International Journal of Future Generation Communication and Networking
Vol. 9, No. 1 (2016), pp. 207-222
http://dx.doi.org/10.14257/ijfgcn.2016.9.1.19

An Optimal Joint Call Admission Control Policy in Heterogeneous Wireless Networks

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Abstract

In heterogeneous wireless networks (HWNs), a scheme called Joint Call Admission Control (JCAC) is demanding for deciding whether or not an incoming service request will be accepted. In this paper, we propose an optimal JCAC policy for HWNs based on semi-Markov decision process (SMDP) to achieve the optimal resource management scheme in terms of minimal the network cost and acquire the required quality of service (QoS) of mobile user. Furthermore, an improved value iteration algorithm with multi-dimensional threshold structure is presented. Numerical results show that the proposed JCAC policy is the overall optimal policy. The proposed algorithm is effective for high QoS performance by reducing the probabilities of dropping and blocking calls. The optimal JCAC policy is ratified by the current trend in the design of next generation wireless networks (NGWNs).

***Keywords**: JCAC, HWNs, SMDP*

1. Introduction

With the development of heterogeneous wireless networks and the widespread use of intelligent mobile terminals, different radio access technologies (RATs) will coexist and also provide always best connected (ABC) communication for anyone, at anyplace and at anytime. The requirement of ABC cannot be satisfied with only one RAT. Therefore, the concept of integrated heterogeneous wireless network is introduced. In heterogeneous wireless networks, the main goal is to provide efficient ubiquitous computing with guaranteed quality of service (QoS) and the key problem is call admission control (CAC).

The traditional CAC is studied with the homogeneous networks, the algorithm is relative simple. The CAC consists of deciding whether an incoming call request is accepted by an admission constraint.

The CAC algorithm is used balancing the overload and avoiding the blocking in order to use the channel resource effectively.

However, the traditional CAC schemes will not cope with heterogeneous wireless networks (HWNs), new CAC should be adapted with the new changes, such as the different QoS requirements of multimedia services, different admission control scheme in RATs and the optimal resource management in HWNs.

Network selection strategy and call admission control scheme have been extensively studied. The first issue is required to select a desired network for the call. The authors

ISSN: 2233-7857 IJFGCN

of [6] give a survey of vertical handover decision in HWNs. IN [3,7-8,16], a network selection strategy that consider the QoS requirements has been introduced. The mobile user selects the network with the optimizing performance of service. In order to reduce the computation complexity of the utility function in [10], an optimal algorithm has been proposed. The authors have proposed network selection algorithm in [17] by using Markov-modulated process. The Markov vertical handoff decision algorithm is dynamic programming for network selection. The cloud computing [18] has also been proposed for selecting the best network for a mobile user. Dynamic programming and Semi Markov decision process (SMDP) [1, 2, 4, and 9] are used in the design of optimal CAC algorithms. However, the computational load for finding an optimal policy by MDP [12] is very high. In [11, 19], the CAC strategy in WiMAX or Wireless Mesh network is the optimal policy based on threshold. Based on dynamic programming methods is an optimal control problems in [14, 15]. However, such researches are not directly applicable to HWNs. It means: (ⅰ) The model do not have system parameters, only focus on the parameter such as bandwidth, capacity or the power, therefore the model get the system reward partly. (ⅱ) The traditional CAC policy is the well-known guard-channel policy can be proved an efficient algorithm, such results are not directly applicable to HWNs for a more complex and dynamic architecture. (ⅲ) In HWNs, the computational load of finding an optimal policy by traditional MDP algorithms is so high that cannot realize effectively. Consequently the new CAC strategy must be designed to adapt with HWNs. Joint CAC is performed a joint cooperative management of all wireless and mobile networks located in certain coverage. The design of JCAC strategies will be relevant for a better radio resource management. In this paper, optimal JCAC strategy for HWNs are considered and some applicable results are presented. We propose model based on a Semi-Markov Decision Process (SMDP). The optimal strategy is made to strike the balance between the network incomes and expenses. The model is introduced the improved algorithm of value iteration which can be applied to multi-dimensional threshold structure. In this paper, we have three main contributions: (ⅰ) The optimal JCAC strategy can minimize the network cost. The JCAC algorithm dictate the decision to accept or reject calls or handoff requests. (ⅱ) The JCAC schemes can achieve a satisfied QoS level for lower blocking probabilities. (ⅲ) We prove the model based on SMDP has a computationally efficient algorithm.

