A connection-level call admission control using genetic algorithm for multi-class multimedia services in wireless networks

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Abstract: Semi-Markov Decision Process (SMDP) can be used to optimise channel utilisation with upper bounds on handoff blocking probabilities as Quality of Service constraints for call admission control in a wireless cell in a Personal Communication System (PCS). However, this method is too time consuming and therefore it fails when state space and action space are large. In this paper, we apply a genetic algorithm approach to address the situation when the SMDP approach fails. We code call admission control decisions as binary strings. The coded binary strings are feed into the genetic algorithm, and the resulting binary strings are founded to be near optimal call admission control decisions. Simulation results from the genetic algorithm are compared with the optimal solutions obtained from linear programming for the SMDP approach. The results reveal that the genetic algorithm approximates the optimal approach very well with less complexity.

Keywords: call admission control; multimedia; Quality of Service (QoS; queuing system; genetic algorithm; Semi-Markov Decision Process (SMDP); wireless/mobile networks.

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1 Introduction

The Quality of Service (QoS) guarantee for multimedia services is important in wireless networks. Call Admission Control (CAC) is vital for the QoS guarantee owing to limited capacity in wireless networks. A good CAC needs to efficiently utilise system resources and satisfy QoS requirements. Furthermore, in order to improve the overall performance of the system, sometimes, denying some resource requests even when excess capacity exists is an essential feature for CAC (Yener and Rose, 1997).

Many CAC schemes in wireless/mobile networks have been proposed in literature (Ayyagari and Ephremides, 1999; Ho and Lea, 1999; Ramjee *et al.*, 1997; Kwon *et al.*, 1999; Kwon *et al.*, 1998; Choi *et al.*, 2000; Kwon *et al.*, 1998; Yoon and Lee, 1999;

Kwon *et al*., 2003; Biswas and Sengupta, 1997; Yener and Rose, 1997; Rose and Yate, 1996; Xiao *et al*., 2001; Xiao *et al*., 2002; Xiao *et al*., 2005). Some studies focus on optimal CAC schemes for handoff calls and new calls in a non-multimedia situation, in which Factional Guard Channel is the optimal approach (Ho and Lea, 1999; Ramjee *et al*., 1997). Quite a few studies seek CAC schemes for multi-classes of multimedia services in a non-adaptive multimedia situation (Ayyagari and Ephremides, 1999; Choi *et al*., 2000; Kwon *et al*., 1998; Yoon and Lee, 1999), in which Choi *et al*. (2000) present a centralised optimal CAC using the Semi-Markov Decision Process (SMDP), and Kwon *et al*. (1998) and Yoon *et al*. (Yoon and Lee, 1999) propose distributed optimal CAC using the SMDP approach. Most recently, many researches have focused on adaptive multimedia services (Kwon *et al*., 1999; Kwon *et al*., 1998; Kwon *et al*., 2003; Naghshineh and Willebeek-LeMair, 1997; Alwan, 1996; Xiao *et al*., 2001; Xiao *et al*., 2002; Xiao *et al*., 2005). In our previous work (Xiao *et al*., 2001), we give an optimal solution using the SMDP approach for adaptive multimedia services. In our previous work, Xiao *et al*. (2002) and Xiao *et al*. (2005), we propose bandwidth degradation QoS provisioning and proportional degradation services, respectively, for multiple classes of adaptive multimedia. QoS over wireless networks is also studied in Wee and Gutierrez (2005). Overflow replacement policies in location management are studied in Lou *et al*. (2004). Genetic algorithm is also used to study the performance of TCP over satellite networks in Karthik *et al*. (2004), and other publications (Wang and Wang, 2005; Biaz and Ji, 2005).

In this paper, we assume m classes of users in a cell. The fixed total number of channels in a cell is C. We can model resource allocation in a cell as an $M/M/C/C$ queuing system with m classes of users. The SMDP approach can be adopted in CAC to provide an optimal solution to optimise the channel utilisation for service providers while satisfying the QoS requirements for end users, i.e. upper bounds on handoff blocking probabilities. Moreover, linear programming can be used to solve optimal decision problems. However, the SMDP method fails when state space and action space are too large. The action space increases exponentially with m, and the state space is extremely large for a large C.

