difference in cell load on two cells. If one cell is in the "very hot" state (PL), it will borrow several channels from the cell in the "very cold" state (NL). 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, a crisp control action is required for the actual control. Fig. 5 shows the membership function for channel borrowing or lending a quantity control number of the channels range [-*C*, +*C*] of the fuzzy output. The function is defined in the interval [0,+c] for the borrowing action, and in the interval [0,□c] for the lending action.

We used the center of area (COA) method because it supports real-time software fuzzy controls to distinguish the difference in the load of two cells. This value is calculated by the formula:

$$Y_{coa}^{o} = \left[\left\lfloor \frac{\sum_{i=1}^{n} w_i \times B_i}{\sum_{i=1}^{n} w_i} \right\rfloor \right] - \mathrm{IN}(c) \qquad (1)$$

Where Y_{coa}^{0} represents the number of migrate channels,

W_i = The antecedent degree of the ith control rule

B_i = The consequent center value of the ith control rule

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

Migrate Channels =***Min [Borrowing cell (*** Y_{coa}^{0} ***), Lending cell (*** Y_{coa}^{0} ***)].***

After multi-CUs are reallocated, we use GA to tune the output fuzzy membership function. The genetic operation should be used in a way to rapidly achieve high fitness individuals in the population without leading to total convergence. In this paper, we used the part random method to achieve high fitness for a short time interval. There are two main factors to be considered in the GA, one is the fitness function and the other is the encoding scheme. The fitness function F uses the following formula for the load index. Note, the parameter gene remained unaltered and merely changes the interpretation of its form. In this way, the complexity of tuning the fuzzy memberships and rules can thus be optimized and the overall structure can be greatly reduced. Each string included in a population is evaluated by the fitness function using the following formula:

$$F = \frac{1}{\alpha \times DP + \beta \times BP + \gamma \times ACQ + \delta \times MES} \qquad (2)$$

Where α : the weight for parameters of DP,

β : the weight for the parameters of BP,

γ : the weight for the parameters of ACQ,

δ : the weight for the parameters of MES,

DP: the handoff call-dropping rate,

BP: the new call-blocking rate,

ACQ: the channel acquisition delays and

MES: the average number of update messages overhead.

4. Experimental Results

The problem domain naturally lends itself to simulating 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 used the number of channels *CH* = 100 in a cell, total of *N* = 98 cells in the system. \The amount of requested CU [specified of minimum basic a channel unit (CU)] is 30*Kbps* of multi-channels migration.] [Editor: I don't understand this part of the previous sentence.] We assume λo = 100 *calls/per* *hour*~ 2000 *calls/per hour* is the call originating rate per cell, $\lambda_h = (\lambda o \times 0.01 \sim \lambda o \times 1)$ is the hand-off traffic density per cell, d = 1 sec the communication delay between cells, and each handoff and new call request delay constraint (*DC*=5) is five seconds. So, from the simulation result, the value of the traffic load is chosen randomly and non-linearly. The maximum numbers of hand-off calls are queued at 10 for the first-class priority, with new calls queued at 10 for the second-class priority, respectively. [Editor: Does the previous sentence keep your intended meaning.] Let the density of simulation be 500 *people/per cell*. We define the time of the sample interval as 3 minutes and the sampling time will influence the previous one. The CU acquires messages transmitted between the hot cell i and cold cell j. In our simulation, three types of traffic services are assumed: voice service, videophone and video on demand. These types are defined on the CUs requirement 30 Kbps, 256 Kbps and interval 1 Mbps to 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 CU from its cluster cells and its waiting time (delay constraint) is over then the calls must be blocked, otherwise they receive a 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 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. Its waiting time (delay constraint) will be over and the calls must be dropped, otherwise they receive service. (3) Update-message complexity: Each cell needs to communicate with the co-channel and cluster cells to exchange the set of load state information. (4) CUs-acquisition delays: For the values it acquires before the selected channels, the cell must simultaneously ensure the selected channels will not be acquired by any of its cluster cells and interference cells. 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 HGACA is compared with the simple borrowing (SB), and existing strategies like channel borrowing directed retry (DR), CBWL, and LBSB. The hand-off call dropping probabilities for HGACA and other methods are plotted in Fig. 5 against the hand-off dropping probability at different traffic loads. In every case, when the hand-off dropping probability is fixed, the HGACA has a lower hand-off call dropping probability than other methods. The improvement in the performance of the HGACA over other methods, however, decreases as the traffic load goes up. Fig. 6 compares the channel-assignment algorithms according to the new call-blocking probability of channel request for the multimedia services. Fig. 7 shows the hand-off 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 HGACA scheme always has a lower hand-off dropping rate than the existing channel-assignment schemes with the same number of channels required. It also indicates the HGACA scheme can improve performance over the other methods with the number of reserved channels by further reducing the hand-off dropping probability. Fig. 8, which depicts the messages of different CU allocation schemes, shows our proposed DCA scheme has the fewest 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. Fig. 9 shows our proposed scheme has the shortest channel acquisition delays. This results in a channel-allocation scheme with efficient channel use in all traffic conditions.