The rest of the paper is organized as follows. Section 2 presents the system model and the proposed algorithms are explained. Section 3 the performance of the model is presented. Numerical results are given in section 4, followed by conclusion in Section 5.

2. System Model

Proposed system model has been designed on the basis of communication scenarios in Figure 1. HWNs contains many different wireless networks, we consider two-type heterogeneous wireless network architecture. These are overlay network (Overlay) and underlay network (Underlay), which is divided by the coverage. In Overlay, there are networks UMTS, GPRS and CDMA. In Underlay, WLAN, Mesh, Ad-Hoc is typical networks.

2.1 Network Structure

From Fig.1, we can see that the call arrival and departure in the system. Proposed optimal JCAC strategy has been designed on the basis of following foundations. It is assumed that new calls (both in Overlay and Underlay) arrive according to a memoryless Poisson process, and also the service times are memoryless. Average service times are μ_O and μ_U. Traditional CAC only consider the reward will be provided by the action. In Table 1, we assume the different network cost subjected to five traffics.

2.2 The System Optimal Objective

Instead of the traditional CAC reward assignment, our proposed optimal JCAC strategy integrates a goal network to learn from reward, and provide the critic network with a minimization network cost. In this paper, we defined the network cost as

$$MinObj : \min g_{\pi} = \sum_{k=1}^{L} C_R^k \lambda_k P_B^k \tag{1}$$

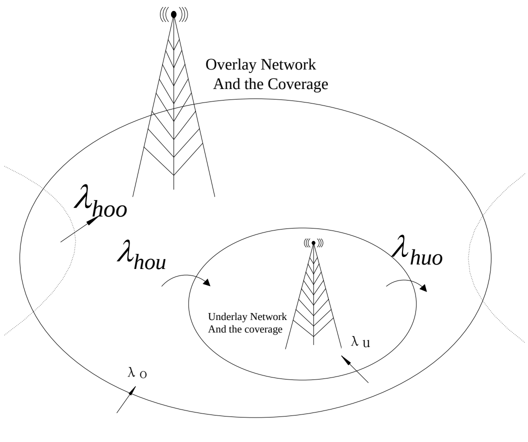

Figure 1. Architecture for Two-Type Heterogeneous Wireless Networks

Table 1. The Traffic Type and the Cost

Traffic Type k	*Rate*	*Cost*	*Description*
1	λ_O	C_{NBO}	New calls to Overlay
2	λ_U	C_{NBU}	New calls to Underlay
3	λ_{hoo}	C_{HDOO}	Handoff to Overlay from Overlay
4	λ_{hou}	C_{HDOU}	Handoff to Overlay from Underlay
5	λ_{huo}	C_{HDUO}	Handoff to Underlay from Overlay

Where C_R^k is the cost of traffic k, λ_k is the arrival rate of class k calls, P_B^k is the blocking or dropping probability of calls and L is the total type of calls.

2.3 Model of JCAC

In this paper, SMDP is introduced in HWNs, with the Poisson arrival process and the exponential service time assumption, any given call admission policy can be modeled as a Markov process. A SMDP model is defined of five components: the state space (S), the actions (A) and the state transition probabilities (P), the expected time until the next decision epoch (β) and the reward function (V).

2.3.1 State Space

Assume that $n_{i,k}$ is the number of ongoing calls in Overlay and $n_{j,k}$ is the number of ongoing calls in Underlay.

$$S = S(l,e) \qquad l = (n_{i,1}, n_{i,2}, \cdots n_{i,k}, n_{j,1}, n_{j,2}, \cdots n_{j,k}) \tag{2}$$

Furthermore, define that at random times, an event $e \in \{r_1, r_2, \cdots r_k, d\}$ can occur where: $e = r_k$ means an arrival of type k traffic; and $e = d$ means a departure of an ongoing call.

2.3.2 Actions

For our JCAC, each time whenever traffic arrives, the decision must to be made either as “accept” or as “reject”, while when the traffic departures, the only action should do is “no action”. That is the action is defined as,

$$A(s) \in \{"accept", "reject", "no\ \ action"\} = \{0,1,-1\} \tag{3}$$

We let a_R denote rejecting a call arrival, a_A mean accepting a call arrival and a_c denote continuing a call.

