Optimizing Admission Control for Multi-Service Wireless Networks with Bandwidth Asymmetry between Uplink and Downlink

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Abstract

Next generation wireless networks need to support multi-class services with asymmetric bandwidth allocation between uplink and downlink to match the asymmetric traffic load brought by some data services. For the design of call admission control (CAC) policy in such networks, how to decrease the average system cost is a key issue. In this paper, we study the optimal admission policy for minimizing a linear cost function to obtain the minimum average system cost. We consider the CAC problem as a decision process. By modelling the admission control problem into a Markov decision process (MDP) and analyzing the corresponding value function, we obtain some monotonicity properties of the optimal policy. These properties suggest that the optimal admission control policy for the bandwidth asymmetry wireless networks should have a threshold structure and the threshold specified for a class of calls may change with the system state. Due to the prohibitively high complexity for computing the thresholds in a system with large state space, we propose a heuristic CAC policy called Call-Rate-based Dynamic Threshold (CRDT) policy to approximate the theoretical optimal policy based on the insights we obtain from the modelling and the analytical study on the properties of the optimal policy. The CRDT policy

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is efficient and can be easily implemented. The numerical results show that the performance of average cost obtained from the proposed CRDT policy is close to that of the optimal policy from the MDP model and is better than that of some known existing CAC schemes, including those performing well in bandwidth asymmetry wireless networks.

I. INTRODUCTION

One of the most prominent features of next generation wireless networks is to support multiple services such as voice, video, web browsing, file transmission, interactive gaming etc. Since some data services such as web browsing and file downloading may bring more traffic load on downlink than on uplink, next generation wireless networks are expected to present distinctive traffic asymmetry between uplink and downlink [1]–[6]. In such environment, it is necessary to allocate different bandwidth between uplink and downlink in order to support the asymmetric traffic load. It has been proved that the asymmetric bandwidth allocation outperforms the symmetric bandwidth allocation in this environment [2]. How to guarantee the QoS of different call classes and improve the system performance in such asymmetric bandwidth allocation wireless networks is an attractive research topic in recent years [1]–[6].

In our previous work [3], we have studied the mismatch problem between the asymmetric bandwidth allocation and the dynamic traffic load in the system. We find that if too many bandwidth-symmetric calls such as real-time (RT) calls are accepted, some downlink bandwidth resources might be wasted. On the other hand, if too many bandwidth-asymmetric calls such as non-real-time (NRT) calls are accepted, some uplink bandwidth might be wasted. We proposed two call admission control (CAC) schemes to address this problem. The proposed schemes improve the bandwidth utilization in the asymmetric bandwidth allocation wireless networks and guarantee the blocking probability of some high priority calls such as the handoff RT calls. We could categorize the problem we addressed in [3] as MAXU problem, which is defined as maximizing system bandwidth utilization subject to constraints on the blocking probabilities of some high priority calls. Actually, MAXU problem in the symmetric bandwidth allocation wireless networks has been intensively studied in the literatures recently [7]–[13].

In this paper, we study the CAC policy in the asymmetric bandwidth allocation wireless networks from another perspective. We consider the CAC policy as a decision process which decides whether or not to accept an arrival call subject to MINCost problem, which is defined as
minimizing a linear objective cost function to obtain the minimum average cost. To the best of our knowledge, there is only very little work focused on modelling and analysis of the MINCost CAC problem especially in the asymmetric bandwidth allocation wireless networks. For the traditional mono-service networks, the MINOBJ problem, which is similar to the MINCost problem, is studied in [14] and the guard-channel scheme [15] is proved be optimal solution. In [16], the authors study maximizing reward problem, which is similar to the MINCost problem except that they consider reward maximization instead of cost minimization. The authors formulate CAC problem in a resource-sharing system into a fluid model and study the optimal admission control for the large-capacity system. They show that the trunk reservation policy is optimal when the calls in the system have identical service time distributions.

In this paper, we focus on the modelling and the analysis of the CAC policy subject to the MINCost problem in the asymmetric bandwidth allocation multi-service wireless networks. By formulating the CAC problem into a Markov decision process (MDP) model and analyzing the corresponding value function, we identify some monotonicity properties of the value function. These properties suggest that the optimal policy in such environment should have threshold structure and the thresholds may vary with the system state. Due to the prohibitively high complexity of computing the values of the thresholds in a large system state space, we propose a heuristic policy called Call-Rate-based Dynamic Threshold (CRDT) policy based on our insights obtained in the modelling and the analysis. The numerical results show that the average cost obtained from the CRDT policy is very close to that obtained by applying the policy from the MDP model in a dynamic traffic load system.

Our contribution in this paper is threefold: 1) We formulate the admission control for the MINCost problem in the asymmetric bandwidth allocation wireless networks into an MDP model; 2) We prove some monotonicity properties of the optimal admission policy in the bandwidth asymmetry wireless networks. These properties may imply certain monotonicity properties of the optimal admission policy, e.g., a threshold structure; and 3) We propose a heuristic policy, which can be readily implemented, and use numerical example to demonstrate the good performance of the proposed policy.

The remainder of this paper is organized as follows. In Section II, we describe the system model and present the MDP formulation in detail. In Section III, we analyze the corresponding value function. We show that the optimal CAC policy for the MINCost problem should have a
threshold structure in the asymmetric bandwidth allocation multi-service wireless networks. In Section IV, we present the proposed CRDT admission control policy. The numerical results are given in Section V. In this section, we compare the average cost of our proposed policy with that of the policy obtained from the MDP model and other known polices, which are also proposed for the bandwidth asymmetry wireless networks. Finally, we conclude our paper in Section VI.

