

Optimal Design of Multiple Fractional Guard Channel Policy in Multiservice Cellular Networks

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Abstract

In this paper we compute the optimal configuration of the Multiple Fractional Guard Channel (MFGC) admission policy in multiservice mobile wireless networks. The optimal configuration maximizes the offered traffic that the system can handle while meeting certain QoS requirements but computing the optimal parameter setting of this policy can constitute a high computational cost. To face these computational limitations an approximation based on Kaufman & Roberts recursion is evaluated and an algorithm is proposed. Moreover, we also propose an adaptative algorithm. The numerical results show that it is not easy to find a fast and accurate algorithm, in this sense the adaptative method yields the best results.

1 Introduction

In the last years mobile cellular networks have experienced a enormous growth. Different service types with different QoS requirements have to be handled and more traffic has to be carried. Moreover, in order to deal with the growing capacity demand there is a trend to reduce the cell size in cellular systems. Reducing the cell size increases the number of handovers that a session undergoes which might have a negative impact on the QoS unless proper mechanisms are in place. Efficient SAC can be used to optimize the resource utilization and fullfil QoS constraints.

For a single service scenario the trunk reservation policies Guard Channel (GC) [1] and Fractional Guard Channel (FGC) [2] provide good results for common QoS objective function, [2]. In [3, 4] several types of admission control policies for cellular multiservice networks have been studied. The MFGC strategy is an efficient admission policy for multiservice mobile wireless networks and its implementation is quite simple. Nevertheless, computing the optimal parameter setting of this policy is computationally costly.

In this paper, we study the optimal design of MFGC policy which is typically based on an iterative analysis procedure that adjusts the configuration parameters of the MFGC to achieve certain blocking probability objectives. In [5] a methodology to determine the exact parameter values of the MFGC policy is proposed, including some speed up suggestions, but its computational cost is prohibitive for practical systems. In [6] an approximation based on the Kaufman and Roberts (K&R) recursion is proposed to compute the parameters of the MFGC policy. Although the computational cost greatly is reduced, no indication is provided about its precision. We propose two new procedures to determine the parameters of the MFGC policy. One is an enhancement of the one proposed in [5] that uses the approximation based on the K&R recursion to quickly approximate to the surroundings of the solution and then we deploy a slightly modified version of [5] to achieve the final solution. The other is based on simulating a slightly modified version and adaptive admission control scheme proposed in [7]. We provide a comparative analysis of the four methods and show that the precision and computational cost of the newly proposed ones lies in between the ones of the previous methods. Henceforth we refer to the approximation based in K&R as CVO and to the algorithm proposed in [5] as PMC after its author's initials. We refer to the modified version of PMC as BGMP algorithm.

The remaining of this paper is structured as follows. In section 2 the system model is described. In section 3 we present the PMC algorithm, the CVO approximation, and the enhanced algorithm. In section 4 we propose an adaptative model and in section 5 we compare and discuss the results obtained. Finally, some concluding remarks are made in section 6.

2 Model Description

We consider a single cell with a total of C resource units, where the physical meaning of a unit of resources will de-

pend on the specific technology of the radio interface. A set of N different classes of services contend for the resource units. For each type of service new and handoff call arrivals are distinguished, so that there are N types of service and $2N$ arrival types. Arrivals are numbered in such manner that for service i new call arrivals are referred to as arrival type i , whereas handoff arrivals are referred to as arrival type $N+i$. For the sake of mathematical tractability we make the common assumptions of Poisson arrival processes and exponentially distributed random variables for cell residence time and call duration. The arrival rate for new (handoff) calls of service i is λ_i^n (λ_i^h). A request of service i consumes b_i resource units, $b_i \in \mathbb{N}$. The call duration of service i is exponentially distributed with rate μ_i^c . The cell residence time of a service i customer is exponentially distributed with rate μ_i^r . Hence, the resource holding time in a cell for service i is exponentially distributed with rate $\mu_i = \mu_i^c + \mu_i^r$. If we denote by $\mathbf{p} = (P_1, \dots, P_{2N})$ the blocking probabilities for each of the $2N$ arrival streams, the new call blocking probability is $P_i^n = P_i$, the handoff failure probability is $P_i^h = P_{N+i}$ and the forced termination probability that by [1] is $P_i^{ft} = P_i^h / (\mu_i^c / \mu_i^r + P_i^h)$.

