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A Grey-Fuzzy Controller for Optimization Technique in Wireless Networks

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Abstract**—**In wireless and mobile communications, this progress provides opportunities for introducing new standards and improving existing services. Supporting multimedia traffic with wireless networks quality of service (QoS). In this paper, a grey-fuzzy controller for radio resource management (GF-RRM) is presented to maximize the number of the served calls and QoS provision in wireless networks. In a wireless network, the call arrival rate, the call duration and the communication overhead between the base stations and the control center are vague and uncertain. In this paper, we develop a method to predict the cell load and to solve the RRM problem based on the GF-RRM, and support the present facility has been built on the application-level of the wireless networks. The GF-RRM exhibits the better adaptability, fault-tolerant capability and performance than other algorithms. Through simulations, we evaluate the blocking rate, update overhead, and channel acquisition delay time of the proposed method. The results demonstrate our algorithm has the lower blocking rate, less updated overhead, and shorter channel acquisition delay.

Keywords**—**radio resource management, grey prediction, fuzzy logic control, wireless networks, quality of service.

I. INTRODUCTION

THE wireless networks consists of a central switching office, namely mobile switching center (MSC), and a set of cells, each with a fixed base station (BS). Although the concept also applies to radio network controller in wireless networks, and a BS directly communicates with all mobile stations (MSs) within its wireless transmission radius [1], [2], [3], [4], [5]. The channel assignment (allocation) problem is an important topic in a cellular system. The objectives of the channel assignment of the existing results are mainly to exploit the channel reuse factor under the constraint of the co-channel reuse distance. Existing results for the channel assignment can be classified into Fixed Channel Assignment (FCA) [3], [7], Dynamic Channel Assignment (DCA) [6], [12], [17], and Hybrid Channel Allocation (HCA) [8]. The advantage of FCA has its simplicity. However, it does not reflect real scenarios where may fluctuate and vary from cell to cell.

DCA schemes can assign/reassign dynamical channels and more flexibility. In the centralized DCA schemes, all channels are placed in a pool and assigned to the new calls as requirement, which all the allocate jobs are done by MSC. In the distributed DCA schemes, which BSs can be need to involve. 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. To be more specific, load balancing is the process of redistributing the channels that is submitted to a network of cells so as to avoid the situation where some cells are idle while others are congested (hot-spots). Since the locations of hot-spots vary from time to time, in fact, the bandwidth increasing of a cell can increase the system capacity but not the efficiency to deal with the time-varying imbalance traffic. This is achievement by transferring channels efficiently from lightly loaded cells (cold) to loaded heavily ones (hot).

The conventional strategies of the channel borrowing for the load balancing usually use some fixed threshold values to distinguish the status of each cell. A cell load is marked as “hot”, if the ratio number of the available channels to the total number of the channels allocated to that cell is less than or equal to some threshold value. Otherwise it is “cold”. The drawback is that threshold values are fixed. Since load state may exhibit the sharp distinction state level, series fluctuation like ping-pong effect may occur when loads are around the threshold [6], [9], [11]. This results waste a significant amount of efforts in transferring channels back and forth. The load information collection can not only estimate the time-varying traffic load about the cellular networks, but also provide useful information for making the channels reallocation decisions.

We use grey prediction to forecast the one-step-ahead which predict load of the cell and develop fuzzy rules to determine how to classify a cell to be very hot, hot, moderate, cold, or very cold. A good load information gathering could be able to reflect our qualitative estimates of the current load on a cell which predicting the cell load in the near future, relative stable, and they have a simple relationship with the resource indices. In a cellular system, the arrival time of the calls may vary significantly, as the call duration times are vague and uncertain. Due to this nature, using grey-fuzzy control which 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. Traditional channel allocation approaches can be classified to update and search [8]. The fundamental idea is that a cell must consult all the interference cells within the minimum reuse distance before it can acquire a channel. We adopt the one-step-ahead predicted the number of the available channels and one-step-ahead predicted cell traffic load as the input variables for fuzzy sets to define a set of membership functions. In addition, our scheme allows a requesting cell to borrow multiple channels at a time,

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based on the traffic loads of the cells and channels availability, thereby reduce the borrowing overhead further. Our grey-fuzzy logic control the consists of five modules: (1) grey predictor (2) a fuzzy rule base, (3) a fuzzy inference engine, (4) fuzzification, and (5) defuzzification modules [13], [14], [15], [25]. The GF-RRM consists of (1) cell load decision-making, (2) cell involved negotiation, and (3) multi-channel migration phases.