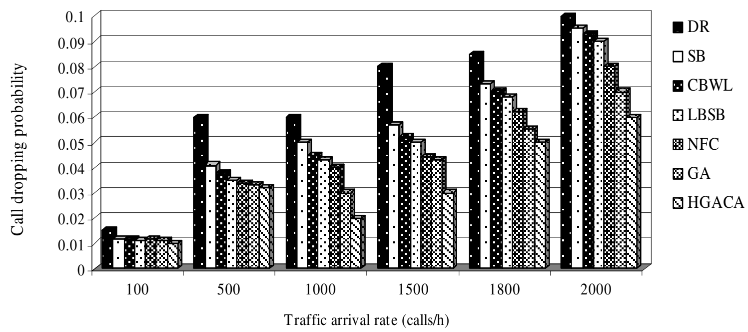

Fig. 5: Compare dropping probability and traffic arrival rate.

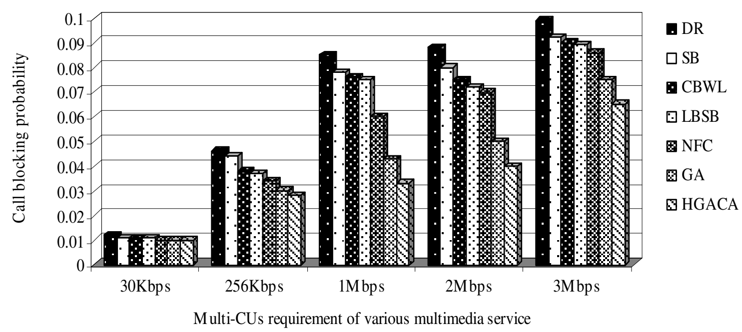

Fig. 6: Blocking probability and multi-CUs requirement of multimedia service.

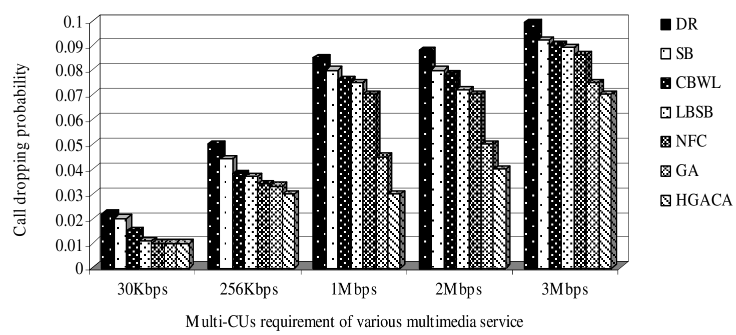

Fig. 7: Dropping probability and multi CUs requirement of multimedia service.

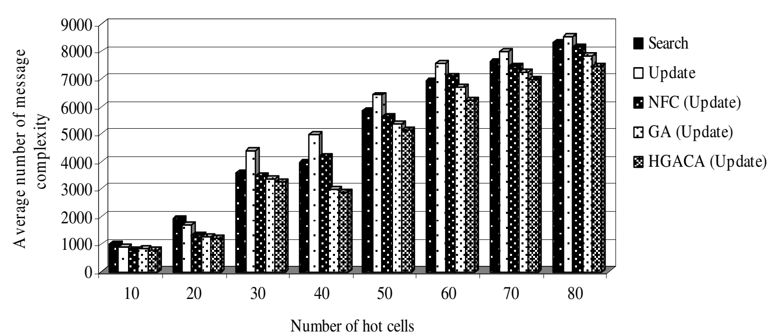

Fig. 8: Average number of update message overhead in our scheme and others.

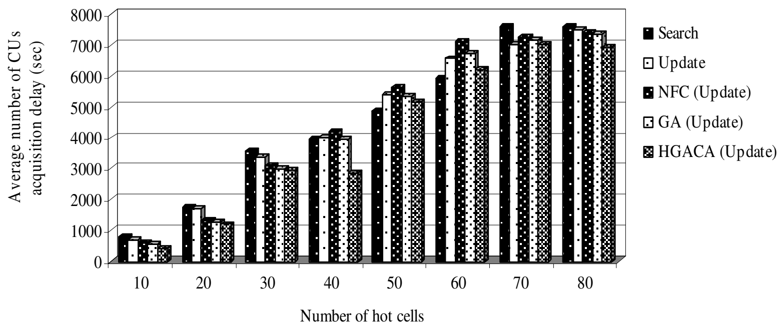

Fig. 9: The CUs acquisition delay of various schemes

5. Conclusion

HGACA are complementary technologies in designing an intelligent wireless cellular network. Neural networks are essentially low level computational structures and algorithms offering good performance in dealing with sensory nonlinear input data, while fuzzy logic techniques deal with reasoning on a higher level than networks. This is the first attempt to formulate the dynamic CUs allocation problem with HGACA and with simulation for various traffic loads and numbers of hot-cell nodes. Since fuzzy logic controls are constructed using linguistic variables, intuitive knowledge is easily integrated into the control system. We believe a HGACA for the control and managing cellular networks is more appropriate than the conventional probabilistic models. It also can efficiently determine the suitable cell for allocation CUs. The performance of the proposed scheme is better than conventional schemes in the blocking rate, dropping rate, message complexity and channel acquisition delay.

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