In this paper, we apply a genetic algorithm approach to address such problems as when the SMDP approach fails. Genetic algorithm is based on natural selection. It mimics nature by combining genetics and natural selection in a computer to find near-optimal solutions. Genetic algorithms are a class of operators that are used to evolve solutions to extremely complex problems. The problems may be too broad, too expensive or too complex to be algorithmically solved. A genetic algorithm uses operators like crossover and mutation to find a solution, which is evaluated by an objective function to determine its fitness. If it is more fitful, it replaces the original solution in the set of solutions under consideration. Genetic operators may not give the theoretically best solution, but it will give a better one. How good a solution is depends on the problem, iterations and genetic operator parameters (Collier, 2000). In this paper, we will show that our genetic algorithm does give a very good solution in this special application.

The rest of this paper is organised as follows. We describe the problem definition in Section 2. Section 3 gives an overview of the optimal approach (SMDP), its limitation and scenarios when it fails. Section 4 demonstrates our genetic algorithm. We illustrate simulation results in Section 5. Finally, we conclude this paper in Section 6.

2 Problem definition

In Section 2.1, we first describe a traffic model. Then, we address objectives of this paper in Section 2.2.

2.1 Traffic model

We assume m classes of users: $\{1, 2, \ldots m\}$. A user in class-i requires b_i units of bandwidth or channels. We can model a cell with an *M/M/C/C* queuing system with m classes of users. Arrival events include new call arrival events and handoff call arrival events; service departures include call completions and handoffs to other cells. We consider only a fixed capacity in a cell, i.e. the total number of bandwidth (channels) is C. We have the following assumptions:

- Call requests of each class follow a Poisson distribution;
- The call holding time (service time) of each class is exponentially distributed;
- All the arrival distributions and the call holding time distributions are independent of each other.

Let $\lambda_{i,n}$ denote the new call arrival rate for class-i users; let $\lambda_{i,h}$ denote the handoff call arrival rate for class-i users; let μ_i denote the service rate for class-i users; let h denote the rate of handoffs to other cells. We assume that the handoff rate h is independent of classes.

2.2 Objectives

Define a system state of a cell as a vector $x = \{x_1, x_2, \ldots, x_m\}$, where x_i denotes the number of active class-i calls in the cell.

Let $P_{i,HB}$ denote handoff blocking probability for class-i users. Let $D_{i,HB}$ denote a predefined upper bound on handoff blocking probability for class-i users. QoS requirements are defined as follows:

$$P_{i,HB} \le D_{i,HB} \text{ for } i = 1,2,\ldots,m. \tag{1}$$

We define the channel utilisation as follows:

$$U = \sum_{i=1}^{m} b_i x_i \ . \tag{2}$$

Our goal is to maximise the channel utilisation (U) for service providers and to satisfy QoS requirements for end users, *i.e.* upper bounds on handoff blocking probabilities.

3 Optimal solution overview

The Semi-Markov Decision Process (SMDP) is a well-known technique for solving optimisation problems (Choi *et al*., 2000; Kwon *et al*., 1998; Yoon and Lee, 1999; Xiao *et al*., 2001). In this section, we first introduce the definition of the SMDP approach in Section 3.1. Then, we summarise its usage to solve optimisation problems in Section 3.2.

We provide an overview of how to use the SMDP approach in Section 3.3. Finally, in Section 3.4, we address limitations of the SMDP approach.

3.1 Semi-Markov Decision Process

The SMDP is a dynamic system with Markovian properties. This dynamic system at random points in time is observed and classified into one of a finite number of states. At the same time, a decision has to be made, and a cost is incurred owing to the decision made (Tijms, 1986). The decision is chosen from a finite decision space that may depend on the current state. Markovian properties mean that if at a decision epoch the action is chosen in the current state, the costs incurred, the time until, and the state at the next decision epoch depend only on the current state and the chosen action, and are thus independent of the past history of the system.

3.2 Optimal solution framework

We summarise a framework to get the optimal solution by the SMDP approach. Firstly, a model should satisfy SMDP definitions/properties. Secondly, we need to properly define system states (**x**), state space (**S**), decision epochs, actions (**a**) and action space (**Λ**). Thirdly, we need to formulate Expected Sojourn Time analytically, when it is in the present state **x** and the action **a** is taken. Fourthly, we need to formulate transition probability analytically, which is the probability that at the next decision epoch the system will be state **y** if the present state is **x** and the action **a** is taken. Fifthly, we need to define a cost function or a reward function. Sixthly, we need to formulate linear programming formulas (Tijms, 1986) with the cost/reward function. Finally, we solve the linear programming formulas. The solution was proved to be optimal mathematically (Tijms, 1986).

