Call Admission Control in Mobile Cellular Systems Using Fuzzy Associative Memory

Sivaramakrishna Mopati, and Dilip Sarkar

***Abstract*— In a mobile cellular system quality of service to mobile terminals (MTs) is measured by the probability of new call blocking P_b, and the probability of forced termination, P_{ft}. Since the available bandwidth in a cell is very limited, both P_b and P_{ft} cannot be reduced or avoided simultaneously. Usually keeping the P_{ft} below a designated level is accepted as the measure of quality of service. Admission of new calls is controlled to reduce P_{ft}. However, there are at least three parameters (new call arrival rate, mean duration of calls, and mobility of users) that can and change dynamically. Moreover, these parameters are related with P_{ft} via complicated non-linear equations. Therefore, Call Admission Control (CAC) for maintaining a desired value of P_{ft} is a very challenging task. No CAC algorithm has been reported in the past that can function well with dynamic changes to all these three parameters. We proposed an algorithm that addresses this issue. The new algorithm uses a fuzzy controller to adjust the call pre-blocking load value with the changing traffic parameters. The fuzzy controller makes use of fuzzy associative memory (FAM) to maintain the required QoS. The use of new system in dynamic traffic conditions is illustrated. Providing the required level of QoS, the algorithm also increases the channel utilization. The proposed CAC with FAM is compared and contrasted with previous CACs.**

***Index Terms*—Call holding time, Cell dwell time, Quality of Service(QoS), Fuzzy Associative Memory, Call Admission Control.**

I. Introduction

WIRELESS cellular networks derive their name from the fact that the service area of these networks is divided into a group of cells, with each cell being controlled by a Base Station (BS). When a user requests a service from the network through a mobile terminal (MT), his request may be accepted or denied based on the availability of required resources in the user's resident cell. This denial of service is known as *call blocking*, and its probability is called *call blocking probability* P_b. A mobile terminal can move from current cell to another during the lifetime of the call, which requires successful handoff from the current cell to the new cell. A handoff will be unsuccessful if enough resource is not available in the new target cell. As a mobile may cross many cell boundaries during the lifetime of a call, failure to get successful handoff at any cell boundary will force the service to end abruptly, which is known as *forced termination*, and its probability is called *forced termination probability* P_{ft}.

With the increase in demand for wireless services, wireless networks are making use of micro/pico cellular architecture. This means reduced cell size and increase in the number of cells in a given geographic area. This in turn increase the number of handoffs and the *Probability of forced termination* for MTs.

The average lifetime of a call in the system is known as *call holding time* or *call duration* (and is denoted by $1/\mu$). The average time that a call resides in a particular cell is known as *residence time* or *cell dwell time* (and is denoted by $1/\eta$). The new calls arrive in a cell at a mean arrival rate of λ calls/sec. The *load* of a cell is the ratio of new call arrival rate to call completion rate, $\rho = \lambda/\mu$ Erlangs/cell.

A. QoS and Variation of System Parameters

The *QoS* of a cellular system can be measured by the three parameters, namely P_b, P_{ft} and P_{hf}. Since terminating of an ongoing call is considered more undesirable than blocking a call which is trying to access the network, we use P_{ft} as measure of QoS of the network. It is known that,

$$P_{ft} = f(n, \lambda, \eta, \mu) \tag{1}$$

where *n* is the number of channels in the cell.

An ideal system should adapt itself to the changes in the network occurring in the real-time without exceeding desired value of the P_{ft} and at the same time should have high channel utilization. In section II we review merits and demerits of various Call Admission Control (CAC) algorithms with emphasis on the CAC with constant pre-blocking. We then propose a novel CAC algotithm that makes use of Fuzzy Associative Memory

Dr. Dilip Sarkar is with the Department of Computer Science, University of Miami. E-Mail: sarkar@cs.miami.edu

Sivaramakrishna Mopati is with the Department of Computer Science, University of Miami. E-Mail: s.mopati@umiami.edu

(FAM) to dynamically adjust the pre-blocking load value. In section IV we present the design of our fuzzy controller for the mobile system. Operation of the entire system is described in section V with an example. The fuzzy controller is evaluated and its performance results are presented in section VI followed by conclusion in section VII.