II. MDP FORMULATION OF CAC FOR MINCOST PROBLEM IN BANDWIDTH ASYMMETRY WIRELESS NETWORKS

A. System Model

We consider a cell in an asymmetric bandwidth allocation multi-service wireless network. Suppose calls from $M$ classes share $B_U$ and $B_D$ units of bandwidth resources in a cell, where $B_U$ and $B_D$ denote the uplink bandwidth and the downlink bandwidth respectively. Call requests of class $i$ $(1 \leq i \leq M)$ arrive according to the Poisson process with parameter $\lambda_i$. A call of class $i$ $(1 \leq i \leq M)$ demands $b_{ui}$ and $b_{di}$ bandwidth on uplink and downlink respectively. The connection holding time of the class $i$ calls is exponentially distributed with mean $1/\mu_i$. The system state is composed by the number of each class of calls in the system and it is determined by the control decisions made by admission control policy and random events. The control decisions include call acceptance and call rejection, and the random events involve call arrival, call connection completion and call handoff. When a call arrives, the system needs to decide whether the call can be accepted or not according to a certain CAC policy based on the current system state. Costs can be associated with the decisions. Thus the admission control problem can be viewed as a continuous time Markov decision process. A Markov decision process is a sequential decision problem where the set of actions, rewards and transition probabilities depend only on the current state of the system and the current decision selected. The history of the problem has no effect on the current decision. By solving the MDP problem, we may find the optimal admission policy, which results in minimum average cost.

B. Problem Formulation

In the following, we formulate the admission control policy for the MINCost problem into an MDP model. The MINCost problem is to minimize a linear objective function to obtain the minimum average cost.
The basic ingredients of an MDP function include states, actions, transitions, costs and an objective function. Let \( x = (x_1, \ldots, x_M) \) denote the system state, where \( x_i \) represents the number of class \( i \) calls in the system. The feasible system state should satisfy \( \sum_{i=1}^{M} b^u_i x_i \leq B_U \) and \( \sum_{i=1}^{M} b^d_i x_i \leq B_D \). Thus the set of the feasible system state, denoted by \( S \), is finite. Let \( W \) and \( w \) denote the set of the random events and the individual random event respectively. There are two events in the system: call arrival (\( w_a \)) and call departure (\( w_d \)) and thus \( W = \{ w_a, w_d \} \). When a call arrives (\( w = w_a \)), a decision needs to be made to accept or reject the call. No decision is needed for the call departure event (\( w = w_d \)), which could be call completion in the cell under consideration or call handoff to the other cells. Thus the set of control space \( U \) is defined as \( U = \{ u_a, u_r \} \), where \( u_a \) and \( u_r \) signify acceptance and rejection respectively.

In the infinite Markov decision process with a finite state space, the state \( x (x \in S) \) transits to the state \( x' (x \in S) \) in a time interval with a given probability \( P_{xx'} \), which depends on a decision from \( U \) on the current state. The time interval between state transition is called “stage”. During the \( k \)th stage, the system is in the state \( x(t_k) (x(t_k) \in S) \) and the control \( u(t_k) (u(t_k) \in U) \) is applied then the system transits to \( x(t_{k+1}) (x(t_{k+1}) \in S) \). During the transition from the \( k \)th stage to the \( k+1 \)th stage, the decision \( u(t_k) (u(t_k) \in U) \) may incur a cost \( \int_{t_k}^{t_{k+1}} g(x(t_k), u(t_k)) dt \), where \( g(\cdot) \) is a given cost function. Let \( u_k \) denote \( u(t_k) \) for simplicity. Then the goal of our admission control problem is to find the optimal policy \( \pi^* = (u^*_1, u^*_2, \cdots) \) to minimize the average cost. The objective average cost function can be formulated as

\[
\min \lim_{N \to \infty} \frac{1}{E\{t_N\}} E\left\{ \sum_{k=1}^{N} G_k \right\},
\]

where

\[
G_k = \int_{t_k}^{t_{k+1}} g(x(t_k), u(t_k)) dt
\]

is the cost of the \( k \)th stage. We assume that the function \( g(\cdot) \) does not depend on the length of time spent in a particular state, then (1) can be expressed as

\[
\min \lim_{N \to \infty} \frac{1}{E\{t_N\}} E\left\{ \sum_{k=1}^{N} g(x(t_k), u(t_k)) \right\} .
\]

Next we define the system state transition probabilities. As the above assumptions, the calls of class \( i \) (\( 1 \leq i \leq M \)) arrive according to the Poisson process with parameter \( \lambda_i \) and the
connection holding time for the class \( i \) \( (1 \leq i \leq M) \) calls is exponentially distributed with mean \( 1/\mu_i \). The overall rate \( \Lambda_x \) at which events occur starting from a state \( x \) is the sum of the rates of all possible events and is given by

\[
\Lambda_x = \sum_{i=1}^{M} (\lambda_i + x_i \mu_i).
\] (4)

If we assume that the decision takes effect immediately, the overall transition rate from state \( x \) \((x \in S)\) to \( x' \) \((x' \in S)\) under the control \( u \) \((u \in U)\) is \( \Lambda_{xx'} \). Thus, the expected value of the average time of the transition from state \( x \) \((x \in S)\) to \( x' \) \((x' \in S)\) under the control \( u \) \((u \in U)\) is

\[
\tau_x(u) = \frac{1}{\Lambda_{xx'}}.
\] (5)

The system state transition probability under the control \( u \) \((u \in U)\) is given by

\[
P_{xx'}(u) = \begin{cases} 
\frac{\lambda_i}{\Lambda_{xx'}}, & w = w_a, 1 \leq i \leq M \\
\frac{x_i \mu_i}{\Lambda_{xx'}}, & w = w_d, x' > 0, 1 \leq i \leq M 
\end{cases}.
\] (6)

So far, we have formulated the admission control problem in the asymmetric bandwidth allocation wireless networks as an average cost MDP problem. Next we solve the MDP problem to obtain the optimal policy.

Let \( v^* \) denote the optimal average cost. \( v^* \) should satisfy the Bellman’s optimality equation

\[
v^* \tau_x(u) + h(x) = \min_{u \in U} \left[ g(x, u) + \sum_{x' \in S} P_{xx'}(u)h(x') \right] \quad \forall x \in S,
\] (7)

where \( h(x) \) is the corresponding differential cost and \( \tau_x(u) \) is the expected value of the time of the transition from state \( x \) to the next state under the control \( u \). We may use the policy iteration to solve (7) to obtain \( v^* \) and at the same time to obtain the optimal policy \( \pi^* = (u_1^*, u_2^*, \cdots) \).