3.3 Optimal solution

Define a system state of a cell as a vector $\mathbf{x} = \{x_1, x_2, \ldots, x_m\}$, where x_i denotes the number of active class-i calls in the cell. The state space is given by

$$\mathbf{S} = \left\{ \mathbf{x} : x_i \geq 0 \text{ for } i = 1,2,...,m; \sum_{i=0}^{m} b_i x_i \leq C \right\} \tag{3}$$

An action is defined as:

$$\mathbf{a} = (a_1, a_2, ...a_{2m}\},\ a_i \in \{0,1\} \text{ for } i = 1,2,...,m. \tag{4}$$

If $a_i = 1$, it means acceptance. If $a_i = 0$, it means rejection. For $i \leq m$, a_i denotes the action for a new call arrival for a class-*i* user. For $i \geq m+1$, a_i denotes the action for a handoff call arrival for a class-(*i-m*) user. A call admission control policy is simply a mapping of a system state to an action. The action space is defined by

$$\Lambda = \{\mathbf{a} : a_i = 0 \text{ if } \mathbf{x} + \mathbf{e_i} \notin \mathbf{S}\} \tag{5}$$

where e_i is a vector of zeros, except for a '1' in the *i*-th position. The reward function is the channel utilisation. The Expected Sojourn Time, the transition probability and the linear programming formulas are defined as follows:

Let **τ(x, a)** denote Expected Sojourn Time if the system in state $\mathbf{x}\in\Lambda$ and an action **a** is taken. Let Pr(**y**|(**x, a**)) denote the transition probability that at the next decision epoch the system will be state **y** if the present state is **x** and the action **a** is taken. Based on Kwon *et al*. (1998) and Xiao *et al*. (2001), we have:

$$\tau(\mathbf{x},\mathbf{a}) = \frac{1}{\sum_{i=0}^{m}\left[\lambda_{i,n}a_i + x_i\mu_i + x_i h + \lambda_{i,h}a_{m+i}\right]} \tag{6}$$

$$\Pr\left(\mathbf{y}\mid(\mathbf{x},\mathbf{a})\right) = \begin{cases} \left(\lambda_{i,n}a_i + \lambda_{i,h}a_{m+i}\right)\tau(\mathbf{x},\mathbf{a}), \text{ if } y = x + e_i \\ \left(x_i\mu_i + x_i h\right)\tau(\mathbf{x},\mathbf{a}), \text{ if } y = x - e_i \\ 0, \text{ otherwise} \end{cases}. \tag{7}$$

Utilisation under (**x**, **a**), *i.e.*, if the present state is **x** and the action **a** is taken, is defined as Equation (2). Therefore, we can define the following linear programming equations (Kwon *et al*., 1998; Xiao *et al*., 2001). The linear programming associated with the SMDP for maximum revenue is given below with decision variables $\pi_{\mathbf{xa}}$, $\mathbf{x}\in S$, $\mathbf{a}\in\Lambda_{\mathbf{x}}$:

Maximise $\sum_{\mathbf{x}\in S}\sum_{\mathbf{a}\in\wedge_x} U\tau(\mathbf{x},\mathbf{a})\pi_{\mathbf{xa}}$ such that:

$$\sum_{\mathbf{x}\in S}\sum_{\mathbf{a}\in\wedge_x}\tau(\mathbf{x},\mathbf{a})\pi_{\mathbf{xa}} = 1 \tag{8}$$

$$\sum_{\mathbf{a}\in\wedge_x}\pi_{\mathbf{ya}} = \sum_{\mathbf{x}\in S}\sum_{\mathbf{a}\in\wedge_x} P\left(\mathbf{y}\mid\mathbf{x},\mathbf{a}\right)\pi_{\mathbf{xa}} \text{ for } \boldsymbol{y}\in\mathbf{S} \tag{9}$$

$$\pi_{\mathbf{xa}}\, 0, \mathbf{x}\in\mathbf{S}, \mathbf{a}\in\Lambda_{\mathrm{x}}, \tag{10}$$

$$\sum_{\mathbf{x}\in S}\sum_{\mathbf{a}\in\wedge_x}(1-a_2)\tau(\mathbf{x},\mathbf{a})\pi_{\mathbf{xa}} \le D_{i,HB} \tag{11}$$

The term $\tau(\mathbf{x},\mathbf{a})\pi_{\mathbf{xa}}$ can be interpreted as the long run fraction of the decision epochs at which the system is in state **x**, and the action **a** is chosen. We consider the QoS parameter's requirement, an upper bound on handoff dropping probability, in the last equation, where $D_{i,\,HB}$ is the upper bound on handoff dropping probability for class-i. Based on the above linear programming equations, we can obtain optimal CAC decisions by a linear programming algorithm known as the Interior-Point Methods (Zhang, 1995; Zhao, 1999).

