Efficient Radio Resource Control in Wireless Networks

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Abstract

In this paper, we propose a novel wireless radio resource manager to control both the transmission power and the bit rate of mobile devices cooperatively; whereas previous work has focused on handling them separately. The proposed scheme is called Genetic Algorithm for Mobiles Equilibrium (GAME). Based on an evolutionary computational model, GAME assigns optimally both the transmitting power and bit rate values to every mobile device in a given cell. Optimal allocation is in the sense that every mobile unit gets only enough resources necessary for meeting or exceeding its QoS requirements. GAME solves an optimization function that strives to maintain the QoS requirements of the different multimedia streams subject to the physical channel characteristics. Having done that, we gain further benefits as well. In addition to maintaining the QoS requirements, GAME tends to prefer assigning lower levels of transmission power thus extending the mobile units battery life, minimizing interference seen by other users, as well as significantly decreasing the call blocking (or dropping) rates. Furthermore GAME radio resources allocations reduce infrastructure costs by requiring fewer base stations per square kilometer. In our experiments, we have seen a 70% average expansion in the base station coverage area with 40% decrease in mobile call outage probability among other benefits.

Keywords- Resource Management, Power Control, Bit Rate Control, CDMA, Genetic Algorithms.

1. Introduction

Third-generation (3G) Mobile Communications Systems are poised to be multi-service platforms supporting voice, video and data services with bit rates up to 2 Mb/s [7, 18]. Essential to the success of 3G systems is their ability to provide guaranteed Quality of Service (QoS) requirements for each type of traffic (i.e., voice, video, and data) while efficiently utilizing the scarce wireless channels capacities. QoS requirements are often expressed by a set of parameters to be met by the network while transporting traffic streams from a source to a destination. For example, a typical set of parameters could include the Bit Error Rate (BER), guaranteed Bit Rate (R^G), end-to-end delay tolerance, jitter, and packet loss. The problem of guaranteeing QoS parameters is essentially a radio resource management one whereby the network strives to allocate just an enough amount of resources (e.g., bandwidth) to meet the users QoS requirements.

Since recent 3G partnership projects [2, 3] indicate that wideband Code Division Multiple Access (WCDMA) is the prevailing air interface in 3G Radio Access Networks (RAN), we concentrate this study on such environments. In a CDMA network, many QoS parameters, including BER, depend on the received bit energy-to-noise density ratio E_b/N_o which in turn depends on both the mobile station (MS) transmitter power and bit rate. Power control is a means primarily designed to compensate for the loss caused by propagation and fading. One of the most powerful methods is the Transmitter Power Control (TPC) specified within the Interim standard 95 (IS-95) [19] that is currently operating in all CDMA based systems. In fact this scheme is also included in all wideband CDMA 3G proposals [7, 18]; however, controlling only the transmitter power has its shortcomings. First, the Base Station (BS) does not differentiate between users' traffic during power assignments, and therefore there is no bit-rate guarantee to any MS. Secondly, a problem arises when an MS reaches its maximum transmitting power level without reaching its required E_b/N_o. This would lead to dropping the MS connection when this condition persists for some time [9].

In order to overcome these shortcomings, we propose a novel radio resources scheduler (RRS) that assigns to every MS not only the transmitter power but also the transmission bit rate, concurrently. Our scheme relies on the Genetic Algorithm for Mobiles Equilibrium (GAME) to allot each MS the minimum resources possible for meeting, or exceeding, its QoS requirements. We first introduced GAME as a standalone RRS [20] for simple outdoors environment. We then integrated GAME with the standard power control of IS-95 and called the integrated scheme (GAME-C) [21]. In this paper, we apply GAME-C in different cellular models including Manhattan streets microcells. Also we report new results showing how GAME-C enhances standard performance measures like spectrum efficiency and coverage efficiency. In addition to QoS provisioning, the MS battery survives longer since GAME will always prefer to assign lower transmission powers. Furthermore, BS coverage efficiency improves, since the call blocking rate significantly drops with our proposed solution.

In this work, our analysis applies to the uplink (MS to BS), which we assume is orthogonal to the downlink, and can be treated independently. We concentrate on the uplink as it is generally accepted that its performance is inferior to that of the downlink [10]. The remainder of this paper is organized as follows. We first present a brief review of state-of-the art CDMA radio resources scheduling techniques in section 2. The proposed scheme is detailed in section 3. In section 4, we discuss the multimedia environment used in our study as well as the different applicable cellular configurations. In section 5, we provide simulations results illustrating the performance improvements of the proposed GAME. We then close with some concluding remarks.

2. CDMA Resources Control

An important goal in a multiple-access system, such as the IMT-2000, is to maximize the number of simultaneous users it can accommodate. If each MS is assigned the minimum resources necessary for meeting or exceeding its QoS requirements, the capacity of the system will be maximized. That is why RRS is an essential component in QoS-aware BS. RRS has two important radio resources to control: MS transmitting power *P*, and bit rate *R*. In this section, we review some scheduling techniques highlighting their pros and cons.

In CDMA networks, the BER, an important QoS measure, depends on the received bit energy-to-noise density ratio E_b/N_o given by [8]

$$\left(\frac{E_b}{N_o}\right)_i = \frac{G_{BSi}P_i / R_i}{\left(\sum_{j\neq i}^{M} G_{BSj}P_j + \eta\right) \Big/ W} \qquad \textbf{(1)}$$

where W is the total spread spectrum bandwidth occupied by the CDMA signals. G_{BSi} denotes the path loss on the path between MS i and its BS. η denotes the background noise due to thermal noise contained in W and M is the number of mobile users. The transmitted power of MS i is P_i which is usually limited by a maximum power level, P_i^{max}, where

$$0 \le P_i \le P_i^{\max}, \qquad for \quad 1 \le i \le M \tag{2}$$

R_i is the information bit rate transmitted by MS i. This rate is bounded by the peak bit-rate R_i^P, designated in the traffic contract once this user has been admitted into the system.

$$0 \le R_i \le R_i^P, \qquad for \quad 1 \le i \le M \tag{3}$$

An increase in the transmission power of a user increases not only its perceived E_b/N_o, but also increases the interference seen by other users. This leads to a decrease in their perceived E_b/N_os. On the other hand, an increase in the transmission bit-rate of a user deteriorates its own E_b/N_o.

As denoted in (1), it is evident that manipulating the transmission powers and bit-rates of the mobile stations amounts directly to controlling the QoS that is partly specified as a pre-specified target E_b/N_o value (Θ).

2.1. Power Control

TPC contains two different power control mechanisms. In the uplink (MS to BS), both open loop (OLPC) and fast closed loop power control (CLPC) are employed. In Open loop scheme, the MS determines its transmitter power based on the measured received signal strength from the BS. In CLPC mode, the BS measures the received E_b/N_o[1] over a 1.25 ms period, and compares that to the target (Θ). If the received $E_b/N_o < \Theta$, a “0” is generated to instruct the MS to increase its power, otherwise, a “1” is generated to instruct the MS to decrease its power. These commands instruct the MS to adjust transmitter power by a predetermined amount, usually 1 dbm.

