Cost Minimization for Admission Control in Bandwidth Asymmetry Wireless Networks

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Abstract—For the design of call admission control (CAC) policy in wireless networks, how to decrease the average system cost is a key issue. In this paper, we study the optimal admission policy for minimizing the system cost. By modeling 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 modeling and the analytical study on the properties of the optimal policy. The CRDT policy is efficient and can be easily implemented. The numerical results show that the performance of average system cost of 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 multi-service applications. In such environment, it is necessary to allocate different bandwidth between uplink and downlink in order to support the asymmetric traffic load. 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 this paper, we focus on the modeling and the analysis of the CAC policy subject to the MINCost problem in wireless networks with bandwidth asymmetry. MINCost problem is defined as minimizing a linear objective cost function to obtain the minimum average cost. By formulating the CAC problem into a Markov decision process (MDP) model and analyzing the corresponding value function, we obtain some monotonicity properties of the value function for the bandwidth asymmetry networks. 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 modeling 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.

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. Finally, we conclude our paper in Section VI.

II. MDP FORMULATION

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. Since blocking a handoff call may incur more cost than blocking a new call, we treat the handoff calls and the new calls as different call classes in our system model. 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 $b_u^i$ and $b_d^i$ 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 of 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 \( \sum_{i=1}^{M} b^i_i x_i \leq B_T \) and \( \sum_{i=1}^{M} b^i_i x_i \leq B_D \) simultaneously. 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 \( Y \) is defined as \( Y = \{y_a, y_r\} \), where \( y_a \) and \( y_r \) signify acceptance and rejection respectively.

In the infinite Markov decision process with a finite state space, state \( x \) \((x \in S)\) transits to 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 \( y(t_k) \) \((y(t_k) \in Y)\) 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 \( y(t_k) \) \((y(t_k) \in Y)\) may incur a cost \( \int_{t_k}^{t_{k+1}} g(x(t_k), y(t_k)) dt \), where \( g(\cdot) \) is a given cost function. Let \( y_k \) denote \( y(t_k) \) for simplicity. Then the goal of our admission control problem is to find the optimal policy \( \pi^* = (y_1^*, y_2^*, \cdots) \) to minimize the average cost. The objective average cost function can be formulated as

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

where

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

is the cost of the \( k \)-th stage. The cost could be composed by the revenue (negative cost) of call acceptance and the cost of call rejection. The revenue may be associated with the call duration and the cost may be determined by the call class. As it is well recognized that the average duration of a specific call class is usually known, we assume that the cost is associated with the call class only for mathematical tractability. Thus the function \( g(\cdot) \) does not depend on the length of time spent at a particular state. (1) is expressed as

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

In (1) and (3), \( N \) is an arbitrary positive integer to denote the number of states that the system has experienced. In order to obtain the average cost of \( N \) states, we need to compute the mean total cost of \( N \) states and the mean time that the system spends on these states. Then we let \( N \) go to infinity and obtain the average system cost per unit time under a specific admission control policy employed in the system.

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 \( 1/\mu_i \). We define the rate of all events occurrences starting from a state \( x \) as the overall rate \( \Lambda_x \), which is the sum of the rates of all possible events and is given by

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

\( \Lambda_x \) can be regarded as the average rate at which the system leaves state \( x \). Thus \( 1/\Lambda_x \) is the average time that the system stays at state \( x \). In order to establish the optimization equation, we still need to obtain the average system transition time, which is defined as the average time that the system transits from state \( x = (x_1, \ldots, x_i, \ldots, x_M) \) \((x \in S)\) to \( x' = (x_1', \ldots, x_i', \ldots, x_M') \) \((x' \in S)\) under control \( y \) \((y \in Y)\). We assume that the control decision takes effect immediately when the decision is made. Thus, the average transition time is determined by the average time spent at state \( x' \), which is \( 1/\Lambda_{x'} \). We use \( \tau_x(y) \) to denote the average transition time from state \( x \) to state \( x' \). Thus

\[
\tau_x(y) = \frac{1}{\Lambda_{x'}}. \tag{5}
\]

The system state transition probability under the control \( y \) \((y \in Y)\) is given by

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

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

\[
v^* \tau_x(y) + h(x) = \min_{y \in Y} \left[ g(x, y) + \sum_{x' \in S} P_{xx'}(y) h(x') \right] \quad \forall x \in S, \tag{7}
\]
where \( h(x) \) is the corresponding differential cost and \( \tau(x, y) \) is the expected value of the time of the transition from state \( x \) to the next state under the control \( y \). We may use the policy iteration to solve (7) to obtain \( \nu^* \) and at the same time to obtain the optimal policy \( \pi^* = (y_1^*, y_2^*, \cdots) \). Since there are many existing methods to solve the MDP problem [7], we will not discuss 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 [8] 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 an initial state \( x \), which can be expressed as