If the system is in statistical equilibrium the handoff arrival rates are related to the new call arrival rates and the blocking probabilities (P_i) [8] through the expression:

$$\lambda_i^h = \lambda_i^n (1 - P_i^n) / (\mu_i^c / \mu_i^r + P_i^n) \quad (1)$$

The blocking probabilities do in turn depend on the handoff arrival rates yielding a system of non-linear equations which can be solved using a fixed point iteration method as described in [8]. The system state is described by an N -tuple $\mathbf{x} = (x_1, \dots, x_N)$, where x_i represents the number of type i calls in the system, regardless they were initiated as new or handoff calls. Let $b(\mathbf{x})$ represent the amount of occupied resources at state \mathbf{x} , $b(\mathbf{x}) = \sum_{i=1}^N x_i b_i$. $\lambda^T = \sum_{1 \leq i \leq N} \lambda_i^n$ is the aggregated call arrival rate and f_i ($0 \leq f_i < 1$, $\sum_{1 \leq i \leq N} f_i = 1$) represents the fraction of λ^T that correspond to service i , i.e. $\lambda_i^n = f_i \lambda^T$. From now on, we refer to the maximum offered rate that the network can handle while meeting certain QoS requirements as λ_{max}^T .

3 Optimal Capacity and computational cost in MFGC policy

A brief definition of the MFGC policy is as follows. Two parameters are associated with service i : t_i^n and t_i^h . In order to decide on the acceptance of a request of type i , upon arrival the amount of resources that will be occupied if it is accepted is compared with the corresponding threshold t_i . if $b(\mathbf{x}) + b_i \leq \lfloor t_i \rfloor$, accept; if $b(\mathbf{x}) + b_i = \lfloor t_i \rfloor + 1$, accept with probability $t_i - \lfloor t_i \rfloor$; if $b(\mathbf{x}) + b_i > \lfloor t_i \rfloor + 1$, reject. On average, the maximum number of resource units

that service i can dispose of is $t_i^{n,h}$. The policy parameters $t_i^{n,h}$ control the amount of resource units that a service can access. The optimal parameters maximize λ^T .

The QoS requirements are given in terms of upper-bounds for the new call blocking probabilities (B_i^n) and the forced termination probabilities (B_i^{ft}). The capacity optimization problem can be formally stated as follows

Given: $C, b_i, f_i, \mu_i^c, \mu_i^r, B_i^n, B_i^{ft}; i = 1, \dots, N$

Maximize: λ^T by finding the appropriate MFGC parameters $t_i; i = 1, \dots, 2N$

Subject to: $P_i^n \leq B_i^n, P_i^{ft} \leq B_i^{ft}; i = 1, \dots, N$

In order to find optimal $t_i^{n,h}$ and λ_{max}^T , PMC algorithm proceeds as follows. The algorithm has a main part (Algorithm `pmc`) from which the procedure `sMFGCpmc` is called. Let us introduce the $2N$ -tuple $\mathbf{p}_{max} = (B_1^n, \dots, B_N^n, B_1^h, \dots, B_N^h)$ as the upper-bound vector for the blocking probabilities, where the value of B_i^h is given by:

$$B_i^h = (\mu_i^c / \mu_i^r) B_i^n / (1 - B_i^{ft}) \quad (2)$$

The procedure `sMFGCpmc` does, in turn, call another procedure (`MFGCpmc`) that calculates the blocking probabilities by solving the balance equations.

The procedure `MFGCpmc`, which is invoked in the inner-most loop of PMC algorithm, is used to obtain the blocking probabilities. ($\mathbf{p} := \text{MFGC}(\mathbf{t}, \lambda_n, \mu^c, \mu^r, \mathbf{b}, C)$).

Algorithm:

$(\lambda_{max}^T, \mathbf{t}_{opt}) = \text{pmc}(\mathbf{p}_{max}, \mathbf{f}, \mu^c, \mu^r, \mathbf{b}, C)$