3.4 The limitation of the SMDP approach

For every possible state, a call admission control policy found by the SMDP approach must be specified by a complete enumeration of the decisions (Rose and Yate, 1996). The SMDP method fails when the state space and the action space are too large. The action space increases exponentially with *m*, and the state space also increases exponentially with *C*. The variable space for the linear programming formulas increases exponentially with *m* and *C*, and so does the number of the linear programming formulas. In other words, the SMDP approach is not scalable at all.

However, the SMDP approach has at least theoretical significance, and it is the criteria for other approaches. A good approach should compare itself with the SMDP approach to ensure getting similar performance with less complexity. The objective of this paper is to provide a similar performance to the SMDP approach with much less computational complexity.

4 Genetic algorithm

In this paper, we propose a near-optimal solution using genetic algorithm, which is based on natural selection that mimics nature by combining genetics and natural selection on a computer. We apply a genetic algorithm approach to address such problems as when the SMDP approach fails. We first present the coding method for CAC in Section 4.1. Then, we present the algorithm and the implementation remarks in Section 4.2.

4.1 Coding

We code the call admission control decisions as a sequence of *2m*-bit binary strings corresponding to Equation (4). A value of '1' of the string stands for the decision to accept a call, and a value of '0' of the string stands for the decision to reject a call. For $i \le m$, the value in the position *i* of the string denotes the action for a new call arrival for a class-i user. For $i \ge m+1$, the value in the position *i* of the string denotes the action for a handoff call arrival for a class-(*i-m*) user. For example, at a system state, a coding is *0011*. Here, *m* equals *2* and it stands for the number of classes. We can interpret the coding *0011* as follows:

- The first *0* in *0011* stands for the rejection of a new call arrival in class-*1*. In other words, if the next call request is a new call and it is from class-*1*, CAC will reject it.
- Similarly, the second *0* in *0011* stands for the rejection of a new call arrival in class-*2*. In other words, if the next call request is a new call and it is from class-*2*, CAC will reject it.
- The first *1* in *0011* stands for the acceptance of a handoff call arrival in class-*1*. In other words, if the next call request is a handoff call and it is from class-*1*, CAC will accept it.
- Similarly, the second *1* in *0011* stands for the acceptance of a handoff call arrival in class-*2*. In other words, if the next call request is a handoff call and it is from class-*2*, CAC will accept it.
- Each system state is associated with such a string. In other words, for each system state, we need to find a decision coding string. The call admission control decision space includes all the possible *2m*-length binary strings. Each such string stands for a unique call admission control decision. The size of the space is 2^{2m}.

Note that this decision space is different from the action space, which is used in the SMDP approach, and is constrained. However, the call admission control decision space is unconstrained. We do allow accepting a call even though there is no available bandwidth. If this happens, the call will be blocked eventually.

The resulting binary strings from the genetic algorithm are the near-optimal call admission control decisions.

4.2 Genetic algorithm

The idea is to use simple genetic operators to optimise by natural selection. Similarly to natural evolution, the more the chromosome fits, the more likely its genes will be propagated through subsequent generations. The algorithm is described in the following steps.

Step 1

We first randomly choose an initial set population of strings among 2^{2m} strings of decision space. We call an individual decision string a chromosome. A string is composed of its genes that are parts of the chromosomes. Members in the initial set population are then grouped together and paired into parents.

Step 2

The parent chromosomes are then mated to generate a new set of offspring chromosomes. This mating procedure is also called crossover. Crossover is the procedure of splitting two chromosomes at some points in their string length and switching with the other chromosome to create two new chromosomes, each consisting of parts of the parent chromosomes. The split point does not have to be in the middle. For example, if $m=3$, and two parent strings are *000000* and *111111*, a mating might produce two strings: *001111* and *110000*. This is illustrated in Figure 1.