2.3.3 Expected Time until a New State

The decision epochs are those time points when a call arriving or leaving the system. Let $F(t|s,a)$ denote the probability the next decision epoch occurs within t time units when the system is in state s and taking action a. For this process, the times between decision epochs are exponentially distributed, if the system is in state s and the action a is chosen, then the expected time until the next decision epoch is given by (5), which b means an event in system, A_n means a new call arriving and A_h denote a handoff call arriving.

$$r(s,a) = k(s,a) - \beta(s,a)c(s,a) \tag{4}$$

$$k(s,a) = \begin{cases} 0, & a = a_c, a = a_R, any b \\ R_n, & a = a_A, b = A_n \\ R_h, & a = a_A, b = A_h \end{cases} \tag{5}$$

$$c(s,a) = \begin{cases} -f(s_n, s_h), & a = a_c, a = a_R, any b \\ -f(s_n + 1, s_h), & a = a_A, b = A_n \\ -f(s_n, s_h + 1), & a = a_A, b = A_h \end{cases} \tag{6}$$

2.3.4 The Expected Reward Function

In the proposed optimal JCAC, the main goal is to determine a rule for maximizing the overall system reward as a random variable associated with the state occupancies and transitions. If at present decision epoch, the system is at state s and action a is chosen, the expected rewards $r(s,a)$ is defined as follows:

$$F(t|s,a) = 1 - e^{-\beta(s,a)t}, t \geq 0 \tag{7}$$

$$\beta(\langle s_n, s_h, b\rangle, a) = \begin{cases} \beta_0 = \lambda_n + \lambda_h + s_n\mu_n + s_h\mu_h, & a = a_c, a = a_R \\ \beta_0 + \mu_n, & a = a_A, b = A_n \\ \beta_0 + \mu_h, & a = a_A, b = A_h \end{cases} \tag{8}$$

When the JCAC decides the new call or handoff call will be accepted, the immediate incurred reward is given by (7). Similar to the reward, the acceptance cost and blocking cost are given by (8).

By discounted reward SMDP model, the discounted expected reward can be defined as follows,

$$\begin{aligned} r(s,a) &= k(s,a) - c(s,a)E_s^a\left\{\int_0^t e^{-\alpha\tau}\, d\tau\right\} \\ &= k(s,a) - c(s,a)E_s^a\left\{\left(1 - e^{-\alpha t}\right)/\alpha\right\} \\ &= k(s,a) - \frac{c(s,a)}{\alpha + \beta(s,a)} \end{aligned} \tag{9}$$

Where α is the discounted factor, $E_s^a\{\cdot\}$ denote the expectation value, then can get the

long-term discounted expected reward by value iteration $V_\alpha^{d^\infty}(s)$.

$$V_\alpha^{d^\infty}(s) = r_d(s) + \frac{\beta_d(s)}{\alpha + \beta_d(s)} \sum_{j \in S} p_d(j|s) V_\alpha^{d^\infty}(j) \tag{10}$$

$p(j|s,d)$ means the probability that the system will be state j at next decision epoch.

2.3.5 Transition Probabilities

Let $p(j|s,a)$ denote the probability that the system occupies state j in the next epoch, if at the current epoch the system is at state s and the decision maker takes action a.

By data transformation, the SMDP model can be converted into a discrete-time MDP model. Choose a data transformation factor c with $[1 - p(s|s,a)]\beta(s,a) \leq c, \forall s \in S, a \in A(s)$. For example, in our model, c can be chosen as

$$c = \lambda_n + \lambda_h + C * \max(\mu_n, \mu_h) \tag{11}$$

The system state space and action space for the discrete-time MDP model is the same as the original SMDP model, while the one-step reward and the transition probabilities can be transformed from the SMDP model by, let $\tilde{S} = S, \tilde{A}(s) = A(s)$,

$$\tilde{p}(j|s,a)=\begin{cases}1-\dfrac{[1-p(s|s,a)]\beta(s,a)}{c}, & j=s\\ \dfrac{p(j|s,a)\beta(s,a)}{c}, & j\neq s\end{cases} \tag{12}$$