Since there are many existing methods to solve the MDP problem [17], we will not describe the solving process further in this paper.

III. MONOTONICITY PROPERTIES OF VALUE FUNCTION

In Section II, we have formulated the CAC problem as an MDP problem. In this section, we use the event based dynamic programming [18] to derive some properties of the value function.
A. Value Function

First we need to define the value function. Let $V_n(x)$ denote the minimum total cost over $n$ stages from a initial state $x$, which can be expressed as

$$V_n(x) = \min E \left\{ \sum_{k=1}^{n} G_k \right\}.$$  

(8)

Then (1) could be rewritten as

$$\lim_{n \to \infty} \frac{1}{E\{t_n\}} V_n(x).$$  

(9)

From (9), we know that the properties of the value function (8) decides the properties of the objective average cost function (1).

Let $x_k$ and $u_k$ denote $x(t_k)$ and $u(t_k)$ respectively and we define the cost function as

$$g(x_k, u_k) = \begin{cases} 
  c_i & \text{reject a class } i \text{ call} \\
  r_i & \text{accept a class } i \text{ call} \\
  0 & \text{others}
\end{cases},$$  

(10)

where $c_i$ is the cost of rejecting a class $i$ call and $r_i$ is the cost of accepting a class $i$ call (it can also be interpreted as a reward equal to $-r_i$). Without loss of generality, we could assume that $\sum_{i=1}^{M} \lambda_i + \min\left( \left\lfloor \frac{B_U}{b_i} \right\rfloor, \left\lfloor \frac{B_D}{b_i} \right\rfloor \right) \mu_i = 1$, where $\left\lfloor \delta \right\rfloor$ is the greatest integer smaller than $\delta$. Let $L_i$ denote $\min\left( \left\lfloor \frac{B_U}{b_i} \right\rfloor, \left\lfloor \frac{B_D}{b_i} \right\rfloor \right)$. Then the optimal cost value function $V(\cdot)$ satisfies

$$V_n(x) = \sum_{i=1}^{M} \lambda_i \min(V_{n-1}(x + e_i) + r_i, V_{n-1}(x) + c_i)$$

$$+ \sum_{i=1}^{M} x_i \mu_i V_{n-1}(x - e_i) + \sum_{i=1}^{M} (L_i - x_i) \mu_i V_{n-1}(x),$$  

(11)

where $e_i$ is the $i$th unity vector. In (11), the first term is the cost incurred by the arrival of a class $i$ call. Here, we have two decision options. Accepting a class $i$ call $(x + e_i)$ may incur a cost $r_i$ while rejecting the call may incur a cost $c_i$. The second term is the contribution to the cost due to call completion or handoff. The last term is a consequence of the uniformization. In order to prevent the state from leaving the state space $S$, we assume that $V_n(x) = \infty$ if $x \notin S$.

B. Event-Based Dynamic Programming

In the following, we employ the event-based dynamic programming approach [18] to deduce some properties of the value function (11).
Let operator $T_{AC(i)}$ model the admission decision on the arrival of a class $i$ call. Then

$$T_{AC(i)}V_n(x) = \min(r_i + V_n(x + e_i), c_i + V_n(x)).$$

(12)

Let the operator $T_{D(i)}$ model the departure of a class $i$ call, which is defined as

$$T_{D(i)}^{k}V_n(x) = \begin{cases} V_n(x - e_i) & \text{if } x_i \geq k \\ V_n(x) & \text{others} \end{cases}.

(13)

Thus (11) could be rewritten as

$$V_n(x) = \sum_{i=1}^{M} \lambda_i T_{AC(i)} V_{n-1}(x) + \sum_{i=1}^{M} \mu_i \sum_{k=1}^{L_i} T_{D(i)}^{k} V_{n-1}(x)$$

(14)

and we define $V_0(x) = 0 \ (x \in S)$. The following lemmas are needed to be established for the optimal policy of the MINCost problem.

**Lemma 1:** For all $x \in S$, $1 \leq j \leq M$ and $n \geq 0$, $V_n(x) \leq V_n(x + e_j)$

**Proof:** Obviously, $V_0(x) \leq V_0(x + e_j)$. We need to prove that if $V_{n-1}(x)$ satisfies this inequality, so does $T_{AC(i)}V_{n-1}(x)$ and $T_{D(i)}V_{n-1}(x)$. Since the inequality is maintained under linear combinations, then the lemma can be proved directly by induction on $n$.

First, we consider $T_{AC(i)}V_{n-1}(x)$. Suppose that $V_{n-1}(x) \leq V_{n-1}(x + e_j)$. From the definition of $T_{AC(i)}V_{n-1}(x)$, we know that $\min(r_i + V_{n-1}(x + e_i), c_i + V_{n-1}(x)) \leq \min(r_i + V_{n-1}(x + e_i + e_j), c_i + V_{n-1}(x + e_j))$. Thus $T_{AC(i)}V_{n-1}(x)$ also satisfies the inequality. In terms of $T_{D(i)}V_{n-1}(x)$, it is easy to prove that $T_{D(i)}V_{n-1}(x) \leq T_{D(i)}V_{n-1}(x + e_j)$ from the definition (13). Thus we have proved that $V_n(x) \leq V_n(x + e_j)$, which means that $V_n(x)$ is non-decreasing for all states $x \in S$ for all $j$.

**Lemma 2:** For all $n$ and $x \in S$,

$$V_n(x + e_i) + V_n(x + e_j) \leq V_n(x) + V_n(x + e_i + e_j).$$

(15)

**Proof:** It is clear that $V_0(\cdot)$ satisfies the above inequality. We follow the same idea used in the proof of Lemma 1. If $V_{n-1}(x)$ satisfies the above inequality, so do $T_{AC(i)}V_{n-1}(x)$ and $T_{D(i)}V_{n-1}(x)$. Then the lemma follows directly by induction.