II. Review of CAC Algorithms

Call admission control plays a key role in maintaining desired level of QoS. The two CAC algorithms namely static Guard Channel Scheme and Channel Pre-request Scheme provide desired QoS under constant traffic conditions. However they fail when one or more of the system parameters vary significantly from the default values. Guard channel scheme under utilizes the channels in the network during low mobility whereas Channel pre-request scheme fails to provide required QoS when the load goes beyond a pre-determined value [3].

A. CAC Algorithm with Call Pre-Blocking

This scheme recently proposed in [3], provides the required QoS by controlling the *observed load* of a cell, irrespective of the *actual load* of the system. A maximum new call arrival rate, and hence load ρ_m for a desirable value of P_{ft} is determined, either by simulation or by an analytical method. The value of ρ_m is chosen such that, any load above ρ_m fails to keep P_{ft} value below desired level. During the operation of the system, the arrival rate and hence the expected load is estimated. If the estimated load is no more than ρ_m *and* a channel is available, the call is accepted into the system. Otherwise, the load is greater than ρ_m, and only a fraction f_r, of the incoming calls is attempted to allocate a channel. The fraction is calculated as $f_r = \rho_m / \rho_0$, where ρ_0 is the estimated load. Thus ρ_m can be considered as the effective load entering into the cell although the actual load is ρ_0. The block diagram describing the main components of this system is shown in Figure 3 in solid lines. This scheme can maintain a predefined level of P_{ft}, irrespective of new call arrival rate, provided the call holding time and the cell dwell time to remain constant. If the average call holding time and/or the average cell dwell time changes from the default values (which is generally the case in real-world systems), the desired level of P_{ft} cannot be guaranteed — either under utilization of network resources or increase in the P_{ft} results.

The curves labelled "P_{ft} withour FAM" in Figures 1 and 2 show the variation of P_{ft} in the system with change in cell dwell time and call holding time respectively. The graphs clearly show that P_{ft} value is close to 2 percent (which is the desired value) only for a short range of values of dwell time and holding time. Most of the time, the P_{ft} is either very high (indicating bad QoS) or very low (indicating low channel utilization). This indicate that any constant value of ρ_m for call pre-blocking cannot maintain a constant P_{ft} with varying parameters. The limitations of the above schemes show us the need for a system which can adjust ρ_m value with the change in system parameters. In the following sections, we introduce fuzzy associative memory and construct a fuzzy controller for the mobile system.