For states $s=\langle s_n,s_h,D\rangle$ and a=a$_C$, we have

$$\tilde{p}(j|s,a)=\begin{cases}\dfrac{\lambda_n}{c}, & j=\langle s_n,s_h,A_n\rangle\\ \dfrac{\lambda_h}{c}, & j=\langle s_n,s_h,A_h\rangle\\ \dfrac{s_n\mu_n}{c}, & j=\langle \bar{s}_n,s_h,D\rangle\\ \dfrac{s_h\mu_h}{c}, & j=\langle s_n,\bar{s}_h,D\rangle\\ \dfrac{(c-\beta_0)}{c}, & j=s\end{cases} \tag{13}$$

For states $s=\langle s_n,s_h,A_n\rangle$ and a=a$_R$, we have

$$\tilde{p}(j|s,a)=\begin{cases}\dfrac{(c+\lambda_n-\beta_0)}{c}, & j=\langle s_n,s_h,A_n\rangle\\ \dfrac{\lambda_h}{c}, & j=\langle s_n,s_h,A_h\rangle\\ \dfrac{s_n\mu_n}{c}, & j=\langle \bar{s}_n,s_h,D\rangle\\ \dfrac{s_h\mu_h}{c}, & j=\langle s_n,\bar{s}_h,D\rangle\end{cases} \tag{14}$$

For states $s=\langle s_n,s_h,A_h\rangle$ and a=a$_R$, we have

$$\tilde{p}(j|s,a)=\begin{cases}\dfrac{\lambda_n}{c}, & j=\langle s_n,s_h,A_n\rangle\\ \dfrac{(c+\lambda_h-\beta_0)}{c}, & j=\langle s_n,s_h,A_h\rangle\\ \dfrac{s_n\mu_n}{c}, & j=\langle \bar{s}_n,s_h,D\rangle\\ \dfrac{s_h\mu_h}{c}, & j=\langle s_n,\bar{s}_h,D\rangle\end{cases} \tag{15}$$

For states $s=\langle s_n,s_h,A_n\rangle$ and a=a$_A$, we have

$$\tilde{p}(j|s,a)=\begin{cases}\dfrac{\lambda_n}{c}, & j=\langle s_n+1,s_h,A_n\rangle\\ \dfrac{\lambda_h}{c}, & j=\langle s_n+1,s_h,A_h\rangle\\ \dfrac{(s_n+1)\mu_n}{c}, & j=\langle s_n,s_h,D\rangle\\ \dfrac{s_h\mu_h}{c}, & j=\langle s_n+1,\bar{s}_h,D\rangle\\ \dfrac{(c-\beta_0-\mu_n)}{c}, & j=s\end{cases} \tag{16}$$

For states $s=\langle s_n,s_h,A_h\rangle$ and a=a_A, we have

$$\tilde{p}(j|s,a)=\begin{cases}\dfrac{\lambda_n}{c}, & j=\langle s_n,s_h+1,A_n\rangle\\ \dfrac{\lambda_h}{c}, & j=\langle s_n,s_h+1,A_h\rangle\\ \dfrac{s_n\mu_n}{c}, & j=\langle \bar{s}_n,s_h+1,D\rangle\\ \dfrac{(s_h+1)\mu_h}{c}, & j=\langle s_n,s_h,D\rangle\\ \dfrac{(c-\beta_0-\mu_h)}{c}, & j=s\end{cases} \tag{17}$$

For each deterministic decision rule d, we have

$$\tilde{V}_\alpha^{d^\infty}(s)=\max_{a\in A(s)}\left\{\tilde{r}_d(s)+\frac{\beta_d(s)}{\alpha+\beta_d(s)}\sum_{j\in S}\tilde{p}_d(j|s)\tilde{V}_\alpha^{d^\infty}(j)\right\} \tag{18}$$

2.4 Optimal Policy

In HWNs, the optimal policy is a prescription for every state, therefore the more complex of HWNs is, the more complex structure of its optimal policy will be. Based on the problem, we propose multi-dimensional threshold structure for value iteration algorithm to simple the complex structure of HWNs. By theoretical results, we get that the optimal policy is a threshold policy. Let us denote by V^{n+1} the optimal reward function for nine event. The V_1 reflect new arrivals to the Overlay, V_2 reflect new arrivals to the Underlay, V_3 reflect the handover in Overlay, V_4 -V_5 account for vertical handover between Overlay and Underlay, the next three terms are for departure events and the last term is in the same state.