We consider $T_{AC(i)}V_{n-1}(x)$ first. Let $u_1$, $u_2$, $u_3$, and $u_4$ denote the access control decision made for $T_{AC(i)}V_{n-1}(x + e_i)$, $T_{AC(i)}V_{n-1}(x + e_j)$, $T_{AC(i)}V_{n-1}(x)$ and $T_{AC(i)}V_{n-1}(x + e_i + e_j)$.
respectively. Given that $V_{n-1}(x + e_i) + V_{n-1}(x + e_j) \leq V_{n-1}(x) + V_{n-1}(x + e_i + e_j)$,
a) If $u_1 = u_2 = u_a$,

$$T_{AC(i)}V_{n-1}(x + e_i) + T_{AC(i)}V_{n-1}(x + e_j) = r_i + V_{n-1}(x + 2e_i) + r_i + V_{n-1}(x + e_i + e_j).$$  \hspace{1cm} (16)$$

When $u_3 = u_4 = u_a$,

$$(16) \leq r_i + V_{n-1}(x + e_i) + r_i + V_{n-1}(x + 2e_i + e_j) = T_{AC(i)}V_{n-1}(x) + T_{AC(i)}V_{n-1}(x + e_i + e_j).$$

When $u_3 = u_4 = u_r$,

$$(16) \leq c_i + V_{n-1}(x + e_i) + c_i + V_{n-1}(x + e_j) \leq c_i + V_{n-1}(x) + c_i + V_{n-1}(x + e_i + e_j) = T_{AC(i)}V_{n-1}(x) + T_{AC(i)}V_{n-1}(x + e_i + e_j).$$

When $u_3 = u_r, u_4 = u_a$, we need to combine $V_{n-1}(x + 2e_i) + V_{n-1}(x + e_i + e_j) \leq V_{n-1}(x + e_i) + V_{n-1}(x + 2e_i + e_j)$ with $V_{n-1}(x + e_i) + V_{n-1}(x + e_j) \leq V_{n-1}(x) + V_{n-1}(x + e_i + e_j)$ together.

Thus $V_{n-1}(x + 2e_i) + V_{n-1}(x + e_j) \leq V_{n-1}(x) + V_{n-1}(x + 2e_i + e_j)$.

Then, $(16) \leq r_i + V_{n-1}(x + 2e_i) + c_i + V_{n-1}(x + e_j) \leq c_i + V_{n-1}(x) + r_i + V_{n-1}(x + 2e_i + e_j) = T_{AC(i)}V_{n-1}(x) + T_{AC(i)}V_{n-1}(x + e_i + e_j)$.

Following the similar way, we can prove that $T_{AC(i)}(V_{n-1}(x))$ also satisfies (15) when $u_1 = u_2 = u_r$.

b) If $u_1 = u_a, u_2 = u_r$,

$$T_{AC(i)}V_{n-1}(x + e_i) + T_{AC(i)}V_{n-1}(x + e_j) = r_i + V_{n-1}(x + 2e_i) + c_i + V_{n-1}(x + e_j).$$  \hspace{1cm} (17)$$

When $u_3 = u_4 = u_a$,

$$(17) \leq r_i + V_{n-1}(x + 2e_i) + r_i + V_{n-1}(x + e_i + e_j) \leq r_i + V_{n-1}(x + e_i) + r_i + V_{n-1}(x + 2e_i + e_j) = T_{AC(i)}V_{n-1}(x) + T_{AC(i)}V_{n-1}(x + e_i + e_j).$$
Under other conditions \((u_3 = u_4 = u_r, u_3 = u_a, u_4 = u_r\) and \(u_3 = u_r, u_4 = u_a\)), the proof is similar to that of a). Thus we prove that \(T_{AC(i)}(V_{n-1}(x))\) satisfies inequality (15). Since we have assumed that \(V_{n-1}(x)\) satisfies (15), it is easy to prove that \(T_{D(i)}(V_{n-1}(x))\) also satisfies (15). Thus we have proved the value function \(V_n(x)\) satisfies the inequality (15).

From Lemma 2, we can obtain the following theorem:

**Theorem 1:** To minimize the average cost of the CAC policy in the bandwidth asymmetry wireless networks, a call of class \(i\) can be accepted if and only if \(x_j < Th_j(x_1, \cdots, x_i, x_k, \cdots, x_M)(j \neq i)\), where \(Th_j(x_1, \cdots, x_i, x_k, \cdots, x_M)\) is a threshold of the class \(j\) calls when the system state is \(x, x = (x_1, \cdots, x_i, x_j, x_k \cdots, x_M), x \in S\).

**Proof:** Let us rewrite (15) as

\[
V_n(x + e_i) - V_n(x) \leq V_n(x + e_i + e_j) - V_n(x + e_j).
\]  

From (18) we know that if \(V_n(x + e_i)\) is greater than \(V_n(x)\), \(V_n(x + e_i + e_j)\) is also greater than \(V_n(x + e_j)\). \(V_n(x + e_i) > V_n(x)\) means that accepting a class \(i\) call will bring more cost than rejecting a class \(i\) call after \(n\) stages from the initial state \(x\) while \(V_n(x + e_i + e_j) > V_n(x + e_j)\) means that accepting a class \(i\) call will bring more cost than rejecting a class \(i\) call after \(n\) stages from the initial state \(x + e_j\). Thus a class \(i\) call is rejected at \(x = (x_1, \cdots, x_i, x_j, \cdots, x_M)\), then it is also rejected at \(x + e_j = (x_1, \cdots, x_i, x_j + 1, \cdots, x_M)\). Thus we can find a threshold in the system state \(x\), if the number of class \(j\) calls in the system is smaller than the threshold, the class \(i\) call can be accepted. Otherwise it is rejected. Therefore, we have proved Theorem 1.