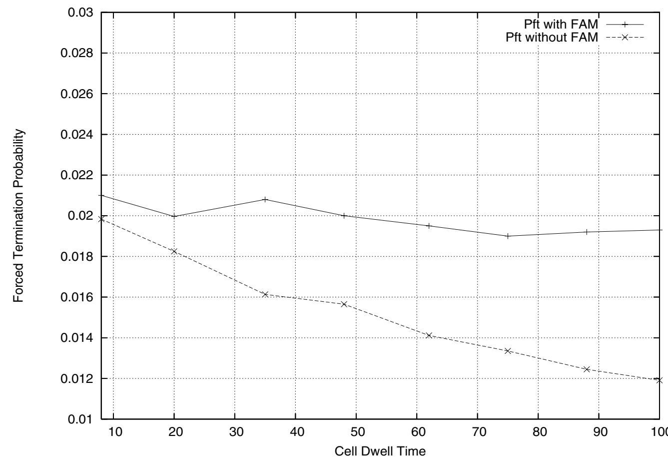

Fig. 1. Variation of P_{ft} with change in $1/\eta$ for constant $1/\mu$

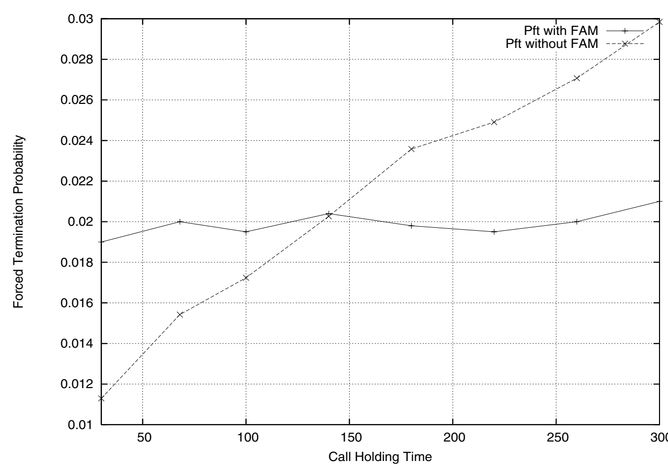

Fig. 2. Variation of P_{ft} with change in $1/\mu$ for constant $1/\eta$

III. Proposed CAC System with FAM

Figure 3 shows a block diagram of the proposed system. A fuzzy controller (shown in dotted lines) has been added to adjust the value of ρ_m for maintaining desired value of P_{ft}. If P_{ft} is smaller than that of the desired value, ρ_m

ought to be increased for better utilization of network resources. On the other hand, if P_{ft} is greater than that of the desired value, ρ_m ought to be decreased for QoS guarantee. Since even for a Markovian system, P_{ft} and ρ_m are related through a set of non-linear equations, real-time on-line computation of preblocking load value ρ_m is impractical. Hence, for estimating the acceptable value of ρ_m, we propose a fuzzy controller. It is assumed that each cell periodically estimates the average values of cell dwell time, call holding time, and forced termination probability for using as inputs to the fuzzy controller. The fuzzy controller computes the change in ρ_m value to maintain the required P_{ft}. This process continues throughout the operation of the system. Thus we have a feedback mechanism which controls ρ_m and in turn P_{ft} dynamically.

Let $P_{ft}[k]$ be the value of call forced termination probability after observation period k. Let the change of forced termination probability, $\Delta P_{ft}[k] = P_{ft}[k] - P_{ft}[k-1]$, between two successive observations be small enough for relating it with that of ρ_m by a linear equation.

$$\Delta P_{ft}[k] = slope \times \Delta \rho_m[k] \tag{2}$$

Thus, we can calculate $\Delta\rho_m[k]$ from the value of the $slope$ and $\Delta P_{ft}[k]$. We develop a FAM for storing a set of rules and an inference mechanism that uses the rules for computing a slope value for a given pair of values for average call holding time and cell dwell time.

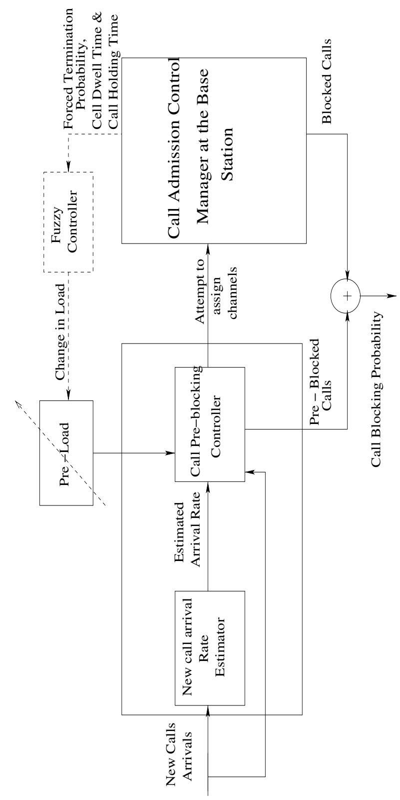

Fig. 3. Block Diagram for CAC with constant pre-load and Varying Pre-load .

IV. Design of FAM for Mobile System

Let the range of average cell dwell time be from dt_{min} to dt_{max}, and that of call holding time be from ht_{min} to ht_{max}. For our experiments we used $dt_{min} = 8$, $dt_{max} = 100$, $ht_{min} = 30$, and $ht_{max} = 300$. The design of fuzzy controller consists of three steps namely fuzzification of control and solution variables, inference mechanism and defuzzification.