Other previous work has focused on finding adequate power levels that maximize the received bit energy-to-noise density ratio (E_b/N_o) where the transmission rate of each user is fixed [9]. Stochastic power control algorithms based on the mobile matched filter output is introduced in [15]. The authors

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[1] IS-95 standard suggests that the received signal strength should be measured. However, in practice usually the SIR or E_b/N_o are used, since they have direct impact on the BER [13].

in [17] proposed a circuit switched multi-rate DS-CDMA system based on a closed-form power control function. Recently, [6] presented an algorithm for controlling mobiles transmitter power levels following their time varying transmission rates.

2.2. Combined Power and Rate Control

Giving equation (1) a closer look, we can deduce that bit rate control gives RRS additional tool to preserve QoS (BER), i.e. E_b/N_o, and hence to overcome power control limitations. Simply, if the BS RRS advises MS i to decrease its rate R_i at bad channel conditions instead of increasing its power P_i, then the E_b/N_o of MS i shall increase thus decreasing its outage probability. The outage probability, a measure of user's satisfaction, is defined as the probability of having MS' E_b/N_o falling below its threshold Θ. Several recent studies investigated this possibility. We discuss here some of them.

The authors in [14] proposed manipulating the spreading gain in CDMA data networks beside power control. Spreading gain is simply the ratio of the system bandwidth (W) to the transmitter bit rate (R). Each BS appropriately balances a user's desire for a high transmission power with the amount of interference it will generate to other users. However, the optimization problem was formulated to handle only data streams as best-effort traffic. Therefore, this method does not preserve pre-specified bit rate QoS constraint (R^G).

Another scheme, proposed in [16] and indicated hereafter as (PRA), considers power and rate adaptation one at a time. The authors presented two alternatives for P-R adaptation. In first mode, *Mode-A*, MS transmitting bit rate is left uncontrolled while power can be increased up to some value ($P^{Limit} < P^{max}$) to preserve the E_b/N_o. In case of bad channel conditions, transmitting power is limited to P^{Limit} while bit rate is reduced or suspended to meet the Θ requirement. As depicted in Fig. 1-(a), TPC set is restricted to simply horizontal lines search since R is not controlled. In the meantime, PRA has more permissible area by including vertical lines corresponding to R adaptation when P reaches the threshold level P^{Limit}. As shown in Fig. 1-(b), PRA also embraces the space origin, which corresponds to transmission suspension. Beside lack of commitment to the QoS guaranteed bit rate level R^G, the major drawback of PRA is its high dependence on the power level limit P^{Limit} especially that the authors have not proposed a procedure for defining, or optimizing it [16]. Fig. 1-(c) illustrates the flexibility of our proposed GAME by allowing the largest area in the search space without breaching the R^G level.

3. GAME-C

The main signaling messages, interchanged between MS and BS in the proposed scheme, are depicted in Fig. 2. Initially, during a call setup, MS and BS negotiate the terms of a traffic contract. This contract includes some traffic descriptors as well as some parameters representing the required QoS. P^{max} is acting as a constraint on the power level that can be recommended by the BS. R^P is the peak bit rate to be generated by the MS application. Connection QoS is represented by the remaining two parameters: Θ and R^G. Θ, the required received E_b/N_o, represents partly the QoS of the call since it is directly related to BER. Finally, R^G, the guaranteed bit rate represents also the QoS. It indicates the maximum bit rate that the BS ought to guarantee to the MS. Any traffic above R^G and below R^P can be accepted or rejected by GAME according to the cell load and channel conditions. In fact, R^G has also a direct relationship with the maximum tolerable delay by this type of traffic. The smaller the bearable delay is, the smaller the difference (R^P - R^G) should be. Immediately, after the end of this call setup phase, and every control period, the BS triggers the GAME who tries to find the optimum power $P*$ and the optimum bit rate $R*$ for each mobile. Optimal solution is in the sense that each MS gets merely enough power, $P*$, to fulfill its Θ with the maximum possible rate, $R*$, where $R^G \leq R* \leq R^P$. Therefore, each MS preserves its battery life and always has a guaranteed QoS. Meanwhile, the BS can admit the maximum number of calls since each one is generating the minimum interference to others.

As illustrated in Fig. 2, While GAME is solving the optimization problem, every control clock, the BS still has the ability to control MS power through CLPC that generates the binary ΔP based on the received E_b/N_o. We opted to use CLPC to guarantee that BS is still in control of MS power while GAME is performing the optimization computation.

3.1. The Objective Function

Based on the above, we can see that the objective here is to find nonnegative power $\underline{P}=[P_1, P_2, ..., P_M]$ and rate $\underline{R}=[R_1, R_2, ..., R_M]$ vectors within some boundaries and maximize the function F proposed initially as

$$F = \sum_{i=1}^{M} F_i^E ,$$

where F_i^E is a threshold function defined for user i as

$$F_i^E = \begin{cases} 1 & (E_b/N_o)_i \geq \Theta_i \\ 0 & otherwise \end{cases} \qquad \textbf{(4)}$$

This function maximizes the number of users who have their signal qualities above the minimum requirement (Θ). This objective function, however, is incomplete since we need to give preferentiality to solutions that use less power. Hence, while limiting the P-R search space to solutions that maximize the number of BER satisfied mobiles through F_i^E, minimizing P is essential. Since low mobile transmitter power means little interference to others and long battery life, we proposed the power objective component, F_i^P (5), that gives credit to solutions that utilize low power and punishes others using high levels.

$$F_i^P = 1 - \frac{P_i}{P_i^{\max}} \qquad \textbf{(5)}$$

Consequently, our main objective function F was modified to reflect this power preference as

$$F = \sum_{i=1}^{M} F_i^E + \frac{1}{M} \sum_{i=1}^{M} F_i^E F_i^P$$

The reason of multiplying F_i^P by F_i^E is to prevent those users who have failed their BER qualification from contributing to the objective score. Notice also that we divide by the number of MSs (M) to give higher priority to the first part $\sum_{i=1}^{M} F_i^E$. Let us take the following example to clarify this. Assume we have 3 MSs (M=3) and we have two solutions to compare.

a) First solution: $F_1^E=1$, $F_2^E=1$, $F_3^E=0$, $F_1^P=0.9$, $F_2^P=0.9$, and $F_3^P=0.1$.

b) Second solution: $F_1^E=1$, $F_2^E=1$, $F_3^E=1$, $F_1^P=0.3$, $F_2^P=0.2$, and $F_3^P=0.2$.

Now, which solution is better? Without dividing by M, the first solution yields higher F. However, we prefer the second solution as it makes all 3 MSs to satisfy their BER requirements thus preventing their outage or calls drop.