$\varepsilon_1 := <\text{precision}>; L := 0; U := <\text{high value}>$

$(\text{ok}, \mathbf{t}) := \text{sMFGCpmc}(\mathbf{p}_{max}, U \mathbf{f}, \mu^c, \mu^r, \mathbf{b}, C)$

atLeastOnce:=FALSE;

while ok **do**

$L := U; t_L := \mathbf{t}; \text{atLeastOnce} := \text{TRUE}; U := 2U$

$(\text{ok}, \mathbf{t}) := \text{sMFGCpmc}(\mathbf{p}_{max}, U \mathbf{f}, \mu^c, \mu^r, \mathbf{b}, C)$

end while /* it makes sure that $U > \lambda_{max}^T */$

repeat

$\lambda := (L + U) / 2$

$(\text{ok}, \mathbf{t}) := \text{sMFGCpmc}(\mathbf{p}_{max}, \lambda \mathbf{f}, \mu^c, \mu^r, \mathbf{b}, C)$

if ok **then** $L := \lambda; t_L := \mathbf{t}; \text{atLeastOnce} := \text{TRUE};$
else $U := \lambda$

until $(U - L) / L \leq \varepsilon_1$ AND atLeastOnce

$\lambda_{max}^T := L; \mathbf{t} := t_L$

Procedure:

$(\text{ok}, \mathbf{t}) = \text{sMFGCpmc}(\mathbf{p}_{max}, \lambda_n, \mu^c, \mu^r, \mathbf{b}, C)$

$\varepsilon_2 := <\text{precision}>; \delta := <\text{small value}>$

$\mathbf{t} := (\delta, \delta, \dots, \delta)$

$\mathbf{p} := \text{MFGC}(\mathbf{t}, \lambda_n, \mu^c, \mu^r, \mathbf{b}, C)$

repeat

```

canConverge:=TRUE; i := 1;
repeat
  if  $p(i) > p_{max}(i)$  then
     $t' := t$ ;  $t'(i) := C$ 
     $p' := MFGCpmc(t', \lambda_n, \mu^c, \mu^r, b, C)$ 
    if  $p'(i) > p_{max}(i)$  then
      canConverge:=FALSE;
    else
       $L := t(i)$ ;  $U := C$ 
      repeat
         $t(i) := (L + U)/2$ 
         $p := MFGCpmc(t, \lambda_n, \mu^c, \mu^r, b, C)$ 
        if  $p(i) > p_{max}(i)$  then  $L := t(i)$ 
        else  $U := t(i)$ 
      until  $(1 - \epsilon_2)p_{max}(i) \leq p(i) \leq p_{max}(i)$ 
    end if
  end if
   $i := i + 1$ 
until  $(i > 2N)$  OR ( NOT(canConverge))
if canConverge then
  if  $p(i) \leq p_{max}(i) \quad \forall i$  then
    ok:=TRUE; exit:=TRUE;
  else exit:=FALSE;
  else ok:=FALSE; exit:=TRUE;
until exit

```

For this computation an iterative procedure is normally required in order to obtain the value of the handoff request rates. The following observation can be used to speed up the algorithm since it permits to eliminate the above mentioned iterative procedure. Each run of `solMFGC` tries to find t , so that $p = p_{max}$ (within tolerance limit). Thus, in order to compute λ_i^h we use the expression $\lambda_i^h = \lambda_i^n(1 - B_i^n)/(\mu_i^c/\mu_i^r + B_i^h)$ instead of (1), in which λ_i^h is explicitly defined.

To determine whether the QoS objectives can be fulfilled for some given parameters it is necessary to calculate the stationary state probabilities (and so, we can obtain the blocking probabilities). Thus, at each new value of $t_i^{n,h}$ for a given λ^T a multidimensional birth and death process has to be solved in the procedure `MFGCpmc`. In PMC algorithm, these stationary state probabilities are obtained from solving the balance equations using Gauss-Seidel method. Solving this process is the most computationally expensive part of the algorithm. In spite of using the speed up technique the computational cost grows enormously when the number of resource units or/and the number of different classes of services is high.

To face these computational limitations a numerical approximation is studied. The CVO approximation consists of converting the multidimensional process to a one-dimensional process where the system state is defined by $b(x)$, the total number of resource units occupied. Hence-

forth, let us refer to $b(x)$ as k . Then, the distribution of k can be generated recursively by the equation (3), where $\beta_{k,j}$ is the probability of accepting a request of type j that arrives in state k . With this distribution the blocking probabilities can be obtained alternatively by (4) and the procedure `MFGCpmc` of the PMC algorithm will be faster.