Fuzzification of control and solution variables: For our system two control variables are the average cell dwell time and the average call holding time. Solution variable is the slope of ρ_m which is required to calculate the change in ρ_m for a particular P_{ft}. To construct the FAM we define eight fuzzy sets on each of the control variables. These sets are denoted by the linguistic (fuzzy) variables: Very Very Low (VVL), Very Low (VL), Low (L), Medium (M), High (H), Very High (VH), Very Very High (VVH), and Very Very Very High (VVVH) respectively. Fuzzification involves scaling and mapping of these input variables to fuzzy sets. This is done by defining the membership functions. We use triangular and trapezoidal membership functions for case of computation. The membership functions for call holding time used in our experiments are shown in Figure 4. Note that the interval be-

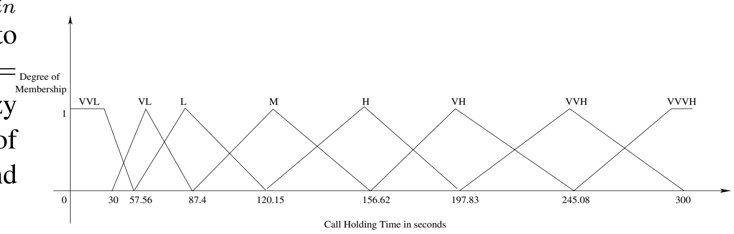

Fig. 4. Membership functions for the *Call Holding Time*

tween ht_{min} and ht_{max} has been divided into seven segments whose lengths are in *geometric progression* (GP). The GP partitioning was based on extensive study and educated guess for spacing ρ vs P_{ft} curves evenly. A set of these curves are shown in Figures 5. Similarly, we defined the membership functions for cell dwell time. The length of segments were a combination of a *arithmetic progression* and a *geometric progression*. We also define the membership functions for the fuzzy solution variable $slope$ by defining eight fuzzy sets with identical names. The range of the values for the solution variable is de-

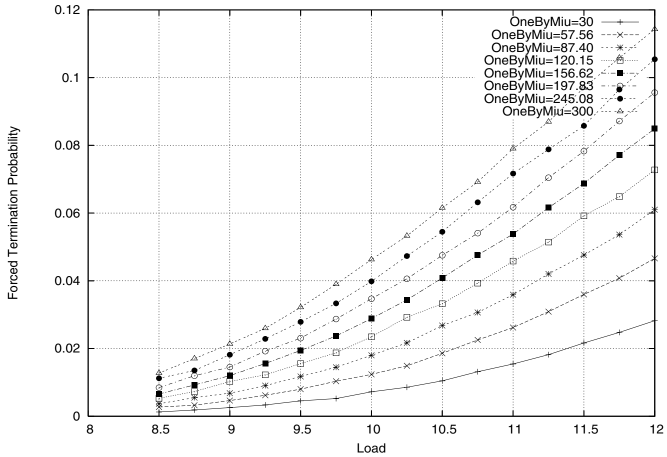

Fig. 5. Variation of P_{ft} with load for $1/\eta$ kept constant at 8 seconds

termined by the ranges of the values of control variables. With $(8 \times 8 =)$ 64 combinations of cell dwell times and call holding times, we plotted 64 curves.

Now for each curve, the point on the X-axis at which the P_{ft} value just crosses the desired forced termination probability (DP_{ft}) mark gives the call pre-blocking load value for that particular combination of cell dwell time and call holding times. For example, in the Figure 5 for $1/\mu$ = 156.6 seconds and $1/\eta$ = 8 seconds, load value of 9.5 Erlangs/cell gives DP_{ft} of about 0.02. In our desired intervals the value of ρ_m changes from a minimum of about 8.9 Erlangs/cell to a maximum of 16.5 Erlangs/cell for the DP_{ft} of 0.02. We computed $slope$s at all required values of ρ_m, and used them to define the fuzzy membership functions for the solution variable $slope$.

FAM and Inference mechanism: This involves defining various fuzzy rules which say how the system adjusts solution variable to maintain the desired QoS. In general, a fuzzy rule is of the form

If <fuzzy proposition>, then <fuzzy proposition>

where the fuzzy propositions are of the form, "x is Y" or "x is not Y," x being a scalar variable and Y being a fuzzy set associated with that variable [5]. The number of rules a system requires is related to the number of control variables. As our mobile system has two control variables, each of which is divided into eight fuzzy regions, there are 64 rules for 64 possible input combinations. All these rules are represented in a matrix form with the combination of inputs giving the required outputs. Such matrix forms the *fuzzy associative memory* for the system. The FAM for our system is shown in Table I. As an example, the following two rules can be derived from the matrix,
If cell dwell time is VS *and* call holding time is H *then* slope shall be VVH.
If cell dwell time is VH *and* call holding time is S *then* slope shall be H.