Another goal is to fulfill every user bandwidth request. Each call is guaranteed a specific bandwidth, R^G, according to the traffic contract. However, a user should not be prevented from getting higher rate if there is a chance. Thus, from bandwidth point of view, the R search space should avoid values below the baseline R^G while encouraging solutions to go as high as the peak bit rate R^P. This bandwidth objective is represented by

$$F_i^R = \begin{cases} \left(R_i - R_i^G\right) / \left(R_i^P - R_i^G\right) & R_i \geq R_i^G \\ 0 & otherwise \end{cases}, \qquad \textbf{(6)}$$

Accordingly, the final main objective function is

$$F = \sum_{i=1}^{M} F_i^E + \frac{1}{M} \sum_{i=1}^{M} F_i^E \left(F_i^P + F_i^R\right) \qquad \textbf{(7)}$$

We preferred F_i^P and F_i^R addition to other operations for two reasons:

a) Addition is a linear operator that implements the desirable cumulative effect. On the other hand, multiplication for instance adds non-linearity to the overall fitness function, which in turn complicates the search process.

b) Addition is one of the least computationally expensive operations to be performed on any microprocessor. This way, we can simplify GAME real-time implementation.

In conclusion, the jointly optimal power and rate is obtained by solving the following optimization problem

$$\max_{(P^*, R^*) \in \Omega} F(P, R) \qquad \textbf{(8)}$$

where F is defined in (7) and the feasible set Ω is subject to power and rate constraints

$$0 \leq P_i^* \leq p_i^{\max}, R_i^G \leq R_i^* \leq R_i^P \quad \forall i \in [1, M] \qquad \textbf{(9)}$$

3.2. Why Genetic Algorithms?

Function optimization can be done analytically or numerically. Basically, using the traditional analytic approaches, optimal P^* and R^* can be found by differentiating the objective function F with respect to every mobile's P and R. However, this simple technique is not suitable in our case since F_i^E is a step function thus not differentiable.

Then, shifting our attention to numerical optimization techniques, we find many methods along the same vein: *hill climbing*. It starts out by choosing an initial point, moving a certain distance in the *local* steepest uphill direction, and repeating until all surrounding directions are downhill. Different hill climbing flavors simply differ in the method used to determine the steepest direction and the size of the step to move in that direction. Among the most popular hill climbing schemes are the simplex method and simulated annealing.

Hill climbing is most efficient when the objective function is uni-modal, i.e., has only one maximum point. If faced with a multi-modal function, hill climbing has to start on the slopes of the global maximum to reach it. Otherwise, it will get stuck in a local maximum point.

Looking back at our objective function, we can assume it is multi-modal since we cannot prove otherwise. Therefore, if decided to use a hill climbing, we have to apply what is known as *iterative* hill climbing where we try various starting points, and select the best resultant local maximum. To increase the chances of reaching the global maximum, the starting points are better being dissimilar by selecting them randomly, which means that each trial is independent from the others. This independence implies we do not learn anything from one starting point before selecting the other, which makes the number of trials unpredictable and no guarantee of finding the global maximum. These shortcomings are what *genetic algorithms* try to address when used as optimization techniques.

Genetic algorithms (GAs), as described in [4], are search algorithms based on mechanics of natural selection and natural genetics. They combine survival of the fittest among string structures with a structured yet randomized information exchange to form a search algorithm with some of the innovative flair of human search. In every generation, a new set of artificial creatures (strings) is created using bits and pieces of the fittest of the old; an occasional new part is tried for good measure.

While randomized, genetic algorithms are no simple random walk. They efficiently exploit historical information to speculate on new search points with expected improved performance. GAs use random choice as a tool to guide search toward regions of the search space with likely improvement.

3.3. Evolutionary Framework

GAs operate on *populations* of strings, where each string is a way of representing the variable(s) in the function F to be optimized. Biologists call this objective function the *fitness* function. The string is also called *Chromosome*. In its simplest form, a chromosome is a string like this: $[P_1, R_1, P_2, R_2, \ldots, P_M, R_M]$, thus concatenating all our mobile stations P and R. Therefore, a chromosome represents simply one point in our search space encoding only one solution to our function F.

GAs form a rich database of points simultaneously (a population of chromosome), climbing many peaks in parallel; thus the probability of finding a false peak is reduced over hill climbing methods that go point to point. This work includes some operators like reproduction, crossover, and mutation, which are applied to successive chromosome populations to create new, hopefully, better populations. *Reproduction* simply assigns more offspring to better individuals as measured by function F. This survival of the fittest mechanism can be implemented through a weighted roulette wheel selection for instance. The main idea is to prefer better solutions to worse ones. *Crossover* is a genetic operator responsible for partial exchange of information between two chromosomes using cross-site chosen at random. The crossover main purpose is to combine parental traits in a novel manner by mixing portions of parental solutions to form new conceivably better offspring. *Mutation* is the occasional (with small probability) random alteration of the value of a chromosome position. By itself, mutation represents a random walk around the parental solution, thus exploiting its neighborhood solutions.

The mechanics of a simple genetic algorithm involve nothing more complex than copying strings and swapping partial strings as follows:

1. Initialize a population of chromosomes.
2. Evaluate each chromosome in the population using the designated fitness function.

3. Create new chromosomes by mating current chromosomes; apply reproduction, crossover, and mutation as the parent chromosomes mate.
4. Evaluate the new chromosomes using the designated fitness function.
5. Delete old weak members of the population to make room for the new strong chromosomes.
6. If time is up or the fittest member of the current population is considered fit enough, stop and return the best chromosome; otherwise go back to step 3.

As can be seen, the genetic search is working along the iterated hill climbing techniques main theme. However, the GA innovation lies in step 3, where information is passed and exchanged across population members. This information transfer addresses the iterated hill-climbing shortcoming of having all trials independent. That is why, statistically, GA has better chance to reach the global maximum than iterated hill climbing techniques while being faster.

3.4. GAME Chromosome

In order to assemble a Genetic Algorithm (GA) [4], we have to define two main building blocks: *Chromosome* and *Fitness Function*. We have already composed our fitness function as in (7), so let us compose our chromosome.

A chromosome is the main data structure manipulated by any GA. It is simply a vector whose elements are the variables of the optimization problem, i.e., the search space components. GAME chromosome is a binary vector that encodes transmitter power, P, and bit rate, R, values of all mobile stations, M, in a cell. Therefore, we have initially:

$$\text{Chromosome Length} = M(N_P + N_R) \text{ bits,}$$

where N_P and N_R are the number of bits used to encode P and R respectively.