The structure of a dynamic channel borrowing for the wireless networks is composed of three design phases by applying fuzzy logic control with grey prediction to them. The cell load decision- making indicates the amount of information regarding the cell as well as the information gathering rules used while making the load redistribution decisions. The goal is to obtain sufficient information and in order to make a decision whether the cell load is very hot, hot, moderate, cold or very cold. The cell involves in negotiation, and selects the cells to or from each channel will be migrated when the load reallocation event takes place. The multi-channels borrowing pertains to manage the migration of channels from one cell to another.

The performance of our GF-RRM is compared with the fixed channel assignment [12], simple borrowing [17], directed retry [16], CBWL [10], and LBSB [6]. The experimental results reveal that our proposed scheme yields better performance as compared with other conventional schemes. Our grey-fuzzy load balancing algorithm not only reduces effectively the blocking rate but also provides the considerable improvement in overall performance such as less update message, 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 based on grey-fuzzy and RRM strategy. The design issues of our proposed cell load decision making is described in Section 3. In Section 4, we propose the cell involved negotiation. The new channel borrowing with multi-channel transferring scheme is presented in Section 5.Simulation model and results are given in Section6. Concluding remarks are made in Section 7.

II. GREY-FUZZY AND RRM STRATEGY

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 the using channel. Each cell is allocated with a fixed set of the channels *CH* and the same set of channels is reused by those identical cells which are sufficiently far away from each other in order to avoid interference. A group of cells use distinct channels form a compact pattern of radius *R*. Given a cell c, the interference neighborhood of c, denoted by $IN(c) = \{c' \mid dist(c, c') < D_{\min}\}$, where $D_{\min} = 3\sqrt{3}R$. If N_i denotes the number of cell in the ring *i*, then for the hexagonal geometry $N_i = 1 \quad if \quad i = 0, \ and \quad N_i = 6_i \quad if \quad i > 0.$ Partition the set of all cells 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 $D_{\min}$ partition the set of all channels into *K* disjoint subsets, $P_0, P_1, \ldots, P_{k-1}$ The channels in $P_i \quad (i = 0,1,\ldots,k-1)$ are called the primary (nominal) channels for the cells in G_i, it is arranged in an ordered list. A channel *i* is either used (U_i) or available (V_i) depending on whether it is assigned to a MS. A channel available for *c* is interfered if it is used by some cell in $IN(c)$. 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 $P_j\,(j \neq i)$, the collection of cells in the coverage of the base stations group is called a cell *cluste*. In a cellular system, the arrival time of the calls, their call duration time and the message passing overhead among the cells are vague and uncertain. The control idea of the grey predictions is used to predict future behaviors of a system based on a collection of the data which regarding the system in order to uncover the development law, if any, of the system, and to perform pre-controls on relevant controlling decisions, by using the predicted future development tendency of the system. In this way, it becomes possible for us to prevent a predicted disaster before it actually occurs, and to impose controls in a timely fashion. Therefore, this method has a relatively stronger adaptability in practical applications. The concept of the fuzzy number plays a fundamental role in formulating quantitative fuzzy variables. These are variables whose states are fuzzy numbers. The fuzzy numbers represent linguistic concepts, such as very hot, hot, moderate, and so on, as interpreted in a particular context. We view this problem as an instance of a more general problem. To transfer a channel from a cell to another cell in order to reduce the blocking rate of the hot-spots is making decisions under uncertain and vague conditions.

Using grey prediction can prevent borrowing or lending channels when cell load is moderate in the early future and avoid the system is busy in transferring channels. In simple borrowing strategy [17], this variant of the fixed assignment scheme proposes to borrow a channel from the neighboring cells provided it not to interfere with the existing calls and lock in those co-channel cells of the lending one. In the directed retry with load sharing scheme [16], 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 [10] 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 the available channel to the total number of the channel allocated to that cell is less than or equal to some threshold value. Otherwise the cell is 'cold'. The LBSB scheme proposes to migrate a fixed number of channels from cold cells to hot one through a centralized channel borrowing algorithm run periodically by an MSC server in charge of a group of cells. Aided by a channel allocation strategy within each cell, it has been presented in that the centralized LBSB achieve to 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. However, the disadvantage of hence, too much depends on the central server in the MSC. Maintenance of continuous status information of the cells are in an environment where the traffic load changes dynamically, lead to enormous amount of the updating traffic, the consumption of wireless bandwidth and message delay.