**C. Discussions**

Next, we discuss the applications of Theorem 1 in different system models. Let us consider a simple system model first. We assume that there are two classes of calls \((M = 2)\): handoff calls (class 1) and new calls (class 2), in the system. The channel holding time of both handoff calls and new calls are exponentially distributed with mean \(1/\mu (\mu_1 = \mu_2 = \mu)\). The bandwidth requirements of a handoff call and a new call are identical and equal to \(b (b_1^a = b_2^a = b and b_1^d = b_2^d = b)\).

In this simple model, the system state is decided by only the total number of calls in the
system. Lemma 2 can be rewritten as

\[ 2V_n(x + 1) \leq V_n(x) + V_n(x + 2), \tag{19} \]

where \( x \) denotes the number of calls in the system. This property is called convexity. We may change (19) as

\[ V_n(x + 1) - V_n(x) \leq V_n(x + 2) - V_n(x + 1). \tag{20} \]

From (20), we may find that if an arrival call is rejected at state \( x \), which means \( V_n(x + 1) - V_n(x) > c_i - r_i (i = 1 \text{ or } i = 2) \) (\( c_i \) and \( r_i \) are the same as that defined in (1)), the call should also be rejected at state \( x+1, x+2, \cdots \). It is obvious that threshold policy could be the optimal policy for the MINCost problem in such system. Actually, it has been proved that the guard channel policy is the optimal policy for the MINCost problem in such simple environment in [14]. So our theorem matches the result of [14] in the simple system model.

Next, let us consider Theorem 1 in an asymmetric bandwidth allocation multi-service wireless network. We classify all the calls into two categories: RT calls (class 1) and NRT calls (class 2), where an RT call requires the same bandwidth on uplink and downlink and an NRT call requires asymmetric bandwidth on uplink and downlink. The RT calls and the NRT calls have different connection holding time \( (1/\mu_1 \neq 1/\mu_2) \) and bandwidth requirements \( (b_u^1 \neq b_u^2 \text{ and } b_d^1 \neq b_d^2) \).

From Theorem 1, we may find that when system state is \( x = (x_1, x_2) \), an arrival RT (NRT) call can be accepted only if the number of NRT (RT) calls in the system does not exceed a certain threshold. This threshold may change with the system state \( x \). Thus the optimal policy for the MINCost problem in such asymmetric bandwidth allocation multi-service wireless networks should be a dynamic threshold policy. However, when the base of system states becomes large, the computational complexity of using value iteration to solve the Bellman equation (7) is prohibitively high and it may be very time-consuming to decide the corresponding threshold values. In a real system, both the RT calls and the NRT calls may have handoff attempts and this makes the procedure of finding the optimal solution more challenging. It is unlikely to design an optimal CAC policy according to the above analysis by on-line computing the dynamical thresholds.

To address the above-mentioned difficulty, we propose a new admission policy called Call-Rate-based Dynamic Threshold (CRDT) admission control policy, which aims at approximating
the optimal CAC policy deduced from the analytical model for bandwidth asymmetry multi-service wireless networks. In order to design a good policy, we need to analyze the system states and make the decisions based on the system states. We can divide all the system states into two sets. In some states, all calls can be accepted and we name these states “unsaturated states”. While in some states, only some classes calls or no calls can be accepted and we name these states “saturated states”. There are two main tasks for an admission policy: 1) Judging the current system state is unsaturated or saturated; 2) Deciding what policy could be used if the system is in the saturated states. Theorem 1 provides a rule to determine the optimal policy to solve the MINCost problem in asymmetric bandwidth wireless networks when the system is in the saturated state. However, how to decide the system is in the unsaturated state or the saturated state and the corresponding thresholds depends on the complicated computation of solving the Bellman equation (7). In the proposed CRDT policy, the bandwidth used by the RT calls and the NRT calls respectively is used to decide the current system state. When the bandwidth used by the RT calls or the NRT calls reaches a pre-calculated threshold, we deem that the current system is in the saturated state. In light of Theorem 1, when system in the saturated state, the decision made for an arrival RT (NRT) call is decided by the estimated arrival rate of the NRT (RT) calls. In stead of computing the threshold of the number of the RT calls or the NRT calls, we use a measurable parameter, the call arrival rate, to make the decision and thus decrease the computational complexity. When the bandwidth used by the RT (NRT) calls in the system reaches the bandwidth threshold set for the RT (NRT) calls on uplink and downlink, whether an arrival RT (NRT) call can be accepted or not is decided by the NRT (RT) call arrival rate. If the NRT (RT) call arrival rate is greater than a reference rate value, the arrival RT (NRT) call is blocked. In the next section, we will describe in detail how to calculate the bandwidth threshold and the reference rate value for a specific class of calls.

IV. CALL RATE BASED DYNAMIC THRESHOLD ADMISSION CONTROL POLICY

A. System Model

In the underlying multi-service wireless networks, we assume that there are four classes of calls: handoff RT call, handoff NRT call, new RT call and new NRT call. An RT call requires the same bandwidth on uplink and downlink while an NRT call requires asymmetric bandwidth on uplink and downlink [3] [4]. The RT call arrival rate and the NRT call arrival rate follow
the Poisson distribution with mean $\lambda_{RT}$ and $\lambda_{NRT}$ respectively. The connection holding time of the RT calls and the NRT calls is exponentially distributed with mean $1/\mu_{RT}$ and $1/\mu_{NRT}$ respectively. The notations and their definitions used in this section are listed in Table I, where the system asymmetry factor $\Gamma_s$ and the NRT call asymmetry factor $\Gamma_{NRT}$ are defined as $\Gamma_s = \frac{B_D}{B_U}$ and $\Gamma_{NRT} = \frac{b_{NRT}^u}{b_{NRT}^d}$ respectively.