Recall that the computational complexity of solving an optimization problem increases with its search space dimensions. Recall that the computational complexity of solving an optimization problem increases with its search space dimensions. In our case, each bit in the chromosome is considered as one additional search space dimension with two possible values ‘0’ or ‘1’. Therefore, to avoid the curse of dimensionality, we chose to cluster MSs before chromosome encoding to shorten its length. Clustering is based on each MS QoS class (or type of traffic), its current traffic activity, and its current distance from the BS. For instance, 100 voice users (conversational class) at the same distance from the BS can be clustered into only two groups: a talking cluster and a silent one. In order to have fair treatment, each MS in the talking cluster has to have the same transmission bit rate and power since they have the same path loss *G*. The same applies for the silent cluster. Therefore, the chromosome length can be reduced from $100(N_P + N_R)$ to only $2(N_P + N_R)$. Now, what happens if the MSs are not at the same distance from the BS? According to the fairness rule [8], any two MSs with the same traffic type and transmitting bit rate have to have same received power at the BS. So we chose to optimize the receiving power at the BS and then calculate the corresponding transmitting power knowing the path loss between each MS-BS. As a consequence, we end up with only *C* clusters whose aggregate *P* and *R* are to be encoded in the chromosome. As depicted in Fig. 3, GAME chromosome length is given by:

$$\text{Chromosome Length} \quad N = C(N_P + N_R) \text{ bits, where } C \le M \qquad \textbf{(10)}$$

In the implementation discussed herein, we used N_P =8 bits and N_R =8 bits.

Fig. 4 depicts the GAME data flow diagram. According to the fitness function used to compare the solutions chromosomes, the fittest vectors $\underline{R}^*$ and $\underline{P}^*$ should be within the boundaries (9). In the mean time the bit rate should be as high as possible while the power level is as minimal as possible. This finest solution also should be able to make each user surmounts its required E_b/N_o value (Θ).

4. Experimental Environments

4.1. Multimedia Traffic Properties

The multimedia services that we have experimented with covered many possible applications. Voice users used in the simulations were following the On-Off model [12]. Talk-spurt and silence periods were independent and exponentially distributed with means of 1.0 and 1.35 s respectively. Talking users generated 9,600 b/s while 512 b/s were generated during silence. This traffic type fits the UMTS *conversational* QoS class. We assumed its guaranteed bit rate R^G (8.4 Kb/s) only 12.5% lower than its peak rate R^P. MSs with video traffic represented the *streaming* QoS class. Video traffic was variable bit rate (VBR) MPEG encoded. A 12 frames group of pictures (GOP) pattern (IBBPBBPBBPBB) was produced at 25 frames/s. Encoder input was 384x288 pixels with 12-bit color information. Mean bit rate was 145Kb/s while the peak rate was 1.125 Mb/s [11]. We assumed its guaranteed rate 25% away from the peak. Data traffic generated 144 Kb/s at its peak and minimum 16 Kb/s following a pareto normal distribution with cut-off [2]. This service is categorized as *interactive* QoS class, and can represent many connectionless services including web browsing. Although in [1] 3GPP has not specified a guaranteed rate for this class, we assumed a guaranteed level of 50 Kb/s (65% away from its peak) to test the efficiency of the proposed scheme in QoS provisioning.

4.2. Cellular Models

4.2.1. General Outdoor Model

We simulated a wideband CDMA system composed of 19 hexagonal cells representing 3 inner rings in cellular hexagonal coordinates. Each BS was situated at its cell center whose radius was 1 km. Mobile users were distributed uniformly over each cell space. We adopted the ITU-R distance loss model [8]. The path loss, G_{ij}, was modeled as a product of two variables

$$G_{ij} = A_{ij} \times D_{ij} \qquad \textbf{(11)}$$

A_{ij} is the variation in the received signal due to shadow fading, and assumed to be independent and log normally distributed with a mean of 0 dB and a standard deviation of 8 dB. The variable D_{ij} is the large-scale propagation loss, which depends on the transmitter and the receiver location, and on the type of geographical environments. Let d_{ij} be the distance in km between transmitter j and receiver i, the ITU-R formula yields the following path loss equation for typical 3G CDMA system parameters [2].

$$10 \log D_{ij} = -76.82 - 43.75 \log d_{ij} \qquad \textbf{(12)}$$

The center frequency was 1975 MHz; antenna heights of the mobile and the base station were 1.5 and 30 m respectively. We assumed that buildings occupied 20% of BS coverage area. The system spreading bandwidth *W* was 5 MHz and the background thermal noise density was –174 dbm/Hz. Each MS maximum transmitter power was set to 1000 mW.

4.2.2. Microcellular Model

A microcell is a relatively small outdoor area such as a street with the BS antenna below the rooftops of the surrounding buildings. The coverage area is small and shaped by neighboring constructions. The main assumptions are relatively short radio paths (200m to 1000m), low BS antenna (3m to 10m).

In our microcellular model, we limit our study to ideal or Manhattan-like street pattern with high-rise buildings. As a consequence, there exists a clear distinction between the line-of-sight (LOS) and non-line-of-sight (NLOS) propagation. We adopt the empirical path loss model for microcells in high-rise environment developed in [5]. We assume an urban mobility model. MSs move along streets and may turn at cross streets with a given probability. MS' position is updated every few meters and speed can be changed at each position update according to a given probability. The mobility model parameters are described in [2]. We calculated the total MS-BS path loss by combining two components: One static and another dynamic. The static (propagation) component, resulting from the MS position relative to the BS, is calculated as in [5]. The dynamic (fading) component, caused by MS mobility relative to the BS, is calculated assuming Rayleigh distributed fade depth [21]. MSs are uniformly distributed in the streets and their directions are randomly chosen at initialization.

In our study, we focus on outdoor environment. However, in order to evaluate the indoor coverage provided by an outdoor BS, an additional loss due to building penetration is to be taken into account. This penetration loss can be simulated by a normal probability distribution function having mean and standard deviation of 12 and 8 dB respectively [2].

5. Results

We have performed several experiments to assess the GAME-C performance. Each of our experiment was repeated three times varying each traffic type at a time. Due to space constraints we were able to present only one figure per experiment.

5.1. System Capacity and Quality of Service

In this experiment we aimed to investigate the effect of the proposed scheme on the quality of service offered to users. We used the outage probability to measure the QoS part related to BER and the average MS bit rate to assess the QoS component related to bit rate guarantee. We tested each traffic type separately to get a clear picture of the effect on each specific class. Results on mixed traffics are reported in subsequent sections. In this experiment we kept increasing the number of users and recording the average outage probability and transmitter bit rate. GAME-C control period was adjusted to 0.1 s. We used the general outdoor model described in the previous section. Unsurprisingly, outage probability increased with the growing number of MSs as shown in Fig. 5. However, the results expressed the GAME-C superiority in users' satisfaction by yielding lower outage than the standard CLPC for the same number of MSs. For instance, in Fig. 5, when the CLPC system reached its peak capacity at 320 users, the outage probability was 0.083. On the other hand, at 320 MSs, GAME-C managed to decrease this probability to 0.037 (55% gain). This enhancement persisted as well for the other two traffic types. When CLPC attained its maximum capacity, Data outage fell from 0.21 to 0.07 (67% gain) and video outage inched down from 0.22 to 0.20 (9% gain) by using GAME-C.