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

Then (1) could be rewritten as

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

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

Let \( x_k \) and \( y_k \) denote \( x(t_k) \) and \( y(t_k) \) respectively and we define the cost function as

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

where \( c_i \) is the cost of rejecting a class \( i \) call and \( r_i \) is the cost of accepting a class \( i \) call. Without loss of generality, we could assume that \( \sum_{i=1}^{M} \lambda_i + \min(\frac{B_U}{b_i^U}, \frac{B_D}{b_i^D}) \mu_i = 1 \), where \( \delta \) is the greater integer smaller than \( \delta (\delta > 0) \). Let \( L_i \) denote \( \min(\frac{B_U}{b_i^U}, \frac{B_D}{b_i^D}) \). Then the optimal cost value function \( V(\cdot) \) satisfies

\[
V_n(x) = \sum_{i=1}^{M} \lambda_i \min(V_{n-1}(x + e_i) + r_i, V_{n-1}(x) + c_i) + \sum_{i=1}^{M} x_i \mu_i V_{n-1}(x - e_i) + \sum_{i=1}^{M} (L_i - x_i) \mu_i V_{n-1}(x),
\]

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 extend the properties in [9] and employ the event-based dynamic programming approach [8] to deduce some properties of the value function (11) for the bandwidth asymmetry multi-service mobile networks.

Let operator \( T_{AC(i)} \) model the admission decision on the arrival of a class \( i \) call. Then

\[
T_{AC(i)} V_n(x) = \min(r_i + V_n(x + e_i), c_i + V_n(x)). \tag{12}
\]

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

\[
T_{D(i)} V_n(x) = \begin{cases} 
  V_n(x - e_i) & \text{if } x_i \geq k \\
  V_n(x) & \text{others}
\end{cases}, \tag{13}
\]

where \( k \) is the number of class \( i \) calls in the system and \( k = 1, \cdots, \min([B_U / b_i^U], [B_D / b_i^D]) \). Thus (11) could be rewritten as

\[
V_n(x) = \sum_{i=1}^{M} \lambda_i T_{AC(i)} V_{n-1}(x) + \sum_{i=1}^{M} \mu_i \sum_{k=1}^{L_i} T_{D(i)}^{k} V_{n-1}(x) \tag{14}
\]

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 \( n \geq 0 \),

\[
V_n(x) \leq V_n(x + e_j). \tag{15}
\]

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

\[
V_n(x + e_i) + V_n(x + e_j) \leq V_n(x) + V_n(x + e_i + e_j). \tag{16}
\]

From Lemma 1 and 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 \( x = (x_1, \cdots, x_i, x_j, x_k, \cdots, x_M) \), \( x \in S \).

Because of space limitation, we do not show the proof of Lemma 1, Lemma 2 and Theorem 1 here. The reader may refer to [10] for the details of the proof.

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 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 $\Gamma_s = \frac{\mu_d}{\mu_u}$ and $\Gamma_{NRT} = \frac{\mu_{dRT}}{\mu_{uRT}}$ respectively.

### TABLE I

| $\Gamma_s$ | system asymmetry factor |
| $\Gamma_{NRT}$ | NRT call asymmetry factor |
| $B_U$ | total uplink bandwidth |
| $b_{uRT}$ | uplink bandwidth required by an RT call |
| $b_{dRT}$ | downlink bandwidth required by an RT call |
| $b_{uNRT}$ | uplink bandwidth required by an NRT call |
| $b_{dNRT}$ | downlink bandwidth required by an NRT call |
| $\lambda_{RT}$ | mean RT call arrival rate |
| $\lambda_{NRT}$ | mean NRT call arrival rate |
| $\mu_{RT}$ | mean RT call departure rate |
| $\mu_{NRT}$ | mean NRT call departure rate |
| $\rho_{RT}$ | traffic load brought by RT calls |
| $\rho_{NRT} = \frac{\lambda_{NRT}}{\mu_{NRT}}$ | traffic load brought by NRT calls |

#### 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

$$\rho_{RT} \cdot b_{uRT} + \rho_{NRT} \cdot b_{uNRT} = B_U$$  \hspace{1cm} (17)

and

$$\rho_{RT} \cdot b_{dRT} + \rho_{NRT} \cdot b_{dNRT} = B_D.$$  \hspace{1cm} (18)