TABLE I

FUZZY ASSOCIATIVE MEMORY

		HOLDING TIME							
D		VVS	VS	S	M	H	VH	VVH	VVVH
W	VVS	VH	VH	VVH	VVH	VVH	VVH	VVVH	VVVH
E	VS	VH	VH	VH	VVH	VVH	VVH	VVH	VVVH
L	S	H	VH	VH	VH	VH	VVH	VVH	VVVH
L	M	M	H	H	H	VH	VVH	VVH	VVH
T	H	S	M	H	H	VH	VH	VVH	VVH
I	VH	S	M	H	H	H	VH	VH	VH
M	VVH	VS	S	M	H	H	VH	VH	VH
E	VVVH	VVS	VS	S	M	H	H	VH	VH

Defuzzification: This involves conversion of the fuzzy outputs into crisp outputs. The fuzzy output value of ρ_m slope which is obtained from the inference mechanism is converted into the real value based on the definition of its membership functions. We used the center of area rule to determine the resultant slope value of the call pre-blocking load.

V. Operation of the System

Operation of the system consists of the following 5 steps

1) Estimation of parameters, namely cell dwell time, call holding time and P_{ft}.
2) Fuzzification of dwell time and holding time.
3) Firing of fuzzy rules using inference mechanism.
4) Estimation of pre-load slope.
5) Computation of change in pre-load from the slope.

The new call pre-blocking load value is then used to block the calls entering into the system. All these steps are repeated periodically during the operation of the system in order to maintain the desired P_{ft}.

For real-time estimation of the parameters μ, η, and P_{ft}, there are several factors that need consideration. They include storage requirements, computation power of the BS, and update period — time interval between two successive estimations and parameter updates. If the update period is too long, the BS will require a large storage to save all call related activities. Moreover, the adjustment of ρ_m as the control parameters change is delayed. On the other hand, if update period is too small, estimation errors are too high. Our experiments used 300 seconds for the update period.

Accurate estimation of P_{ft} is the most difficult problem. Especially, when desired P_{ft} value is very small, such as 0.02. During an update period there may be only a few forced terminated calls; even during some update periods no call may be forced terminated. To keep the effect of long observation period and that of small update period, we used what is known as exponential averaging. A fraction α of the observed value of forced termination probability OP_{ft} during the observation period k is added with $(1-\alpha)EP_{ft}[k-1]$, that is,

$$EP_{ft}[k] = \alpha OP_{ft}[k] + (1-\alpha)EP_{ft}[k-1] \quad (3)$$

Thus, the difference between the desired and estimated forced termination is $\Delta EP_{ft}[k] = (DP_{ft} - EP_{ft}[k]$ and the change in the pre-blocking load is obtained from

$$\Delta\rho_m[k] = \Delta EP_{ft}[k] \times slope \quad (4)$$

For calculation of $slope$ the fuzzy inference mechanism is invoked. Since the fuzzy membership functions may overlap (and most of the time they do), each $slope$ calculation may trigger as many as $(2 \times 2 =)$ four fuzzy rules. An example of slope calculation using fuzzy inference mechanism is shown next.

A. Example

Let the estimated value of cell dwell time be 18 seconds and the value of call holding time be 120 seconds. Also let the desired P_{ft} be 0.02. From our definitions of membership functions, cell dwell time of 18 seconds is 70 percent Small and 30 percent Medium. Likewise, the value of 120 seconds for call holding time is 100 percent Medium. These values trigger the following two rules from the knowledge base.

If cell dwell time is S *and* call holding time is M *then* slope shall be VH.

If cell dwell time is M *and* call holding time is M *then* slope shall be H.