<table>
<thead>
<tr>
<th>Notation</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Gamma_s$</td>
<td>system asymmetry factor</td>
</tr>
<tr>
<td>$\Gamma_{NRT}$</td>
<td>NRT call asymmetry factor</td>
</tr>
<tr>
<td>$B_U$</td>
<td>total uplink bandwidth</td>
</tr>
<tr>
<td>$B_D$</td>
<td>total downlink bandwidth</td>
</tr>
<tr>
<td>$b_{RT}^u$</td>
<td>uplink bandwidth required by an RT call</td>
</tr>
<tr>
<td>$b_{RT}^d$</td>
<td>downlink bandwidth required by an RT call</td>
</tr>
<tr>
<td>$b_{NRT}^u$</td>
<td>uplink bandwidth required by an NRT call</td>
</tr>
<tr>
<td>$b_{NRT}^d$</td>
<td>downlink bandwidth required by an NRT call</td>
</tr>
<tr>
<td>$\lambda_{RT}$</td>
<td>mean RT call arrival rate</td>
</tr>
<tr>
<td>$\lambda_{NRT}$</td>
<td>mean NRT call arrival rate</td>
</tr>
<tr>
<td>$\mu_{RT}$</td>
<td>mean RT call departure rate</td>
</tr>
<tr>
<td>$\mu_{NRT}$</td>
<td>mean NRT call departure rate</td>
</tr>
<tr>
<td>$\rho_{RT} = \frac{\lambda_{RT}}{\mu_{RT}}$</td>
<td>traffic load brought by RT calls</td>
</tr>
<tr>
<td>$\rho_{NRT} = \frac{\lambda_{NRT}}{\mu_{NRT}}$</td>
<td>traffic load brought by NRT calls</td>
</tr>
</tbody>
</table>

B. Threshold Calculation

We consider the system at the steady state with heavy traffic load. From statistical point of view, if no bandwidth is wasted, the uplink bandwidth and the downlink bandwidth used by the RT calls and the NRT calls should satisfy

$$\rho_{RT} \cdot b_{RT}^u + \rho_{NRT} \cdot b_{NRT}^u = B_U$$  \hspace{1cm} (21)

and

$$\rho_{RT} \cdot b_{RT}^d + \rho_{NRT} \cdot b_{NRT}^d = B_D.$$  \hspace{1cm} (22)

Given that $b_{RT}^u = b_{RT}^u$, $b_{NRT}^d = \Gamma_{NRT} b_{RT}^u$ and $B_D = \Gamma_s B_U$, (22) minusing (21) yields

$$\rho_{NRT} = \frac{\Gamma_s - 1}{\Gamma_{NRT} - 1} \cdot \frac{B_U}{b_{NRT}^u}.$$  \hspace{1cm} (23)
Since $\rho_{NRT} = \frac{\lambda_{NRT}}{\mu_{NRT}}$, we can obtain the average NRT call arrival rate in this system state as

$$\lambda_{NRT} = \frac{\Gamma_s - 1}{\Gamma_{NRT} - 1} \cdot \frac{B_U}{b_{NRT}^u} \cdot \mu_{NRT}. \quad (24)$$

The average RT call arrival rate in this system state can be obtained by combining (21) and (23) and it is shown as

$$\lambda_{RT} = \frac{\Gamma_{NRT} - \Gamma_s}{\Gamma_{NRT} - 1} \cdot \frac{B_U}{b_{RT}^u} \cdot \mu_{RT}. \quad (25)$$

Let us use $\bar{\lambda}_{RT}$ and $\bar{\lambda}_{NRT}$ to denote the value of $\lambda_{RT}$ and $\lambda_{NRT}$ in this system state. $\bar{\lambda}_{RT}$ and $\bar{\lambda}_{NRT}$ are used as the reference rate value for the RT calls and the NRT calls respectively. The meaning of $\lambda_{RT}$ and $\lambda_{NRT}$ are as follows. When the RT call arrival rate is $\lambda_{RT}$ and the NRT call arrival rate is $\lambda_{NRT}$, the bandwidth allocated to the uplink and the downlink is able to satisfy the traffic load requirements of the RT calls and the NRT calls exactly without bandwidth waste.

We use $B_{RT}^{u}$ and $B_{RT}^{d}$ to denote the bandwidth used by the RT calls on the uplink and the downlink respectively when the RT call arrival rate is $\lambda_{RT}$. Thus $B_{RT}^{u} = B_{RT}^{d} = \frac{\Gamma_{NRT} - \Gamma_s}{\Gamma_{NRT} - 1} B_U$. Accordingly, let $B_{NRT}^{u}$ and $B_{NRT}^{d}$ denote the bandwidth used by the NRT calls on the uplink and the downlink respectively when the NRT call arrival rate is $\lambda_{NRT}$. Thus $B_{NRT}^{u}$ and $B_{NRT}^{d}$ are equal to $\frac{\Gamma_s - 1}{\Gamma_{NRT} - 1} B_U$ and $\frac{\Gamma_s - 1}{\Gamma_{NRT} - 1} B_U \cdot \Gamma_{NRT}$ respectively. $B_{RT}^{u}$, $B_{RT}^{d}$, $B_{NRT}^{u}$ and $B_{NRT}^{d}$ are just four bandwidth thresholds set for the RT calls and the NRT calls in our policy.

C. Call Rate Estimation

Our policy is composed by two functional components: call rate estimation algorithm and admission control algorithm. Let us describe the call rate estimation algorithm first. The call rate estimation algorithm is based on the exponential smoothing method [19]. We define a certain period of time ($T$) as the time interval between two estimations. The call rate estimation is performed at the end of each time interval. For example, at the end of time interval $N$, the system scales the average call arrival rate $\lambda_N$ of the current time interval and estimates the call arrival rate of the time interval $N + 1$ by using (26), where $\hat{\lambda}_N$ is the estimated call arrival rate obtained in the time interval $N - 1$ and $\alpha (0 < \alpha < 1)$ is a parameter used to determine how fast the algorithm responds to the changes of the arrival rate. At the beginning, we can set $\hat{\lambda}_1 = \lambda_1$ as the initial value and then use (26) recursively to estimate the call arrival rate of the next time interval.

$$\hat{\lambda}_{N+1} = \alpha \lambda_N + (1 - \alpha) \hat{\lambda}_N. \quad (26)$$
D. CRDT Policy

Next, we present the proposed admission control policy, which needs to make use of above call rate estimation algorithm. In order to simplify the description of the proposed CRDT policy, we assume that there is sufficient uplink and downlink bandwidth to satisfy the call requests. This is because if the remaining bandwidth on the uplink and/or the downlink cannot satisfy the bandwidth requirement of the arrival call, the call is blocked directly. Then there is no need to make a CAC decision in this case. The proposed CRDT policy can be described as follows.