$$\sum_{i=1}^N \frac{\beta_{k-b_i,i} \lambda_i^n + \beta_{k-b_i,i+N} \lambda_i^h}{\mu_i^c + \mu_i^h} b_i q(k - b_i) = k q(k) \quad (3)$$

$$P_i^n = \sum_{r=0}^C (1 - \beta_{r,i}) q(r); \quad P_i^h = \sum_{r=0}^C (1 - \beta_{r,i+N}) q(r) \quad (4)$$

As shown later, the accuracy of this approximation is poor. Therefore, we proposed an new algorithm (BGMP algorithm) that uses the CVO approximation to improve the PMC algorithm. We observe that an enhancement of the PMC algorithm is possible by initializing the value of the parameters $t_i^{n,h}$ and the aggregated call arrival rate λ^T as close as possible to the optimal values. So, in BGMP algorithm, $t_i^{n,h}$ and λ^T are initialized with the values obtained using the CVO approximation in the procedure `MFGCbgbmp`. In a first step we initialize $t_i^{n,h}$ with small values and λ^T inside a large interval. CVO approximation is used to obtain a first estimation of λ^T and t . In the second step, these results are the initial values and the procedure `MFGCbgbmp` solves the multidimensional birth and death process using Gauss-Seidel method. Thus, the cost of the PMC algorithm is reduced considerably.

In the second step, the initial interval of λ^T will be narrower, therefore the search of the optimal λ^T can be faster. Moreover, in each evaluation of a new λ^T the initial values of $t_i^{n,h}$ will not be the same small initial values but they will be the calculated values in the previous evaluation. These changes improve the algorithm since there are less new values of $t_i^{n,h}$ for a new λ^T that must be evaluated and so, less multidimensional birth and death processes have to be solved.

Initialization:

$(\lambda_{max}^T, t_{opt}) = \text{Initial } (p_{max}, f, \mu^c, \mu^r, b, C)$
$\lambda_0^T := <\text{high value}>; \delta := <\text{small value}>$
$t_0 := (\delta, \delta, \dots, \delta); s = 1;$
$(\lambda_0^T, t_0) := \text{bgmp}(\lambda_0^T, t_0, p_{max}, f, \mu^c, \mu^r, b, C, s)$
$s = 2;$
$(\lambda_{max}^T, t_{opt}) := \text{bgmp}(\lambda_0^T, t_0, p_{max}, f, \mu^c, \mu^r, b, C, s)$

Algorithm:

$(\lambda_{max}^T, t_{opt}) = \text{bgmp}(\lambda_0^T, t_0, p_{max}, f, \mu^c, \mu^r, b, C, s)$
$\varepsilon_1 := <\text{precision}>; L := \lambda_{ini}^T; U := L$
$(ok, t) := \text{sMFGCbgbmp}(p_{max}, f, t_0, \mu^c, \mu^r, b, C, s)$
atLeastOnce:=FALSE;

```

if ok then
  while ok do
     $L := U$ ;  $t_L := t$ ; atLeastOnce:=TRUE ;
    if  $s==1$  then  $U := 2U$ 
    else  $U := 1.1 * U$ 
    ( $ok, t$ ) := sMFGCbmp( $p_{max}, U f, t_0, \mu^c, \mu^r, b, C, s$ )
  end while /* it makes sure that  $U > \lambda_{max}^T$  */
else
  while not(ok) do
     $U := L$ ;  $t_L := t$ ; atLeastOnce:=TRUE ;
     $L := 0.9 * U$ 
    ( $ok, t$ ) := sMFGCbmp( $p_{max}, U f, t_0, \mu^c, \mu^r, b, C, s$ )
  end while /* it makes sure that  $L < \lambda_{max}^T$  */
end if
repeat
   $\lambda := (L + U)/2$ 
  ( $ok, t$ ) := sMFGCbmp( $p_{max}, \lambda f, t_0, \mu^c, \mu^r, b, C, s$ )
  if ok then  $L := \lambda$ ;  $t_L := t$ ; atLeastOnce:=TRUE;
  else  $U := \lambda$ 
until  $(U - L)/L \leq \varepsilon_1$  AND atLeastOnce
 $\lambda_{max}^T := L$ ;  $t := t_L$ 