III. Cell Load Decision-Making

The cell load collection is one of the most important issues in the distributed wireless networks for load balancing approach. This section addresses our strategy of estimating of load status in a distributed wireless networks. Such 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 meets the above criteria. Our proposed scheme seems to be approximating these criteria. This information shall indicate not only the amount of the information about the system but also the information gathering rules used in making the load redistribution decisions. This decision indicates various load information which regards with the cellular system. We can construct different available channels membership function, traffic load membership function, and center value for linguistic labels through *fuzzy c-means clustering algorithm* [15] according to various cell's characteristics of system behavior 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 that regards with the cellular system. Many researchers use available channel as the single load index for BS in cellular system [18], [19], [20]. Although the number of available channel is the obvious factor impacting on the system load, also there are certain other factors influencing the system load, such as call arrival rate and call duration, etc. 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 grey-fuzzy control. The FLC is to incorporate the "expert experience" of a human operator in the design of the controller in controlling a process whose input – output relationship is described by a collection of fuzzy control rules (e.g., IF_THEN rules) involving linguistic variables rather than a complicated dynamic model. This linguistic utilization variables, fuzzy control rules, and approximated reasoning provides a method to incorporate human expert experience in designing the controller [13], [14], [15]. In this section, we shall introduce the architecture, the design methodology, and the stability analysis of the fuzzy logic controllers with grey prediction. Some practical application examples will also be discussed.

The architecture of a (Grey-Fuzzy Controller) GFC, which is comprised of five principal components: a grey predictor, a fuzzifier, a fuzzy rule base, an inference engine, and a defuzzifer. If the output form the defuzzifier is not a control action for a plant, then the system is a fuzzy logic decision system with the grey prediction. The grey predictor forecasts the one-step-ahead value from data series. The fuzzifier has the effect of the transforming crisp measured data into suitable linguistic values. The fuzzy rule base stores on the empirical knowledge of the operation of the process of the domain experts. The inference engine is the kernel of GFC, and it has the capability of simulating human decision-making by performing approximated reasoning to achieve a desired control strategy. The defuzzifier is utilized to yield a non-fuzzy decision or control action from an inferred fuzzy control action by the inference engine. *Fuzzification* function is introduced for each input variable to express the associated measurement uncertainty.

A. Grey Prediction Model

The grey theory was first proposed by Prof. Deng in 1982 [21]. If all the information of a system is known, we call the system "white system". On the other hand, if we don't have any information about a system, the system is called "black system". Thus a grey system is a system which we have only a little information about it. The grey system theory include the following fields: (a) grey generating, (b) grey relational analysis, (c) grey forecasting,(d) grey decision making, and (e) grey control. The grey prediction has been widely used in many domains [21], [22], [23], [24]. It uses only a few data through the accumulated generating operation (AGO) technique to approach the system behavior. The raw data output from the system may not possess any regularity. However, the original data may become more regular after a repeatedly accumulated generating operation. Therefore, we can utilize grey model (GM) which describes a system behavior via a first-order differential equation to approximate such a regularity and hopefully to predict the next output from the system. This is why it is applicable to the time-varying nonlinear system prediction problem. Grey Prediction is summarized as follows:

Step1: Given the original data sequence

$$x^{(0)} = \left(x^{(0)}(1), x^{(0)}(2), \cdots x^{(0)}(n)\right) \tag{1}$$

,where $x^{(0)}$ corresponds to the system output at time i, $n \geq 4$ .We try to predict the next $x(n+k)$, $k \geq 4$.

Step2: Before constructing the GM(1,1) model, the original data need to be ratio tested.

$$\text{Meanwhile } \sigma^{(0)}(k) = \frac{x^{(0)}(k-1)}{x^{(0)}(k)} \tag{2}$$

, where $k = 2, 3, \ldots, n$,and $\sigma^{(0)}(k)$ is called class ratio.

When the value of class ratio falls within 0.1345-7.389, it means that the original data sequence $x^{(0)}$ satisfy the grey model.

Step3: From the original data sequence $x^{(0)}$ a new sequence $x^{(1)}$ is generated by the accumulated generating operation (AGO)

$x^{(1)}=\left(x^{(1)}(1),x^{(1)}(2),\cdots x^{(1)}(n)\right)$, where $x^{(1)}=x^{(0)}$,

$$x^{(1)}(k)=\sum_{m=1}^{k}x^{(0)}(m),\ k=2,3,\ldots,n. \quad (3)$$

Step4: According to GM (1,1), we can define the source model

$$x^{(0)}(k)+aZ^{(1)}(k)=b, k=2,3,...n. \quad (4)$$

By mean value generating operation we obtain the background value is $z^{(1)}(k)=\alpha x^{(1)}(k)+(1-\alpha)x^{(1)}(k-1)$.α is a adjusting factor, on general situations, $\alpha=0.5$. a is the development coefficient of GM and b is the grey controlled variable. The normally differential equation $\frac{dx^{(1)}}{dt}+ax^{(1)}=b$ is to replace the source model; we call it as "whiteness processing" and $\frac{dx^{(1)}}{dt}+ax^{(1)}=b$ is called the shadow equation.

Step5: Parameters a and b can be obtained by the minimum least square estimation.