We plotted in Fig. 6 the average bit rate versus the number of MSs. As illustrated in the plots, using GAME-C, the rate cut increased with the number of users since more mobiles means more interference, which tweaked the solution towards cutting the bit rate. It is also clear that the amount of bit rate reduction depends on the traffic type. In order to assess the damage in bit rate caused by GAME-C, let us compare the difference in bit rates at CLPC maximum number of possible users. At 320 users, in the case of voice traffic, the average rate drop was 1.2%. Average Rate reduction was 21.2% at 30 data users and 4.2% at 13 video users as shown in Fig. 6. It is clear that the rate cut in the data users case was the biggest since they had the most flexible delay constraints and the least guaranteed bit rate compared to the peak one R^P.

5.2. Power Conservation

In this experiment we aimed to study the effect of applying GAME-C on the mobile transmitter power. We combined different services users simultaneously to ensure the ability of the proposed algorithm to deal with the mix as good as the solo traffic type. Again, we varied the number of service users from 1 to a maximum number. This maximum number is reached once a call dropping case is attained. Each time we collected the transmitting power level of each MS. We adjusted the GAME-C control period to 0.1 s. The experiment was repeated three times with varying mobiles number from each service type each time. The outdoor general model was used in this experiment.

As expected, GAME-C was able to reduce mobile power consumption as illustrated in Fig. 7. The major reason for that savings is again the bit rate manipulation that gave the base station another degree of freedom in the restricted power allocation problem. If we go through the numbers at the maximum CLPC users capacity, we find the following: Power savings were 50% at 45 voice users, 60% at 15 data users (Fig. 7), and 32% at 6 video users. As seen, again in these plots, the average power consumed rose steadily with the growing number of users. This is natural since more users mean more produced interference, which needs more power to overcome it. It is obvious again, from these numbers, that data users were the primary beneficiaries of the power reserves. No surprise, since they were the most willing to trade their bit rate with less power and thus adding more users.

5.3. Spectrum Efficiency

System level simulations have been performed for voice and data types of services to evaluate the Spectrum Efficiency as described in Annex B of [2]. The spectrum efficiency (ξ) is defined as the system load, measured in kb/s/cell/MHz, where there are exactly 98 % satisfied users. We consider a user as satisfied when the following conditions are fulfilled: a) the user does not get blocked when arriving to the system; b) the user's QoS is well preserved throughout the session, i.e., outage probability < 5% and $R > R^G$; c) the user does not get dropped. A call is dropped if E_b/N_o remains below Θ for more than 5 seconds. MSs were allowed to move in our microcellular environment according to the mobility model described in previous section. Periodically, we measured the system load and counted the corresponding number of satisfied users. Fig. 8 is a plot of the experiment outcome when users were involved in voice and data traffic respectively. We used up to 200 voice and 40 data users to generate wide range of system loads. As expected, GAME-C outperformed the standard TPC by yielding higher spectrum efficiency in both traffic type cases. As shown in Fig. 8, ξ increased from 117 to 145 kb/s/cell/MHz and from 224 to 387 kb/s/cell/MHz for voice and data types respectively by using GAME-C instead of TPC. These results demonstrate GAME-C competence as an RRS that utilizes the available scarce spectrum efficiently.

5.4. Coverage Efficiency

To trim cost, all cellular network builders strive to minimize the number of BSs required for providing adequate coverage. That is why system designers give close attention to an important performance measure: Coverage Efficiency (μ). Expressed in km^2/cell, μ specifies the largest cell area corresponding to the maximum tolerable outage probability by an MS. Using this figure, we can determine how many BSs per square kilometer are needed to offer MSs ample radio access services. The objective of this experiment was determining μ of our microcellular system for both voice and data traffic types. Users were moving according to the mobility model described in previous section. We selected the maximum tolerable MS outage probability to be 0.05. Coverage efficiency has to be evaluated at traffic levels corresponding to low network load, since the system will be most probably interference limited at high traffic loads. As proposed in [2], we kept voice traffic density (*TD*) constant at 10 kb/s/km^2. Every simulation course we increase the cell area (*A*) in square kilometer. Next we calculate the number of MSs necessary to keep TD constant according to the following formula:

$$\text{Number of MSs} = \left(A \cdot TD\right)/\overline{R} \qquad \textbf{(13)}$$

where $\overline{R}$ represents each user's average transmitted bit rate in kb/s.

At the end of each simulation course, we recorded the resultant outage probability and the cell coverage area. We measured the outage probability as the ratio of the total time intervals spent by an MS having

$E_b/N_o < \Theta$ over the entire simulation duration. Fig. 9 depicts the results recorded from seven different simulation cycles using voice MSs. It is evident that outage increased with cell size due to increasing permissible BS-MS distance. A snapshot of both curves in Fig. 9 demonstrates that GAME-C was able to increase μ from 9.6 to 11.5 km^2/cell (Fig. 9-(a)) in case of voice traffic compared to standard TPC. Also, GAME-C provided more than double coverage efficiency for data users. μ jumped from 0.54 to 1.3 km^2/cell (Fig. 9-(b)). As we expected, the gain in the data users was the greatest since they were the most flexible in terms of their guaranteed bit rate that reflected their high delay tolerance.

5.5. Control Period Effect

In this experiment, our objective was to study the impact of varying the control period T on GAME-C effectiveness in managing the wireless resources and protecting MSs QoS. We combined several calls of different service types and kept them constant throughout the experiment. This mix was: 7 video, 12 data, and 50 voice users. We repeated the simulation while varying T from 0.01 s to 1 full second. At each run, we used a constant control period during the simulation. We used the outdoor general model. Again, this experiment was repeated several times to be able to catch a reasonable average statistics. The data recorded was: the outage probability, the average mobile E_b/N_o, the average mobile transmitter power, and the average mobile transmitter bit rate. Note that the CLPC values are always constant since T affects only GAME-C. Fig. 10 indicates that the outage probability rose with increase in the control period. This is normal, since at small T, GAME was activated more frequently, and that made it able to solve any problem as soon as it appeared. On the contrary, at large T, a user E_b/N_o was forced to spend more time below its threshold and wait for GAME to solve it on its next launch. We confirmed this conclusion, when we saw the extra E_b/N_o faded way with T increment. In general, the proposed scheme outperformed the standard IS-95 for all T values even at maximum one. At the smallest T (0.01 s), the gain of using GAME-C was at its summit. The outage probability decreased to 0.064, which is an enhancement of 51.3% and the spare E_b/N_o improved by 75.2% at 0.68dB. On the other extreme, at T=1 s, this enhancement eroded to 9.6% when the probability stood at 0.119 and the additional E_b/N_o enrichment faded to 10.3% at 0.43 dB. Note also the behavior of GAME-C plot in Fig. 10; they started with high dynamics, and then moved to a nearly saturated performance against the control period. This is normal, given the fact that as T tends to ∞; GAME-C tends to be pure CLPC. We noticed also that the bit rate recommended by GAME-C to mobiles increased with the growing control period. Consequently, the mobile transmitting power also increased with T in order to support the higher bit rate. This was the reason as well for the outage probability escalation with T. At small T, GAME was constantly there to shave out excess R in order to keep $E_b/N_o > \Theta$ if necessary. That is why at T=0.01 s we had the lowest bit rate, lowest outage probability, highest extra E_b/N_o and lowest power. As T moved higher, GAME launch frequency decreased. Accordingly, this setback permitted the survival of the additional bit rate despite E_b/N_o suffering. Therefore, at T=1 s, we had the highest bit rate, highest outage probability, lowest extra E_b/N_o and highest power. Overall, GAME-C managed to surpass the standard CLPC for any T. At T=0.01 s, the power savings was 65.2% at 43.7 mW while the price, which is the rate cut, was the highest: 34.7% at 51.7 Kbps. On the other end, at T=1 s, the power savings was the lowest: 49.8% at 69.2 mW while the rate cut was 20.5% at 63 kbps.