The first of these rules gives the resultant slope to be 70 percent VeryHigh. As both the premises are combined using AND operator, we take the minimum of the degrees of membership. This is depicted in Figure 6. The next rule gives the slope to be 30 percent High. This is shown in Figure 7. By combining these two rules, we get the resultant area as shown in Figure 8. To combine the rules, we OR them together by taking the larger of the two values as the value of the combination at each point on the horizontal axis. The resultant area is shown in Figure 8. Using center of area method the pre-load slope is computed and is found to be 0.013. This slope value is used in equation 4 to compute $\Delta\rho$.

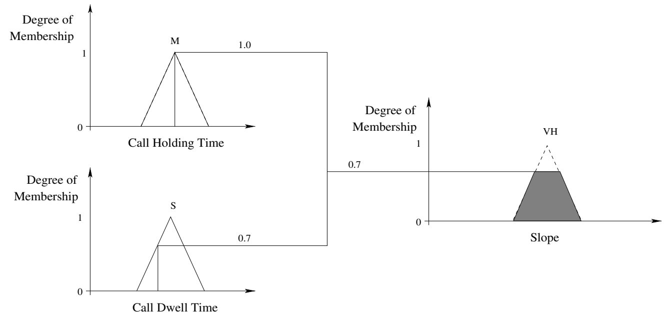

Fig. 6. Here we take the minimum of the degrees of the membership as the premises are connected by AND

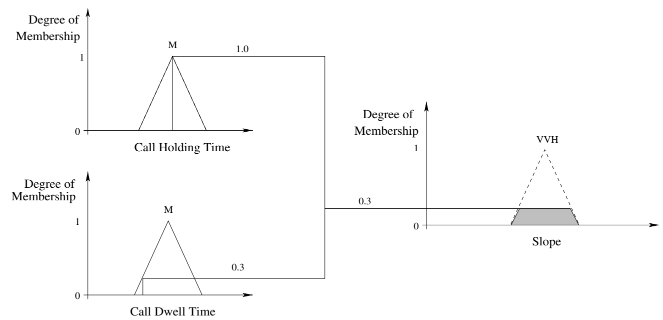

Fig. 7. Again we take the minimum of the degrees of membership as the premises are connected by AND

VI. Evaluation of the Fuzzy Controller

In this section we discuss the simulation model and results of our simulation. We used wraparound topology with 49 cells to eliminate boundary effect as in [7]. The mobility of MTs is modeled using a simple Brownian-motion or random walk approximation [8], [9]. A MT can move to any of the current cell's neighbors with equal probability - 1/6 for the hexagonal layout. It is assumed

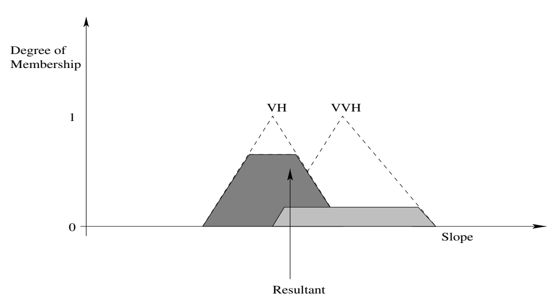

Fig. 8. Defuzzification

that the motion of the MTs is random between the cells and the trajectory of their motion is not known. Each cell is assigned 20 channels. New call arrivals into the network follow a Poisson distribution, call holding and cell dwell times are exponentially distributed. The desired on-going call forced termination probability, $DP_{ft} = 0.02$.

A. Results

Figure 1 shows the variation of P_{ft} with change in cell dwell time($1/\eta$). Call holding time and load ρ are kept constant at 120 seconds and 30 Erlangs/cell respectively. Two curves, one showing the system with FAM and the other without FAM are plotted. The system with FAM shows value of P_{ft} to be very close to 2% for all the values of $1/\eta$ as compared with the one without FAM which shows gradual decrease in P_{ft} with increase in $1/\eta$. This improvement in efficiency is obtained because the extended system adjusts the pre-blocking load value ρ_m with change in the value of $1/\eta$. Figure 2 shows the variation of P_{ft} with change in call holding time($1/\mu$). Cell dwell time and load ρ are kept constant at 12 seconds and 30 Erlangs/cell respectively. The figure shows the value of P_{ft} to be again very close to 2% for all the values of $1/\mu$ for the system with FAM. This can be compared to the system without FAM which shows gradual increase in P_{ft} with increase in $1/\mu$. This stability in P_{ft} is achieved because the proposed system using fuzzy controller adjusts the pre-blocking load value ρ_m with the changes in value of $1/\mu$.