According to the source model $x^{(0)}(k)+aZ^{(1)}(k)=b$ for all k=2,3,…n, we can get

$$\begin{aligned} &x^{(0)}(2)+aZ^{(1)}(2)=b\\ &x^{(0)}(3)+aZ^{(1)}(3)=b\\ &\quad\vdots\\ &x^{(0)}(n)+aZ^{(1)}(n)=b \end{aligned} \quad (5)$$

Transferring the terms of the source model, it can be rewritten as

$$x^{(0)}(k)=-aZ^{(1)}(k)+b \quad (6)$$

Set $B=\begin{bmatrix}-Z^{(1)}(2) & 1\\ \cdots & \\ -Z^{(1)}(2) & 1\end{bmatrix}, y_N=\begin{bmatrix}x^{(0)}(2)\\ \vdots\\ x^{(0)}(n)\end{bmatrix}, \theta=\begin{bmatrix}a\\ b\end{bmatrix}$.

, equation (6) can be rewritten as $y_N=B\theta$ .Resolving the matrix relation, we get

$$\begin{bmatrix}a\\ b\end{bmatrix}=\left(B^TB\right)^{-1}B^Ty_N \quad (7)$$

Step 6: By solving the whitening equation, we can get the prediction function for the grey system

$$\hat{x}^{(1)}(k+1)=\left(x^{(0)}(1)-\frac{b}{a}\right)e^{-ak}+\frac{b}{a} \quad (8)$$

Step 7: Taking inverse accumulated generating operation (IAGO) on $x^{(1)}$.The corresponding IAGO sequence $x^{(0)}$ is denoted as $x^{(0)}=IAGO*x^{(1)}$, we can get

$\hat{x}^{(0)}(k+1)=\hat{x}^{(1)}(k+1)-\hat{x}^{(1)}(k)$, where $\hat{x}^{(0)}(k+1)$ the predicted value of $x^{(0)}(k+1)$.

Then, we use the predicted value as the value of the input variable for the fuzzifier.

The number of available channels is the indicator used as an example of the calculation procedures for the prediction formula, and the predicted calculations for other variables follow the same way. We will adopt four-data series from T1 to T4 as original data to forecast the number of available channels at T5. Before we start the procedure, we must check the data by ratio tested whether it can be used or not. If the data is accepted, we can use it. The example of estimation will involve the following steps:

1. the original data of the number of available channels between T1 and T4
   $x^{(0)}$=(*5 ,10,8,3*)
2. Do the ratio test
   5/10=0.5, 10/8=1.25, 8/3=2.67
   The data satisfies the class ratio test.
3. Applying AGO on the original data yields the data sequence
   $x^{(1)}$=(*5,15,23,26*)
4. From grey differential equation $Z(k)$,
   $z^{(1)}=(z^{(1)}(2), z^{(1)}(3), z^{(1)}(4))$=(10,19, 24.5)
5. Matrix B and fixed vector Y are accumulated as follows:
   $$B=\begin{bmatrix}-10 & 1\\ -19 & 1\\ -24.5 & 1\end{bmatrix}, Y=\begin{bmatrix}10\\ 8\\ 3\end{bmatrix}$$
6. Solve the development coefficients a and b in Equation (7) by the least-square method
   a=0.4572 , b=15.1540
7. From the grey shadow equation,
   $\hat{x}^{(1)}(k+1)=-28.1452e^{-0.4572k}+33.1452$
8. Restore the predicted value by IAGO,

$$\hat{x}^{(0)}(5)=\hat{x}^{(1)}(4+1)-\hat{x}^{(1)}(4)=28.6249-26.0047=2.6202$$

In a grey prediction control system, we often apply metabolic models to do predictions. Hence, the parameters of the prediction equipment vary with time. When a new data value is collected and is accepted by the sampling equipment, an older data value will be deleted so that a newer model is established, and a series of new predicted values will appear accordingly. This end guarantees a strong adaptability of the system [50].If the data sequence don't pass through the class ratio test, we don't adopt the predicted value, but we take the original value instead. We have considered an interval of real numbers and the notation $A=\int_u u_x(x)/x$, and $B=\int_u u_x(y)/y$, where x is the actual input value for the available channel and y is the actual input value for the traffic load, respectively. A is the available channel membership function and B is the traffic load membership function. Let a_i present the center value for linguistic labels of available channel membership function for $0 \le i \le 6$, and let b_i present the center value for linguistic labels of traffic load membership function for $0 \le i \le 2$. The status of A may be very cold (VC), cold (C), moderate (M), hot (H) or very hot (VH) for different value of available channels (x) and the status of B may be low (L), moderate (M) or high (H) for different value of traffic load (y). The fuzzified information is then passed on to the fuzzy inference engine.