Step 3

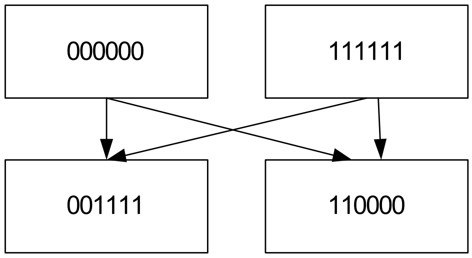
The individual bits of the offspring gene strings are then changed with small probability corresponding to mutation. Mutation is the random changing of one or more bits in a chromosome. It is useful for creating new genes that are not in the initial set population, or those that have evolved out of the population, but now would be beneficial (Ladd, 1996; Collier, 2000). For example, the two offspring might become 001101 and 110100. This is illustrated in Figure 2.

Step 4

The objective function is defined as channel utilisation in Equation (2), with the constraints defined in Equation (1). The objective function is channel utilisation with the constraints. We evaluate each of these strings including parents and offspring with the objective function via simulation, and we choose new parents probabilistically among the strings according to the fitness. The probability we chose is proportional to its fitness as follows:

$$p_i = \frac{U_i}{\sum_j U_i}. \tag{12}$$

Figure 1 Example of mating/crossover



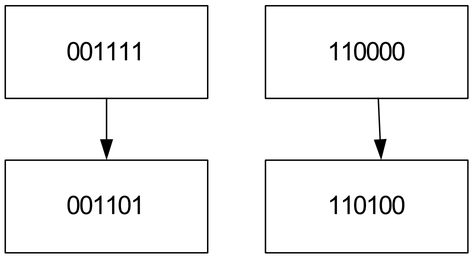


Figure 2 Examples of mutation

We assume that all the strings satisfy the constraints. Otherwise, we can let the probability be zero.

For those that have not been chosen, we will delete them with probability $1\text{-}p_i$. We call the chosen ones those that have not been deleted in the population. We will keep the size of the population constant by stopping to choose or stopping to delete when some threshold is reached. The population are then grouped together and paired into parents.

Step 5

If it has been more than N iterations without improvement, go to Step 6. Otherwise, go to Step 2. N is a pre-defined constant. Improvement is defined by comparing the average fitness with that of the previous generation.

Step 6

We choose the best fitful decision in terms of Equation (12) among all the members in the population.

The above algorithm can run online or offline. Note that the above algorithm just finds one near-optimal decision string for one system state. If this algorithm is running online, when the system state changes, the algorithm needs to run again to find the near-optimal decision string at the new system state. However, we can run this algorithm offline to find all near-optimal decision strings for all system states.

5 Simulation results

In this section, we compare our genetic algorithm with the SMDP approach. Simulation parameters are illustrated in Table 1. We assume that the handoff arrival rate is proportional to the new arrival rate, $\lambda_{i,h}=\alpha\lambda_{i,n}$. We let $\alpha=0.5$, that is $\lambda_{i,h}=0.5\ \lambda_{i,n}$. N is the number of iterations.

Table 1 Simulation parameters

Experimental parameters	*Value*
N	150
m	2
b_1	1
b_2	2
$D_{1,HB}$	0.01
$D_{2,HB}$	0.02
C	25
$1/\mu_1$	500 sec.
$1/\mu_2$	500 sec.
$\lambda_{1,h}/\lambda_{1,n}$	0.5
$\lambda_{2,h}/\lambda_{2,n}$	0.5
1/h	100 sec.

Figure 3 compares the channel utilisation for the SMDP approach and the genetic algorithm approach as Erlang load increases. Erlang load is defined as $\lambda_{i,n}/\mu_i$. It is shown that the genetic algorithm approach's channel utilisation is very close to the optimal channel utilisation produced by the SMDP approach. The results reveal that the genetic algorithm approximates the optimal solution very well.

Figure 3 Channel utilisation versus Erlang Load

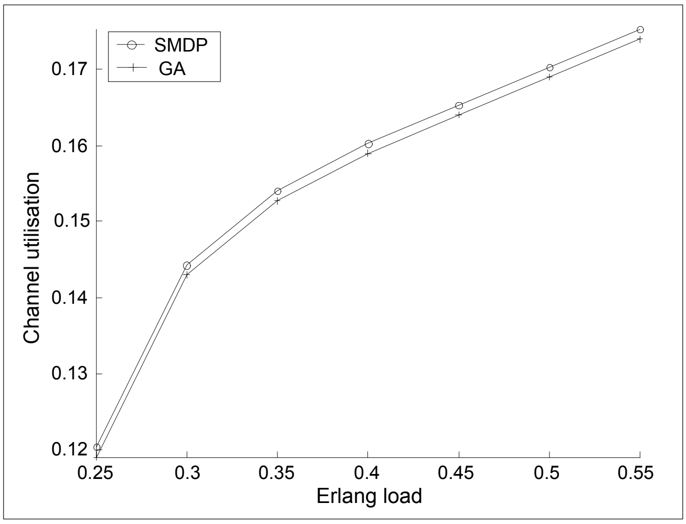


Figure 4 and Figure 5 show handoff dropping probabilities for class-1 and class-2, respectively. We observe that handoff dropping probabilities are bounded for both schemes and for both classes. In other words, QoS requirements are satisfied.