6. Discussions

In this study, we introduced a novel scheme for wireless resource management in CDMA networks and applied it to wideband multimedia environment with dissimilar QoS requirements. Our proposed method, GAME-C, integrates the **G**enetic **A**lgorithm for **M**obiles **E**quilibrium (GAME) technique with the regular **C**losed **L**oop **P**ower **C**ontrol (CLPC) specified in several standards. The main algorithm is to be implemented in the base station that forwards the controlling signals to its mobile stations. Actually, GAME trades bit rate for higher users' density, less connections dropping/blocking, and lower transmitting power. This rate reduction is subject also to a maximum, so the resulting allotted bandwidth is always above the guaranteed level specified in the traffic contract. Hence, QoS requirements are always met or exceeded. The advantages of using genetic algorithms for optimization are numerous. Parallelism, GAME can be implemented as multiple synchronized threads to take advantage of the full processing power of the used hardware. Evolving nature, GAME can be stopped any moment while having the assurance that the current solution is better than all the previous ones. Scalability, mobiles can be added or removed simply by adjusting the chromosome length and leaving everything else intact. In fact we conducted some analysis to study the feasibility of GAME implementation in real time. We found that GAME needed on the average 200 chromosome operations to surpass 95% of the fitness value. According to our implementation, 200 chromosome operations translated into 7.25 milliseconds on a typical 100 MFLOPS (Million FLoating point OPeration per Second) machine. The proposed scheme performed acceptably during the experiments done to test it. The enhancements over the standard CLPC case are substantial. The outage probability has decreased by an average of 40% with better corresponding signal quality (E_b/N_o). In the mean time, the average power consumption has been saved by 46%. Moreover, the Base station coverage area expanded on the average by 70%. Certainly, this efficiency will be translated into lower construction cost of network infrastructure. Meanwhile, the spectrum efficiency has been stretched on the average by 48% implying the increase of QoS-satisfied users and therefore realizing the intended objectives. To pay for these enhancements, the transmitter bit rate declined on the average by 11% but without breaching the guaranteed bit rate specified in QoS requirements. Current research work is in progress to apply the GAME on the downlink (BS to MS). We plan also to investigate some hardware implementation issues.

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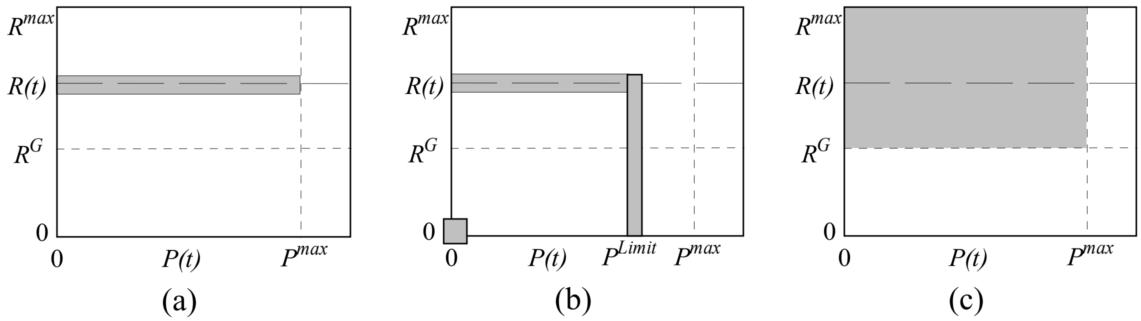


Fig. 1 *P-R* space with shaded permissible search regions. (a) TPC [19], (b) PRA [16], and (c) GAME schemes.

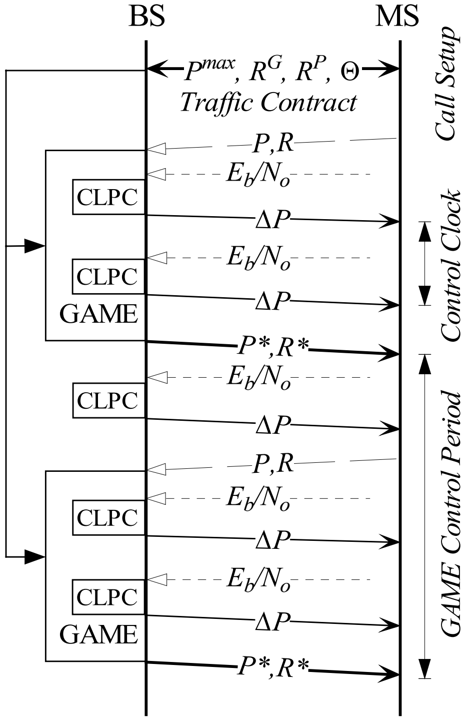


Fig. 2 BS-MS interface in GAME-C Protocol. After traffic contract negotiation, GAME is launched every *control period*, measures current power *P* and rate *R*, and retrieves current traffic contract values. While optimization is being performed, the regular CLPC Δ*P* is maintained every clock. GAME returns to MS its optimal *P and *R**.**

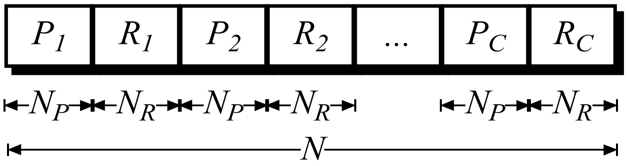


Fig. 3: GAME Chromosome Format: *N* bits. Each mobile cluster occupies N_P and N_R bits to represent its power and Rate respectively. *C* is the total number of clusters controlled by the base station.