IV. CELL INVOLVED NEGOTIATION

After cell load level of each BS has been decided by the load information, the objective of the cell negotiation is to select the cell to or from which channels will be borrowed when the cell load reallocation event takes place. The traditional channel allocation algorithm in negotiation can be classified into *update* and *search* methods [8]. In the search approach, a cell does not inform its neighbors of its channel acquisitions or releases. When a cell needs a channel, it searches all neighboring cells to compute the set of currently available channels, and then acquires one according to the underlying DCA strategy. In the updated approach, a cell always informs its neighbors whenever it acquires/releases a channel so that each cell knows the set of channel available for its use and underlying DCA strategy. Both approaches have advantages and disadvantages. The updated approach has short acquisition delay and good channel reuse, but it has higher message complexity. In other word, the search approach has lower message complexity, but it has longer acquisition delay and ineffective channel reuse. 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 GF-RRM algorithm is activated requesting its cluster for help, and attempts to borrow sufficient free channels to satisfy its demand. Our researchers took advantage of fuzzy logic control and presented an enhance version of 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 fuzzy enhanced algorithm can enhance the overall system performance effectively. 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. Each BS keeps the state information of the cells and runs the channel borrowing algorithm to update load state in period.

A. Inference Engine

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

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

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

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

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

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

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

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

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.

TABLE I FUZZY RULES FOR CHANNEL BORROWING/LENDING CONTROL

	Low	**Moderate**	**High**
Very Cold	(Lending) Negative Large (1)	(Lending) Negative Moderate (2)	(Lending) Negative Small (3)
Cold	(Lending) Negative Moderate (4)	(Lending) Negative Small (5)	(Stable) Approximately Zero (6)
Moderate	(Lending) Negative Small (7)	(Stable) Approximately Zero (8)	(Borrowing) Positive Small (9)
Hot	(Stable) Approximately Zero (10)	(Borrowing) Positive Small (11)	(Borrowing) Positive Moderate (12)
Very Hot	(Borrowing) Positive Small (13)	(Borrowing) Positive Moderate (14)	(Borrowing) Positive Large (15)

Pertaining to the given control problem is formulated in terms of a set of fuzzy inference rules. We use five load actions, which are Very Cold, Cold, Moderate (stabilize-state), Hot, and Very Hot. This Section consists of $5 \times 3 = 15$ possible rules as shown in Table 1. The two axes of the matrix are for available channel membership function and traffic load membership function. The entries of the matrix represent the effects of the actions to the goal. So an entry matrix of Table 1 means that action and individual steps of the GF-RRM three design phases.

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 cells or cold cells whenever it finds any very hot cell or hot cell. The moderate cells are neither allowed for reallocation any channels from nor to any other cells nor updated interfering cluster cells.

V. MULTI-CHANNEL MIGRATING

The new channels migrating with multi-channels transferring can reallocate channels well especially in an unpredictable variation of cell load. Our mechanism for multi-channel transfer calculates the amount of transferred channels by the number of available channels and traffic load. The GF-RRM, we have discussed in the last section have a common property; when a requesting cell and a probed cell are decided, the number of reallocated channels is just one channel in each iteration. It is very inefficient if the cell load of two cells differ with a large value. Our idea is to borrow several channels once instead of only one between two cells. For example, in the next generation multi-media mobile network, a call may need multiple channels at a time. In this idea, we could make the cell load between two cells more balanced. The channel requesting messages transmitted between hot cell i and cold cell j are classified into four categories as follows.

1. Request message, *request* (i): Message sent by the hot cell i to cluster cells to request the free channels.
2. Reply message, *reply* (j,V_j,U_j): Message from cold cell j, $j \in cluster$ cells responding to borrow cell i. The message also includes the information on the reserved channels in cell j.
3. Inform message, *inform* (i,B_{ij}): Message sent by borrowing cell i to the lending and the other cells in the cluster to inform them about its channel acquisition decision, where B_{ij} is set of channels borrowed by hot cell i from cold cell j .The message also includes the requests of the reserved channels if any.
4. Confirm message, confirm (j,L_{ij})*:* Message sent by cold cell j to borrow hot cell i to inform it the availability of the requested channels that have been reserved at lend cold cell j. Where L_{ij} is the set of confirmed channels lent from cold cell j to hot cell i, and cold cell j can still assign the reserved channels to new arrival calls before sending the confirm message back to hot cell i.