When a handoff RT call arrives, it is accepted since there is sufficient bandwidth on uplink and downlink to satisfy the call bandwidth requirement. On the other hand, when a new RT call arrives, the system checks the uplink bandwidth and the downlink bandwidth occupied by the RT calls in the system ($\hat{B}^u_{RT}, \hat{B}^d_{RT}$). If accepting the call does not cause the bandwidth used by the RT calls to exceed the threshold $\bar{B}^u_{RT}$ and $\bar{B}^d_{RT}$ on the uplink and the downlink respectively, the call can be accepted. Otherwise, the system checks the estimated NRT call arrival rate $\hat{\lambda}_{NRT}$ in the current time interval. If $\hat{\lambda}_{NRT} < \bar{\lambda}_{NRT}$, the arrival new RT call can be accepted; else, it is blocked.

When a handoff NRT call arrives, the system checks the uplink bandwidth and the downlink bandwidth occupied by the NRT calls in the system ($\hat{B}^u_{NRT}, \hat{B}^d_{NRT}$). If accepting the call does not cause the bandwidth used by the NRT calls to exceed the threshold $\bar{B}^u_{NRT}$ and $\bar{B}^d_{NRT}$ on the uplink and the downlink respectively, the call can be accepted. Otherwise, the system checks the estimated RT call arrival rate $\hat{\lambda}_{RT}$ in the current time interval. If $\hat{\lambda}_{RT} < \bar{\lambda}_{RT}$, the arrival handoff NRT call can be accepted; else, it is blocked.

The treatment to the new NRT calls is similar to that of the handoff NRT call except that only if $\hat{\lambda}_{RT} < \bar{\lambda}_{RT} \cdot \Delta$, the arrival new NRT call can be accepted, where $\Delta$ ($0 < \Delta < 1$) is a design parameter used to guarantee the priorities of the RT calls and the handoff NRT calls. Since the new NRT calls have lowest priority, it is necessary to limit the number of the new NRT calls in the system and thus avoid these low priority calls from overusing system resources. We will discuss in detail the effect of this parameter on the system performance in next section. Fig. 1 shows the pseudo code of the proposed algorithm.
if (enough uplink and downlink bandwidth)
if (handoff RT call)
    accept
if (new RT call)
    if (h ≤ B_u + b_u < B_u and h ≤ B_d + b_d < B_d)
        accept
    else if (λ < λ)
        accept
    else
        reject
if (handoff NRT call)
    if (h ≤ B_u + b_u < B_u and h ≤ B_d + b_d < B_d)
        accept
    else if (λ < λ)
        accept
    else
        reject
if (new NRT call)
    if (h ≤ B_u + b_u < B_u and h ≤ B_d + b_d < B_d)
        accept
    else if (λ < λ · ∆)
        accept
    else
        reject
else
    reject

Fig. 1. Pseudo code of the proposed CRDT policy

V. NUMERICAL RESULTS

In this section, we use simulation experiments to examine the performance of the CRDT policy and compare the average cost of the CRDT policy with that of some known CAC policies. We assume that the call arrival process is according to Poisson distribution and the call connection holding time is exponentially distributed. We assume that the system allocates 10 channels on the uplink and 16 channels on the downlink respectively. The parameters used in the simulation are listed in Table II.

In the simulation, we choose three policies as our comparison bases. The first is the policy obtained from Bellman equation (7). As we mentioned in Section II, we may use policy iteration to obtain the optimal policy from the Bellman equation (7) and we call this policy “calculated policy” in our simulations. The other two are Jeon’s policy [4] and the scheme 2 in [3] which is proposed by us and we call it “Yang’s policy” in the simulations. Both of these two policies are designed for the asymmetric bandwidth allocation wireless networks and good performance in terms of call blocking probabilities and bandwidth utilization has been demonstrated.

This section is composed by two parts. In the first part, we examine how the parameters (i.e.
TABLE II
TRAFFIC MODEL

<table>
<thead>
<tr>
<th></th>
<th>RT call</th>
<th></th>
<th>NRT call</th>
<th></th>
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</thead>
<tbody>
<tr>
<td></td>
<td>Uplink</td>
<td>Downlink</td>
<td>Uplink</td>
<td>Downlink</td>
</tr>
<tr>
<td>Number of channels</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>3</td>
</tr>
<tr>
<td>required per call</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean Call Duration</td>
<td>180sec</td>
<td></td>
<td>600sec</td>
<td></td>
</tr>
<tr>
<td>Mean Cell Dwell Time</td>
<td>200sec</td>
<td></td>
<td>1200sec</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Handoff</td>
<td>New</td>
<td>Handoff</td>
</tr>
<tr>
<td>Rejection cost</td>
<td>8</td>
<td>4</td>
<td>5</td>
<td>1</td>
</tr>
<tr>
<td>Acceptance cost</td>
<td>-2</td>
<td>-2</td>
<td>-4</td>
<td>-4</td>
</tr>
</tbody>
</table>

$\alpha$, $T$ and $\Delta$) used in the CRDT policy affect the system performance. In the second part, we compare the average cost of the proposed CRDT policy with that of other three policies under two scenarios. Let $q$ be the ratio of the number of the RT calls over the number of all calls. In the first scenario, we assume a relatively static traffic load environment, which means $q$ does not change with time dynamically. While in the second scenario, $q$ may change with time according to a given probability distribution. Compared with the first scenario, the second scenario assumes a more dynamic environment.

A. Setting of Parameters

We first examine how the system average cost is affected by the parameters $\alpha$, $T$ and $\Delta$ in a dynamic traffic load environment. We assume that $q$ varies with time according to the normal distribution with mean 0.7 and variance 0.2.