From the above simulations and results, it is evident that the new system functions efficiently in changing traffic conditions. It maintains required P_{ft} at the same time having better channel utilization.

VII. Conclusion

Call admission control algorithms aim to provide desired level of QoS by following a particular strategy in admitting the calls into the system. Few such algorithms namely Guard channel scheme, Channel prerequest scheme and CAC with pre-blocking, although provide the required QoS at known traffic conditions, fail to reflect the dynamic nature of the system. The CAC with pre-determined call pre-blocking proposed in [3], assumes that both cell dwell time and call holding time to be constant for accurately controlling the actual load observed by a cell.

We proposed an algorithm that takes into consideration the all parameters of a cell for call admission control. The algorithm adjusts the new call pre-blocking load value based on changes in both of the parameters namely $1/\eta$ and $1/\mu$ to maintain the required value of P_{ft}. Since the value of change in pre-load to maintain a constant P_{ft} with random changes in $1/\eta$ and $1/\mu$ cannot be computed using mathematical equations, we used a fuzzy controller to determine its value. The fuzzy controller takes the values of P_{ft}, $1/\eta$ and $1/\mu$ at a given instant and gives the change in pre-load value to maintain the QoS.

With extensive simulation, we observed that FAM-based controller can maintain any desired P_{ft}. For further extension of this study, one may address the problem of maintaining QoS in the network servicing multiple classes of users with different QoS requirements.

References

[1] Y. B. Lin, S. Mohan, and A. Noerpel, *Queuing priority channel assignment strategies for PCS hand-off and initial access*, *IEEE Transactions on Vehicular Technology*, vol. 43, pp. 704-712, no. 3, August 1994.

[2] Qiang Ren and G.Ramamurthy, *A Real-Time Dynamic Connection Admission Controller Based On Traffic Modelling, Measurement, and Fuzzy Logic Control*, *IEEE Journal on Selected Areas in Communications*, vol. 18, no. 2,pp. 184-196, February 2000.

[3] Satya Kovvuri, Dipak Ghosal, Biswanath Mukherjee,and Dilip Sarkar, *A Call-Admission Control(CAC) Algorithm for Providing Guaranteed QoS in Cellular Networks*, *Proceedings of the International Conference on Broadband Wireless Access Systems*, April 2000.

[4] V.K. Garg and J.E. Wilkes, *Wireless and Personal Communication Systems*, Prentice Hall, 1996.

[5] Earl Cox, *Fuzzy Fundamentals IEEE Spectrum*, October 1992.

[6] Shigeo Abe, *Neural Networks And Fuzzy Systems - Theory and Applications*, 1997.

[7] L.O. Guerrero and A.H. Aghvami, *A prioritized handoff dynamic channel allocation strategy for PCS*, *IEEE Transactions on Vehicular Technology* vol. 48, No. 4, July 1999.

[8] Y.B. Lin, L.F. Chang, and A. Neorpel, *Modeling hierarchical microcell/macrocell PCS architecture*, *Proceedings of ICC*, (Seattle, WA), 1995.

[9] A.D. May, *Traffic Flow Fundamentals*, *Pentice Hall*, 1990.

[10] Elvino S. Sousa and John A. Silvester, *Spreading Code Protocols for Distributed Spread-Spectrum Packet Radio Networks*, *IEEE Transactions on Communications* vol. 36, No. 3, March 1988.

[11] Y.B. Lin, S. Mohan, and A. Noerpel, *PCS channel assignment strategies for hand-off and initial access*, *IEEE Personal Communications*, vol. 1, no. 3,pp 47-56,1994.

[12] Y.C. Kim, D.E. Lee, B.J. Lee, Y.S. Kim, and B. Mukherjee, *Dynamic channel reservation based on mobility in wireless ATM network*, *IEEE Communications Magazine*, pp. 47-51, Nov. 1999.