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

The purpose of defuzzification is to convert each result obtained from the inference engine, which is expressed in terms of fuzzy sets, to a single real number. Defuzzification is a mapping from a space of fuzzy control actions defined over an output universe of discourse into a space of non-fuzzy (crisp) control actions. This process is necessary because in many practical applications crisp, control action is required for the actual control. Figure 1 shows the membership function for the channel borrowing/lending a quantity control number of the channel range [*-d,+d*] of the fuzzy output. The function is defined on the interval [*0,+d*] for borrowing action, and on the interval [*0, - d*] for lending action. We have used *center of area* (*COA*) method because it supports software real time fuzzy controls to differentiate the difference of load on two cells. This value is calculated by the formula

$$Y^{o}_{COA} = \left[\left| \frac{\sum_{i=1}^{n} W_i * B_i}{\sum_{i=1}^{n} W_i} \right| - IN(C) \right]$$

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.

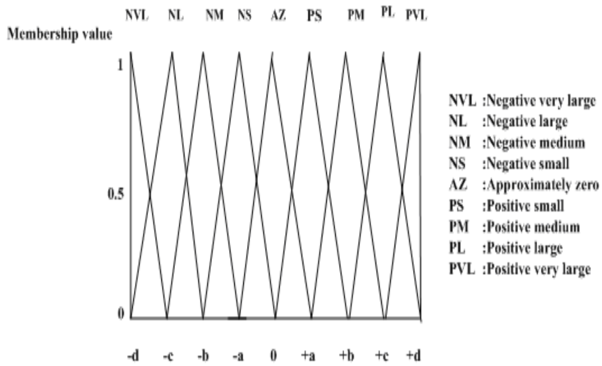

Fig. 1 The membership function of the fuzzy output.

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

Migrate restrict = Min [borrowing cell (Y^{o}_{COA}), lending cell (Y^{o}_{COA})]

VI. EXPERIMENTAL RESULTS

The problem domain naturally lends itself to simulate using multiple threads since there is a lot of concurrence and global resource management issues in the system. The simulated model consists of 14 clusters. Each cluster consists of 7 homogeneous cells. 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 30Kbps of multi-channels migration. We assume $\lambda_0 = 100 - 2000$ calls calls/per hour be the call originating rate per cell and $\lambda_h = \lambda_0 \times 0.01 - \lambda_0 \times 1$ be the hand-off traffic density per cell. We assume that traffic density pattern for performance analysis as λ_h / λ_0 , and the *d*=1 sec communication delay between cells, and each handoff and new calls request delay constraint DC=5 sec. 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, respectively. Let the density of simulation be 500 peoples per cell and the velocity is from 0km to 100 km/h. We define that the time of the sample interval is 3 minutes 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.

1. Request message, request (*i*): Message sent by the hot cell i to cluster cells to request the free channels.
2. Reply message, reply (*j*, V_j ,Uj): Message from cold cell *j*, $j \in$ cluster cells responding to borrow cell *i*. The message also includes the information on the reserved channels in cell *j*.
3. Inform message, inform (*i*,B_{ij}): Message sent by borrowing cell *i* to the lending and the other cells in the cluster to inform them about its channel-acquisition decision, where B_{ij} is set of channels borrowed by hot cell *i* from cold cell *j*. The message also includes the requests of the reserved channels if any.
4. Confirm message, confirm (*j*,L_{ij}): Message sent by cold cell *j* to borrow hot cell *i* to inform it the availability of the requested channels that have been reserved at lend cold cell *j*. Where L_{ij} is the set of confirmed channels lent from cold cell j to hot cell *i*, and cold cell *j* can still assign the reserved channels to new-arrival calls before sending the confirm message back to hot cell *i*.

In order to represent various multi-media services, three different types are assumed based on the channel requirement and QoS. The duration of calls are distributed by different means for different multi-media traffic types. In our simulation three types of traffic services are assumed: voice service, video phone and video on demand. These types are defined on the channel requirement 30Kbps, 64Kbps and interval 128Kbps - 256Kbps, respectively. The assumptions of three performance metrics for our simulation study are as follows:

1. *Blocking calls*: If all the servers are busy, and the cell does not succeed to borrow a channel from its cluster cells, then handoff and new calls, generated at this particular cell are stored in the queue, otherwise they get service. If new and handoff calls do not get service of neither free channels nor borrowed channels, then the handoff and new calls are requested. When it's waiting time (delay constraint) is over, the calls must be blocked.
2. *Update Message complexity:* Each cell needs to communicate with co-channel and cluster cells in order to exchange the set of load state information.
3. *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 grey-fuzzy controller for radio resource management (GF-RRM) is compared with the fixed channel assignment (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 numbers of hot cells vs. blocked calls have been observed in our scheme. Figure 2 compares blocking probability and traffic arrival rate. The call blocking probability is defined as the ratio of the number of new calls initiated by a mobile host which cannot be supported by existing channel arrangement to the total number of new calls initiated (i.e., a call arriving to a cell finds both fixed and dynamic channels busy).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 fixed channel assignment algorithms blocks more than the other methods. When the traffic load increases, the number of blocked channel request also increases. For fixed channel assignment, it increases at faster blocking rate than by using other methods. The reason for this is that a BS can only use its nominal channels. When traffic load becomes hot, nominal channels are used up in many BSs. In cell cluster, while fixed channel assignment algorithms reject all the new channel requests, the other schemes can handle the imbalance and satisfy new channel requests by borrowing channel from BSs with cold traffic load. Figure 3 compares the channel assignment algorithms according to the call blocking probability of channel request for multi-media services. When the traffic load increases, call blocking rate of channel requests increases at a slower rate than the other schemes. In Figure 4 depicts the messages of different channel borrowing schemes, and we found that our proposed DCA 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. Figure 5 show that our proposed scheme has the shortest channel acquisition delays. This result is used in all traffic conditions in a channel allocation scheme with efficient channel.