```

Procedure:

```

( $ok, t$ ) = sMFGCbmp ( $p_{max}, \lambda_n, t^{n,h}, \mu^c, \mu^r, b, C, s$ )
 $\varepsilon_2 := <$  precision  $>; t := t^{n,h}$ 
 $p := MFGCbmp(t, \lambda_n, \mu^c, \mu^r, b, C, s)$ 
repeat
  canConverge:=TRUE;  $i := 1$ ;
  repeat
    if  $p(i) > p_{max}(i)$  then
       $t' := t$ ;  $t'(i) := C$ 
       $p' := MFGCbmp(t', \lambda_n, \mu^c, \mu^r, b, C, s)$ 
    if  $p'(i) > p_{max}(i)$  then
      canConverge:=FALSE;
    else
       $L := t(i)$ ;  $U := C$ 
      repeat
         $t(i) := (L + U)/2$ 
         $p := MFGCbmp(t, \lambda_n, \mu^c, \mu^r, b, C, s)$ 
        if  $p(i) > p_{max}(i)$  then  $L := t(i)$ 
        else  $U := t(i)$ 
      until  $(1 - \varepsilon_2)p_{max}(i) \leq p(i) \leq p_{max}(i)$ 
    end if
  end if
  if  $p(i) < 0.99p_{max}(i)$  then
     $L := 0.9t(i)$ ;  $U := t(i)$ 
    repeat
       $t(i) := (L + U)/2$ 
       $p := MFGCbmp(t, \lambda_n, \mu^c, \mu^r, b, C, s)$ 
      if  $p(i) < 0.99p_{max}(i)$  then  $U := t(i)$ 
      else  $L := t(i)$ 
    until  $(1 - \varepsilon_2)p_{max}(i) \leq p(i) \leq p_{max}(i)$ 
  end if

```

```

 $i := i + 1$ 
until  $(i > 2N)$  OR ( NOT(canConverge))
if canConverge then
  if  $p(i) \leq p_{max}(i) \quad \forall i$  then
    ok:=TRUE; exit:=TRUE;
  else exit:=FALSE;
  else ok:=FALSE; exit:=TRUE;
until exit

```

4 Adaptative scheme

The adaptive scheme operates in coordination with the Multiple Guard Channel (MGC). The definition of MGC policy is as follows: one threshold parameter is associated with each class $s_i, l_i \in \mathbb{N}$. An arrival of s_i in state x is accepted if $b(x) + b_i \leq l_i$ and blocked otherwise. Therefore, l_i is the amount of resources that s_i has access to and increasing (decreasing) it reduces (augments) P_i . For the sake of clarity, the operation of our scheme is described assuming that the arrival processes are stationary and the system is in steady state. In practice, we can assume without loss of generality that the QoS objective for class i can be expressed as $B_i = c_i/o_i$, where $c_i, o_i \in \mathbb{N}$. Then it is expected that if $P_i = B_i$ the class i will experience, in average, c_i rejected requests and $o_i - c_i$ admitted requests, out of o_i offered requests. For example, if the QoS objective for s_i is $B_i = 1/100$, then $c_i = 1$ and $o_i = 100$.

It seems intuitive to think that the adaptive scheme should not change the threshold parameters of those arrival classes meeting their QoS objective and, on the contrary, adjust them on the required direction if the perceived QoS is different from its target. Therefore, given that the MGC policy deploys integer values for its threshold parameters, we propose to perform a probabilistic adjustment each time a request is processed in the following way.

First of all, we choose an arrival type α that for simplicity we assume that it is the new arrival type $s_i = 1$. For arrival types $\in [2, 2N]$: i) if accepted, do $\{l_i \leftarrow (l_i - \Delta l)\}$ with probability $1/(o_i - c_i)$; ii) if rejected, do $\{l_i \leftarrow (l_i + \Delta l)\}$ with probability $1/c_i$, where $\Delta l \in \mathbb{N}$ is the adjustment step for the thresholds parameters. For arrival type $\alpha = 1$: i) if accepted, do $\{\lambda^T \leftarrow (\lambda^T + \Delta \lambda)\}$ with probability $1/(o_1 - c_1)$; ii) if rejected, do $\{\lambda^T \leftarrow (\lambda^T - \Delta \lambda)\}$ with probability $1/c_1$, where $\Delta \lambda \in \mathbb{N}$ is the adjustment step for the λ^T .

Therefore, under stationary traffic if $P^i = B^i$ then, in average, l^i is increased by Δl and decreased by Δl every o^i offered new requests, i.e. its mean value is kept constant.