In Fig. 2 (a) and (b), we compare the average cost of the CRDT policy with different $\alpha$ values as a function of the new call arrival rate when $T$ is 1 minute and 10 minutes respectively. From Fig. 2 (a), we find that the average cost is sensitive to the value of $\alpha$ when $T$ is small (1 minute) and a small value of $\alpha$ ($\alpha = 0.1$) results in a lower average cost. It is obvious that the estimated rate depends on the “past” estimation not the rate of the “current” time interval when $T$ is small. When $T$ is relatively large (10 minutes), we can find that the average costs of the CRDT policy with different $\alpha$ values are very close. Fig. 3 compares the average costs when $T$ is 1 minute, 10 minutes, 30 minutes and 1 hour, respectively. From this figure, we can find that the difference
Fig. 2. Average costs of the CRDT policy when $T = 1$ minute and $T = 10$ minute

Fig. 3. Average costs of the CRDT policy with different $T$

of the average costs is trivial. When the traffic load is light (new call arrival rate is smaller than 0.02), the small interval ($T < 1$ hour) may obtain lower average cost. Thus in the following simulation experiments, we set $\alpha$ to be 0.1 and $T$ to be 1 minute.

Fig. 4 shows the average costs of the CRDT policy when $\Delta$ is set to different values. From the figure, we can observe that the average cost increases with the value of $\Delta$. When $\Delta$ is smaller than 0.1, the difference is small. In the subsequent simulation experiments, we set $\Delta$ to be equal to 0.1.

Actually, we have conducted extensive simulation experiments for understanding the effects of different parameter settings. We show only some representative results in above figures. In the following part, we focus on performance evaluation and comparison.
Fig. 4. Average costs of the CRDT policy with different $\Delta$

B. Simulation Scenario 1

Fig. 5. Average cost of the CAC policies when $q = 70\%$ in Scenario 1 ($T = 1$ minute, $\alpha = 0.1, \Delta = 0.1$)

Fig. 5 shows the average cost obtained from the proposed CRDT policy and other policies when $q = 70\%$. When the new call arrival rate is low, from the figure, we can observe that the average cost of the policies except Jeon’s policy monotonically decreases with the new call arrival rate. The average costs obtained from the CRDT policy, the calculated policy and Yang’s policy are very close and smaller than that of Jeon’s policy. With the increase of the new call arrival rate, the difference between the average cost of Yang’s policy and that of the calculated policy becomes more evident while the average cost of the CRDT policy is also close to that of the calculated policy and is smaller than that of Yang’s policy and Jeon’s policy obviously.
When the new call arrival rate is very high and the system is overloaded, the average cost of the proposed CRDT policy still smaller than that of Jeon’s policy and Yang’s policy.

Fig. 6 shows the average cost of the CAC policies when \( q = 90\% \) in Scenario 1 \((T = 1 \text{ minute}, \alpha = 0.1, \Delta = 0.1)\)

When the new call arrival rate is very high and the system is overloaded, the average cost of the proposed CRDT policy still smaller than that of Jeon’s policy and Yang’s policy.

Fig. 6 shows the average cost of the CAC policies when \( q = 90\% \). In this case, most traffic load in the system is generated by the RT calls. From the figure, we can find that the average cost of the proposed CRDT policy is very close to that of the calculated policy and is smaller than that of Yang’s policy and Jeon’s policy significantly. In order to decrease the handoff call blocking probability, Yang’s policy and Jeon’s policy may reserve too much bandwidth for the handoff calls and thus blocking some new calls unnecessarily. With the increase of the new call arrival rate, the average costs of Yang’s policy and Jeon’s policy increase obviously. The proposed CRDT policy focuses on not only one specific class of calls but the average cost of the whole system and thus it can guarantee the low average cost and keeps the average cost close to that of the calculated policy.

C. Simulation Scenario 2

Fig. 7 shows the average cost in a dynamic traffic load environment where \( q \) varies with time according to the normal distribution with mean 0.7 and variance 0.2. From the figure, we can find that the average cost obtained from the CRDT policy is close to that of the calculated policy and smaller than that of Yang’s policy and Jeon’s policy significantly when the new call arrival rate increases. Although the bandwidth thresholds are also defined for the RT calls and
the NRT calls in Yang’s policy to avoid a specific call class from overusing the bandwidth, such policy with fixed thresholds may be inflexible in a dynamic traffic load environment, leading to deteriorated system performance. The average cost of Yang’s policy is higher than that of the proposed CRDT policy. When the new call arrival rate is low, the average costs of Yang’s policy and Jeon’s policy are close to that of the CRDT policy and the calculated policy. When the new call arrival rate increases, the average cost of Yang’s policy and Jeon’s policy is higher than that of the calculated policy more obviously while the average cost of the proposed CRDT policy is still close to that of the calculated policy and smaller than that of Yang’s policy and Jeon’s policy. Thus, when the traffic load in the system varies with time, the proposed CRDT policy approximates well the optimal policy. In summary, the proposed CRDT policy provides a sub-optimal solution to the optimal policy for the MINCost problem in the bandwidth asymmetry wireless networks.

VI. CONCLUSION

In this paper, we have studied the admission control policy for the MINCost problem in the bandwidth asymmetry wireless networks. By formulating the CAC problem into the MDP model and analyzing the corresponding value function, we find that the optimal admission policy for the MINCost problem in such asymmetric bandwidth allocation multi-service wireless networks should have a threshold structure. The threshold specified for a class of calls may vary with the system state. Due to the prohibitively high computational complexity, it is hard to on-line
calculate the threshold for each call class in a real-time system with the large system state space. Based on the analysis, we have proposed a heuristic policy called Call-Rate-based Dynamic Threshold (CRDT) policy as a suboptimal solution to the MINCost problem for the bandwidth asymmetry wireless networks. The values of the thresholds in the CRDT policy can be calculated readily. The numerical results show that the performance of the proposed CRDT policy is very close to that of the optimal policy obtained from the MDP model and better than that of other two known policies, which are also proposed for the bandwidth asymmetry multi-service wireless networks.

REFERENCES