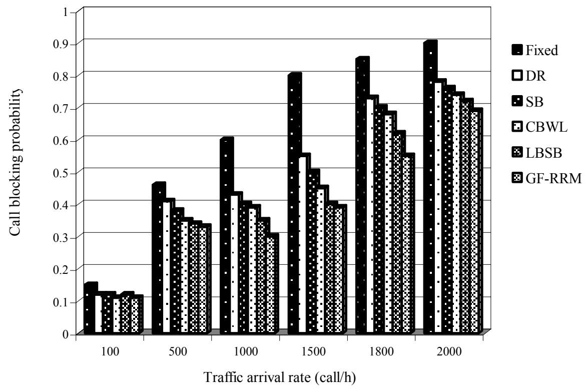

Fig. 2: Compare blocking probability and traffic arrival rate.

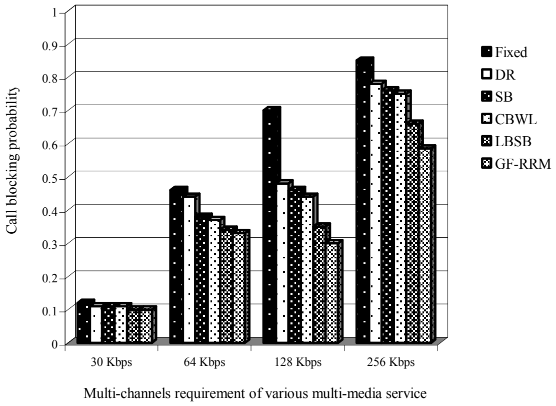

Fig. 3: Compare blocking probability and multi-channels requirement of multi-media service.

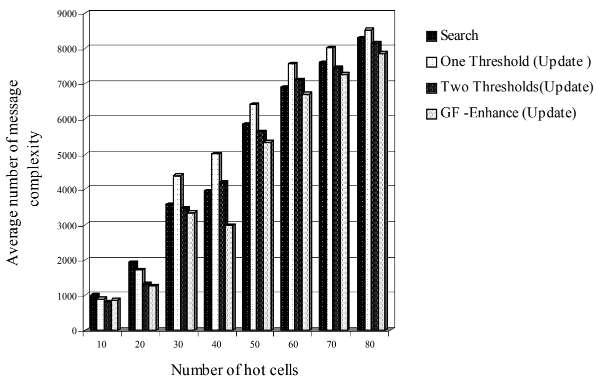

Fig. 4: Compare the average number of update messages overhead of our proposed scheme with others.

VII. CONCLUSION

Our work is the first propose attempt a dynamic channel-borrowing problem with grey-fuzzy control. The presented paper has highlighted the role of grey-fuzzy and its application in wireless cellular networks. In addition, GF-RRM has shown a faster and smoother response time than conventional systems. Based on predicted input parameters, a set of fuzzy inference rule is established.

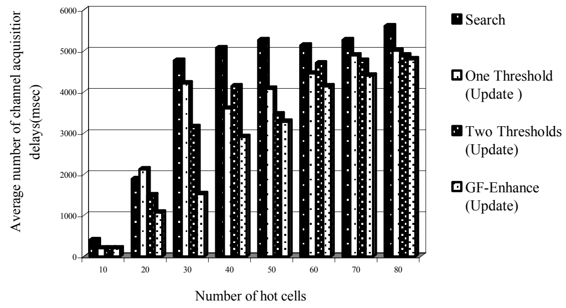

Fig. 5: The channel acquisition delays of various schemes.

Since grey-fuzzy control rules are constructed by using linguistic variables, intuitive knowledge is easily integrated into the control system. We believe that a fuzzy decision making with grey prediction for the control and management cellular networks is more appropriate than the conventional probabilistic models. It also can efficiently determine the suitable cell for borrowing channels. The performance of the proposed scheme is better than that of the conventional schemes on the blocking rate, messages complexity and channel acquisition delays. The work is evaluated through simulated comparisons with other proposals in terms of admission ratios and message complexity. As aforementioned, the main drive of this work is creating a system that is adaptable, and that is independent from specific traffic models. The advantage of the proposed scheme might be the result of the borrowing channels in batches instead of a single channel at a time, in addition to rectifying the types that are to borrow/lend channels during a cell overload.