The thresholds l_i of classes with high priority are adjusted independently from each other according to whether their requests are accepted or rejected. If a lot of requests of arrival type s_i are rejected, it can be that $l_i \geq C$. In this case, l_1 is decremented. Thus, class $\alpha = 1$ does not control its own threshold l_1 but controls its QoS as the other

Table 1. System A, $C = 50$

	PMC	CVO	BGMP	Adapt.
PB_1^n	0.09943	0.09702	0.09994	0.09910
PB_2^n	0.00994	0.00540	0.01000	0.00996
PB_1^h	0.05032	0.04074	0.05042	0.04991
PB_2^h	0.00331	0.00148	0.00332	0.00322
t_1^n	44.74443	43.83188	44.91298	44.82806
t_2^n	48.82751	48.76477	48.92838	48.88065
t_1^h	45.77865	45.08508	45.87985	45.84007
t_2^h	49.83517	49.87696	49.93598	49.90395
λ_{max}^T	0.15033	0.14560	0.15106	0.14954
Time(seg)	2433	11	343	511

Table 2. System A errors (%), $C = 50$

	PMC	CVO	BGMP	Adapt.
PB_1^n	-0.57432	-2.98151	-0.05704	-0.89836
PB_2^n	-0.63786	-45.96094	-0.00039	-0.37312
PB_1^h	-0.37420	-19.34385	-0.17438	-1.17438
PB_2^h	-0.67059	-55.63054	-0.59164	-3.46418

classes. When $P_1 > B_1 = c_1/o_1$, λ^T is decremented and if all objectives are fulfilled, λ^T is incremented.

Note also that in the operation of this simple scheme no assumption has been made concerning the arrival processes or the distribution of the session duration and cell residence times.

5 Numerical evaluation

In this section we make a comparative evaluation of the accuracy and the numerical complexity of the PMC

Table 3. System A, $C = 100$

	PMC	CVO	BGMP	Adapt.
PB_1^n	0.09975	0.09237	0.09978	0.09971
PB_2^n	0.00994	0.00476	0.09950	0.00994
PB_1^h	0.05044	0.03804	0.05016	0.05002
PB_2^h	0.00333	0.00119	0.00334	0.00317
t_1^n	94.52733	93.32424	94.26572	93.62424
t_2^n	98.82735	98.67493	98.58161	97.90181
t_1^h	95.68229	94.82066	95.41835	94.76769
t_2^h	99.84418	99.88144	99.61287	98.94442
λ_{max}^T	0.34564	0.33617	0.34458	0.33851
Time(seg)	27018	32	3265	956

Table 4. System A errors (%), $C = 100$

	PMC	CVO	BGMP	Adapt.
PB_1^n	-0.24742	-7.63467	-0.22287	-0.28577
PB_2^n	-0.58398	-52.42965	-0.51142	-0.58824
PB_1^h	-0.13079	-24.68383	-0.67992	-0.95639
PB_2^h	-0.13712	-64.24339	-0.00101	-5.09746

algorithm, PMC algorithm using the CVO approximation, BGMP algorithm and the adaptative method.

For the numerical examples we have considered two systems. System A with two services ($N = 2$), and parameters, [5]: $\mathbf{b} = (1, 2)$, $\mathbf{f} = (0.8, 0.2)$, $\boldsymbol{\mu}^c = (1/180, 1/300)$, $\boldsymbol{\mu}^r = (1/900, 1/1000)$, $\mathbf{B}^n = (0.1, 0.01)$, $\mathbf{B}^{ft} = (0.01, 0.001)$, by (2) $\mathbf{B}^h = (0.05051, 0.00334)$;

Tables 1 and 3 show the results obtained in system A, with $C = 50$ and $C = 100$ respectively. Rows $P_i^{n,h}$ are the blocking probabilities obtained using the parameters $t_i^{n,h}$ and λ_{max}^T calculated with each method. The row Time shows the computational cost for each method in seconds in an Intel Pentium IV HT 3.4GHz. Each column defines the results obtained using the indicated algorithm, where the column CVO has the results obtained when the CVO approximation is used in the PMC algorithm. Table 2 and 4 contain the relative error (%) value of each method in relation to the upper-bounds for the blocking probabilities. Negative errors show that the results are lower than the objectives. Otherwise, if the error is positive, the blocking probabilities obtained are higher than the upper-bounds.