Given that $b_{uRT} = b_{uNRT} = \Gamma_{NRT} b_{uRT}$ and $B_D = \Gamma_s B_U$, (18) minus (17) yields

$$\rho_{NRT} = \frac{\Gamma_s - 1}{\Gamma_{NRT} - 1} \cdot \frac{B_U}{b_{uNRT}}.$$  \hspace{1cm} (19)

Since $\rho_{NRT} = \frac{\lambda_{NRT}}{\rho_{NRT}}$, we can obtain the average NRT call arrival rate in this system state as

$$\lambda_{NRT} = \frac{\Gamma_s - 1}{\Gamma_{NRT} - 1} \cdot \frac{B_U}{b_{uNRT}} \cdot \mu_{NRT}.$$  \hspace{1cm} (20)

The average RT call arrival rate in this system state can be obtained by combining (17) and (19) and it is shown as

$$\lambda_{RT} = \frac{\Gamma_s - 1}{\Gamma_{NRT} - 1} \cdot \frac{B_U}{b_{RT}} \cdot \mu_{RT}.$$  \hspace{1cm} (21)

Let us use $\lambda_{RT}$ and $\lambda_{NRT}$ to denote the value of $\lambda_{RT}$ and $\lambda_{NRT}$ in this system state. $\lambda_{RT}$ and $\lambda_{NRT}$ 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 $\bar{B}_{uRT}$ and $\bar{B}_{dRT}$ 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 $\bar{B}_{uRT} = \bar{B}_{dRT} = \frac{\Gamma_{NRT} - \Gamma_s}{\Gamma_{NRT} - 1} B_U$. Accordingly, let $\bar{B}_{uNRT}$ and $\bar{B}_{dNRT}$ 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 $\bar{B}_{RT} = \bar{B}_{uRT} + \bar{B}_{dRT}$ and $\bar{B}_{NRT} = \bar{B}_{uNRT} + \bar{B}_{dNRT}$ respectively. $\bar{B}_{RT}$, $\bar{B}_{NRT}$ and $\bar{B}_{uRT}$ 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 of 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 [11]. 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 (22), where $\lambda_N$ 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 $\lambda_1 = \lambda_1$ as the initial value and then use (22) recursively to estimate the call arrival rate of the next time interval.

$$\hat{\lambda}_{(N+1)} = \alpha \lambda_N + (1 - \alpha) \hat{\lambda}_N.$$  \hspace{1cm} (22)

#### 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. 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 ($\bar{B}_{uRT}, \bar{B}_{dRT}$). If the call does not cause the bandwidth used by the RT calls to exceed the threshold $\bar{B}_{uRT}$ and $\bar{B}_{dRT}$ on the uplink and the downlink respectively, the call can be accepted. Otherwise, the system checks the estimated NRT call arrival rate $\lambda'_{NRT}$ in the current time interval. If $\lambda'_{NRT} < \lambda_{NRT}$, 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 ($\bar{B}_{uNRT}, \bar{B}_{dNRT}$). If the call does not cause the bandwidth used by the NRT calls to exceed the threshold $\bar{B}_{uNRT}$ and $\bar{B}_{dNRT}$ 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 \( \hat{\lambda}_{RT} < \lambda_{RT} \), 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 \( \hat{\lambda}_{RT} < \lambda_{RT} \cdot \Delta \), the arrival new NRT call can be accepted, where \( 0 < \Delta < 1 \) 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 the next section.

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 uplink and 16 channels on downlink respectively. The parameters used in the simulation are listed in Table II.

TABLE II
TRAFFIC MODEL

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

The treatment to the new NRT calls is similar to that of the handoff NRT call except that only if \( \hat{\lambda}_{RT} < \lambda_{RT} \cdot \Delta \), the arrival new NRT call can be accepted, where \( 0 < \Delta < 1 \) 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 the next section.

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.

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. Simulation Scenario 1

![Fig. 1. Average cost of the CAC policies when \( q = 70\% \) in Scenario 1 (\( T = 1 \text{ minute}, \alpha = 0.1, \Delta = 0.1 \)).](image1)

![Fig. 2. Average cost of the CAC policies when \( q = 90\% \) in Scenario 1 (\( T = 1 \text{ minute}, \alpha = 0.1, \Delta = 0.1 \)).](image2)

Fig. 1 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. 2 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. 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.

B. Simulation Scenario 2

![Fig. 3. Average cost of the CAC policies when q changes with time (T = 1 minute, α = 0.1, Δ = 0.1).](image)

Fig. 3 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