REFERENCES

[1] "http://www.3gpp.org", 2002.
[2] H. Holma and A. Toskala (eds.), WCDMA for UMTS. Wiley, 2000.
[3] 3rd Generation Partnership Project Technical Specification Group Radio Access Network. Working Group 1, "Physical Layer – Measurements." TS25.225 v4.0.0. 2001.
[4] 3rd Generation Partnership Project. Technical Specification Group. Radio Access Network "Radio Interface Protocol Architecture." TS25.301 v4.2.0. 202.
[5] 3rd Generation Partnership Project. Technical Specification Group. Radio Access Network "Radio Resource Control (RRC); Protocol Specification." TS25.331" 4.4.0, 2002.
[6] S. K. Das, S. K. Sen and R. Jayaram, A structured channel borrowing scheme for dynamic load balancing in cellular networks, IEEE Distributed Computing Systems Conference, pages 116-123, 1997.
[7] J. Kim, T. Lee, and C. S. Hwang, A dynamic channel assignment scheme with two thresholds for load balancing in cellular networks, IEEE Radio and Wireless Conference, pages 141-145, 1999.
[8] X. Dong and T. H. Lai, Distributed dynamic carrier allocations in mobile cellular networks: search vs. update, IEEE Distributed Computing Systems Conference, pages 108–115, 1997.
[9] 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.
[10] 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.
[11] S. Kim and P. K. Varshney, Adaptive Load Balancing with Preemption for Multimedia Cellular Network, IEEE Wireless Communications and Networking Conference, pages 1680–1684, 2003.

[12] T. S. Yum and M. Zhang, Comparisons of channel-assignment strategies in cellular mobile telephone systems, IEEE Transactions on Vehicular Technology, pages 211–215, 1989.
[13] Y. -T. Wang and J.-P. Sheu, A Dynamic Channel Borrowing Approach with Fuzzy Logic Control in Distributed Cellular Networks, the special issue of Simulation Modeling Practice and Theory, Vol. 12, pages 287 – 303, 2004.
[14] Y. T. Wang, A Fuzzy-Based Dynamic Channel Borrowing Scheme for Wireless Cellular Networks, IEEE Vehicular Technology Conference, pages 1517–1521, 2003.
[15] L. A. Zadeh, Fuzzy Algorithm. Information and Control, pages 94–102, 1968.
[16] Y. Zhang, A new adaptive channel assignment algorithm in cellular mobile systems, IEEE Systems Sciences Conference, pages 1–7, 1999.
[17] J. S. Engel and M. Peritsky, Statistically-optimum dynamic sever assignment in systems with interfering severs, IEEE Vehicular Technology Conference, pages 1287-1293, 1973.
[18] H. Haas and S. McLaughlin, A novel decentralized DCA concept for a TDD network applicable for UMTS. IEEE Transactions on Vehicular Technology, pages 881-885, 2001.
[19] J. Karlsson and B. Eklundh, A cellular mobile telephone system with load sharing-an enhancement of directed retry, IEEE Transactions on Communications, pages 530-535, 1989.
[20] S. Mitra and S. DasBit, A load balancing strategy using dynamic channel assignment and channel borrowing in cellular mobile environment, IEEE Personal Wireless Communications Conference, pages 278-282, 2000.
[21] J. L. Deng , Control problem of grey systems, System and Control Letters, Vol. 1, pages 288-294, 1982.
[22] Ren C. Luo and Tse Min Chen , Autonomous Mobile Target Tracking System Based on Grey-Fuzzy Control Algorithm, IEEE Transactions on Industrial Electronics, VOL. 47, NO. 4, pages 920-931, 2000.
[23] C.-Y. Kung, K.-T. Hsu, T.-M. Yan and P.-W. Liu, An Application of the Grey Prediction Theory to the Annual Medical Expense of Taiwan's National Health Insurance, Journal of Grey System, Vol. 9, No. 2, pages 75-86, 2006.
[24] W.-N. Pi and L.-C. Liou, Electric Power Demand Forecasting in Taiwan via Grey Prediction, Journal of Science and Engineering Technology, Vol. 3, No. 2, pages 11-18, 2007.
[25] Y.-T. Wang and K.-M. Hung "Fuzzy Logic Based Neural Network Model for Load Balancing in Wireless Networks. " KICS Communications Society, International Journal of Communications and Networks, Vol. 10, pp.38- 43, 2008.