The results presented indicate that PMC algorithm is the most computationally costly method and the CVO approximation is not the best solution to compute the parameters in terms of accuracy since the blocking probabilities calculated using the parameters obtained do not adjust to the objectives. In terms of computational cost CVO approximation is the faster method. The BGMP algorithm gives good results but the computational cost can be high if there are a lot of resource units. The adaptative method achieves good precision and when the system has few resource units its computational cost is higher than using the BGMP algorithm but when the number of resource units is high the adaptative method is faster than the BGMP algorithm.

System B offers four services ($N = 4$), and parameters, [9]: $\mathbf{b} = (1, 2, 4, 6)$, $f_i = 0.2$; $p = [1, 2, 3, 4]$; $f_c = f_i^{p-1}$; $F = \sum f_c$; $f = f_c/F$, $\boldsymbol{\mu}^c = (1/300, 1/300, 1/300, 1/300)$, $\boldsymbol{\mu}^r = \boldsymbol{\mu}^c$, $\mathbf{B}^n = (0.05, 0.04, 0.03, 0.02)$, $\mathbf{B}^{ft} = (0.005, 0.004, 0.003, 0.002)$, by (2) $\mathbf{B}^h = (5.03 \cdot 10^{-3}, 4.02 \cdot 10^{-3}, 3.01 \cdot 10^{-3}, 2.004 \cdot 10^{-3})$.

Table 5 shows the results obtained in system B, with $C = 50$. Table 6 contains the relative error (%) value of each method in relation to the upper-bounds for the block-

Table 5. System B, $C = 50$

	CVO	BGMP	Adapt.
PB_1^n	0.05177	0.04995	0.04989
PB_2^n	0.04141	0.03978	0.03983
PB_3^n	0.02996	0.02980	0.02998
PB_4^n	0.01909	0.01989	0.01994
PB_1^h	$4.04 \cdot 10^{-3}$	$5.01 \cdot 10^{-3}$	$5.00 \cdot 10^{-3}$
PB_2^h	$3.01 \cdot 10^{-3}$	$4.00 \cdot 10^{-3}$	$3.01 \cdot 10^{-3}$
PB_3^h	$2.14 \cdot 10^{-3}$	$2.99 \cdot 10^{-3}$	$3.01 \cdot 10^{-3}$
PB_4^h	$1.20 \cdot 10^{-3}$	$2.00 \cdot 10^{-3}$	$1.91 \cdot 10^{-3}$
t_1^n	39.46525	40.06401	39.76525
t_2^n	40.93308	41.54805	41.25667
t_3^n	43.59322	44.54805	43.78052
t_4^n	46.39994	46.80984	46.51919
t_1^h	43.83370	43.93660	43.66337
t_2^h	45.13726	45.21995	44.90065
t_3^h	47.56039	47.53540	47.23811
t_4^h	49.97023	49.84798	49.69260
λ_{max}^T	0.07761	0.07873	0.07807
Time(seg.)	38	325446	2298

Table 6. System A errors (%), $C = 50$

	CVO	BGMP	Adapt.
PB_1^n	3.54486	-0.10341	-0.21834
PB_2^n	3.51654	-0.55375	-0.41724
PB_3^n	-0.13102	-0.66719	-0.08090
PB_4^n	-4.56965	-0.55693	-0.31166
PB_1^h	-19.63747	-0.38595	-0.56349
PB_2^h	-22.64110	-0.37032	-0.02899
PB_3^h	-28.94904	-0.51524	-0.00591
PB_4^h	-40.14390	-0.44688	-4.52181

ing probabilities. The results show the same conclusions as in the system A. In this case, the column PMC does not exist because this algorithm is too computationally costly.

6 Conclusions

We have proposed a new algorithm (BGMP) based in a previous algorithm (PVM), and an adaptative method to compute the optimal parameters setting of the MFGC policy.

We have observed that when the system has a large number of resource units and/or various classes of service the computational cost can be prohibitive for the PMC algorithm. The CVO approximation does not adjust to the objectives, although the BGMP algorithm presents good results it can be too computationally costly. The adaptative

method achieves good precision and its computational cost is between the CVO approximation and the BGMP algorithm.

Acknowledgements

This work was supported by the Spanish Government (30% PGE) and the European Commission (70% FEDER) through projects TSI2005-07520-C03-03 and TSI2007-66869-C02-02 and by *Cátedra Telefónica de Internet y Banda Ancha* (e-BA) from the Universidad Politécnica de Valencia. Besides Elena Bernal-Mor was supported by the Spanish Ministry of Education and Science under contract BES-2007-15030.

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