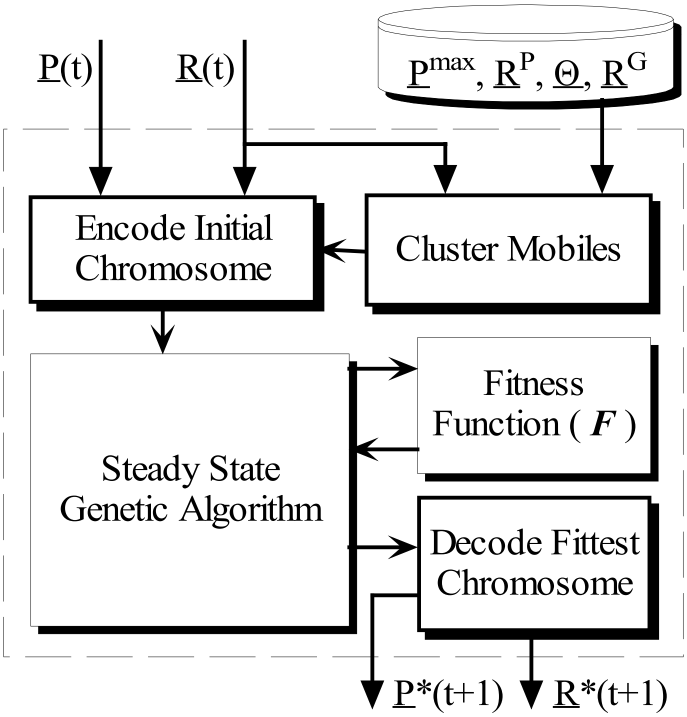


Fig. 4 GAME Skeleton Flow Diagram.

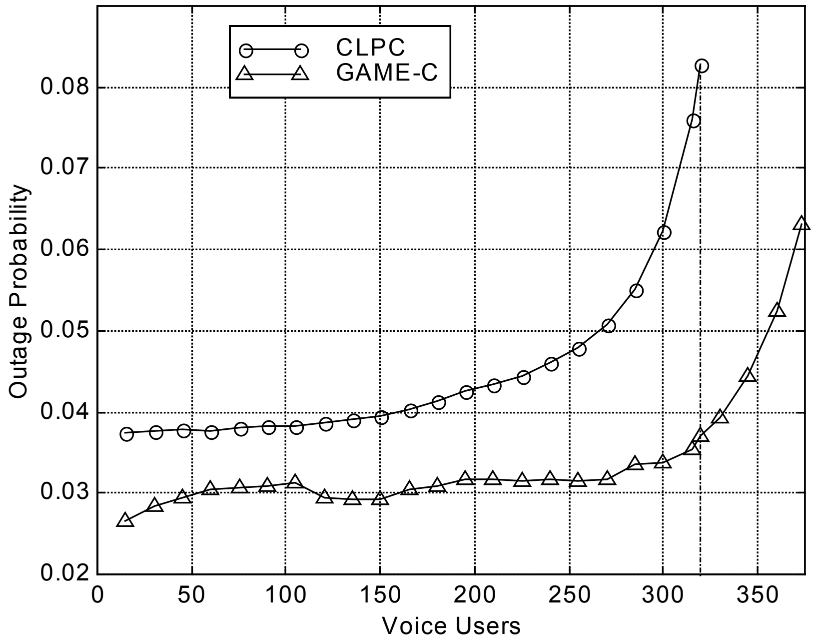


Fig. 5 Outage Probability vs. Number of Voice Users. 'o' represents TPC. 'Δ' represents GAME-C, *T* =0.1 s.

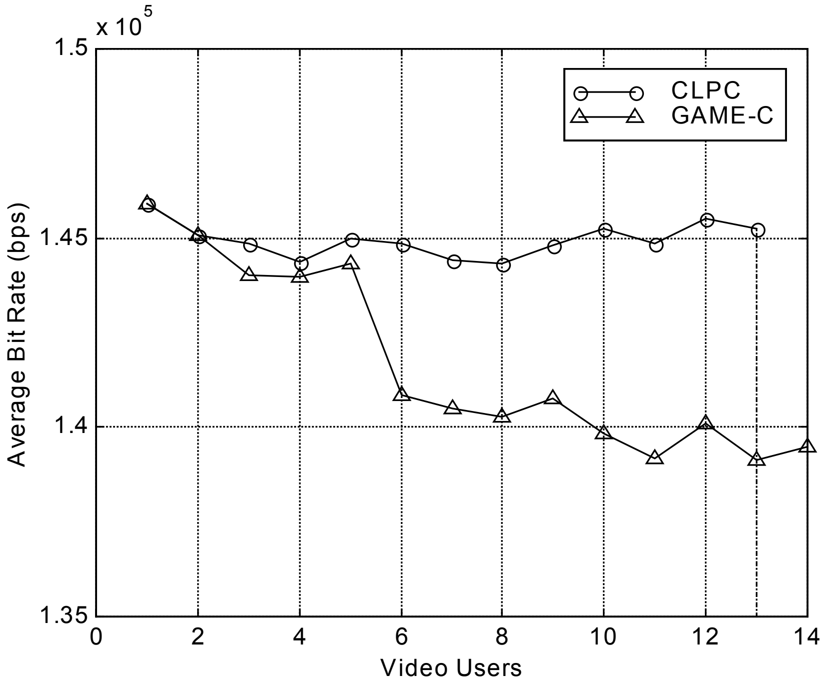


Fig. 6 Average transmitter bit Rate vs. Number of Video Users. 'o' represents TPC. 'Δ' represents GAME-C, *T*=0.1 s.

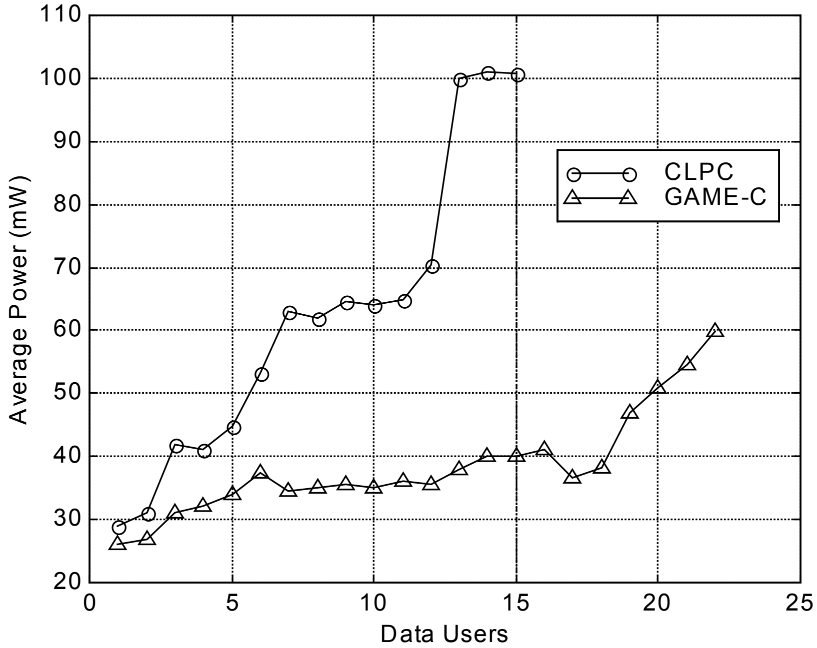
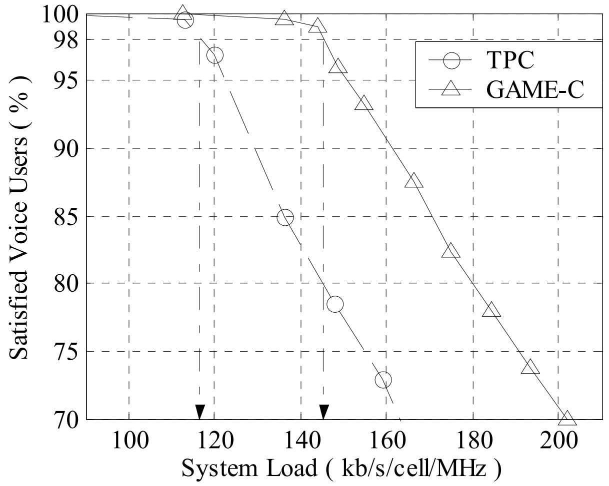
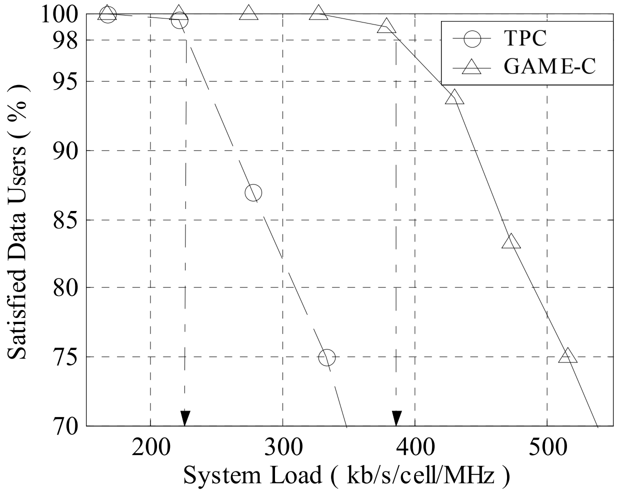