Figure 4 Handoff dropping probability for class-1

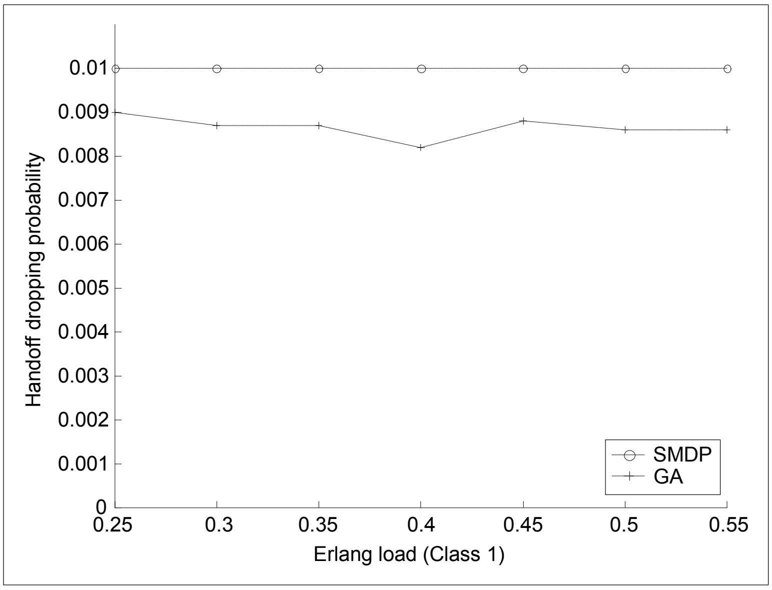
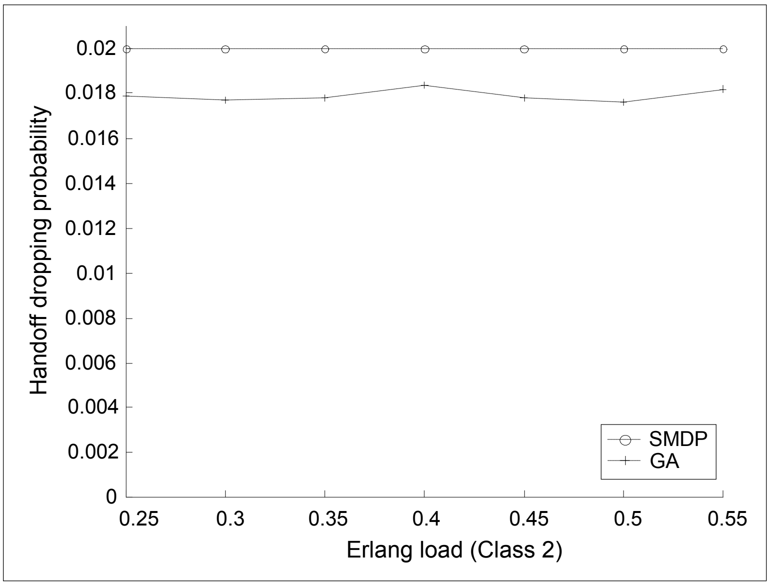


Figure 5 Handoff dropping probability for class-2



6 Conclusion

The Semi-Markov Decision Process (SMDP) approach can be used in CAC to provide an optimal solution. However, such a method fails when the state space and the action space are too large. The action space increases exponentially with m, and the state space is extremely large for the large C.

In this paper, we apply a genetic algorithm approach to address such problems as when the SMDP approach fails for multi-class multimedia services. This method overcomes the computational limits of the SMDP approach. We present the coding method and the genetic algorithm itself. Simulation results from the genetic algorithm are compared with the optimal solution obtained from linear programming for the SMDP approach. The results reveal that the genetic algorithm approximates the optimal solution very well, and at the same time QoS requirements are satisfied.

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