Fig. 7 Average transmitter Power vs. Number of Data Users, Voice Users=50, Video Users=6. 'o' represents TPC. 'Δ' represents GAME-C, *T*=0.1 s.



(a)



(b)

Fig. 8 Percentage of Satisfied mobile voice users versus System Load. (a) Voice Traffic. (b) Data Traffic. 'Δ' represents GAME-C while 'o' represents TPC. Spectrum Efficiency is defined as the System Load at 98% satisfied users.

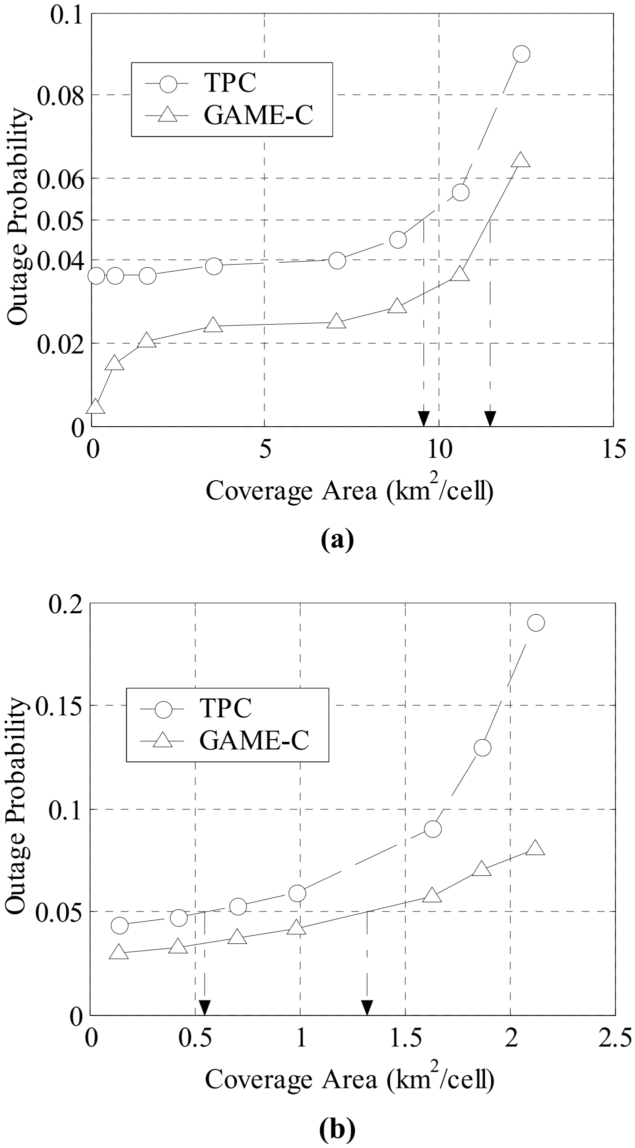


Fig. 9 Outage Probability versus Base Station coverage area. (a) Voice Traffic. (b) Data Traffic. '∆' represents GAME-C while 'o' represents TPC. Coverage Efficiency is defined as the coverage area at 0.05 outage probability.

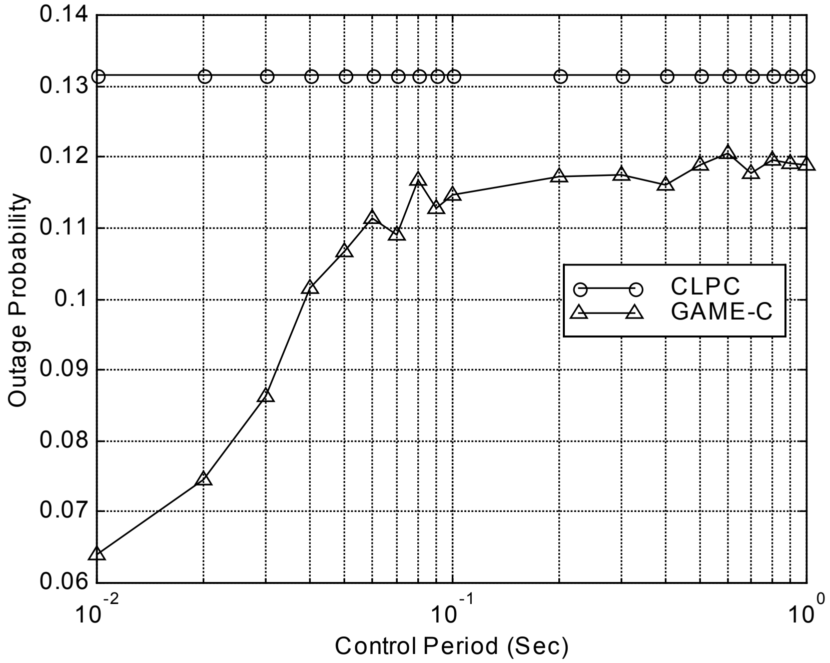


Fig. 10 Control Period Effects on Outage Probability of Data Users. 'o' represents TPC. 'Δ' represents GAME-C. Video Users=7, Data Users=12, and Voice Users=50.