$$\begin{aligned}V^{n+1}&=\max(V_1{}^n(n_{i,k},n_{j,k}),r_{NBO}+V_1{}^n(n_{i,k}+1,n_{j,k}))\\&+\max(V_2{}^n(n_{i,k},n_{j,k}),r_{NBU}+V_2{}^n(n_{i,k},n_{j,k}+1))\\&+\max(V_3{}^n(n_{i,k},n_{j,k}),r_{HDOO}+V_3{}^n(n_{i,k}+1,n_{j,k}))\\&+\max(V_4{}^n(n_{i,k}-1,n_{j,k}),r_{HDOU}+V_4{}^n(n_{i,k}-1,n_{j,k}+1))\\&+\max((V_5{}^n(n_{i,k},n_{j,k}-1),r_{HDUO}+V_5{}^n(n_{i,k}+1,n_{j,k}-1))\\&+V_6{}^n(n_{i,k}-1,n_{j,k})+V_7{}^n(n_{i,k},n_{j,k}-1)+V_8{}^n(n_{i,k}-1,n_{j,k})\\&+(1-\frac{\beta(s,d)}{\alpha+\beta(s,d)})V_9{}^n(n_{i,k},n_{j,k})\end{aligned} \tag{19}$$

For example, as a handoff call arrives, the total expected discounted reward is defined as,

$$V^{n+1} = \sum_{m=1}^{9} V_m(n_{i,k}, n_{j,k}) \tag{20}$$

$$D_m(n_{i,k}, n_{j,k}) = V_m(n_{i,k}, n_{j,k}) - V_m(n_{i,k} - 1, n_{j,k}) \tag{21}$$

We can get the optimal decision，

$$\Delta V_h(n_{i,k}, n_{j,k}) = \sum_{m=1}^{9} D_m(n_{i,k}, n_{j,k}) \tag{22}$$

$$d(n_{i,k}, n_{j,k}, A_h) = \begin{cases} a_A, & \Delta V_h(n_{i,k}, n_{j,k}) \succ -R_h \\ a_R, & \Delta V_h(n_{i,k}, n_{j,k}) \le -R_h \end{cases} \tag{23}$$

3. Performance Measurement

The performance of JCAC can be evaluated by two metrics. The metric of QoS performances should be represented by the new call blocking probability and the handover dropping probability. In this sub-section, we deduce the call blocking probability and the handover dropping probability of JCAC model based on SMDP.

In the proposed model of JCAC, different action can attain the different reward for each state, we choose the action can maximize the reward. By the model based on SMDP, we get the optimal call admission policy and the state transition probabilities for our SMDP model. To get the steady state probabilities, we have a set of linear equation

$$\begin{cases} \pi_j = \sum_{i \in I} \pi_i \cdot \tilde{p}_{ij} \\ \sum_{j \in I} \pi_j = 1 \end{cases} \tag{24}$$

Where Π_j is the steady state probability for state *j*, and $\tilde{p}_{ij}$ is the transition probability from state *i* to state *j*, which is the result from the improved algorithm for value iteration. Once we have the steady state probability for each state, the measurement like blocking probabilities, the dropping probabilities is just trivial calculation.

4. Simulation and Performance Assessment

In order to evaluate the performance of the proposed methods, we select the typical sets of parameters are provided in Table 2. First, an optimal policy is found through iterative numerical simulations in MATLAB 7.0. Then, it is used to find the system QoS performance. The rejecting cost and admitting reward are provided in Table 2.

Table 2. Parameter Values

Parameter	*Value*	*Parameter*	*Value*
λ_o	4 calls/s	λ_u	2 calls/s
μ_o	6 s^{-1}	μ_u	4 s^{-1}
C_{NBO}	5	C_{HDOU}	10
C_{NBU}	3	C_{HDUO}	25
C_{HDOO}	45	R_o	0.164
R_u	0.3	λ_{hoo}	0.005 s^{-1}
λ_{hou}	0.01 s^{-1}	λ_{huo}	0.02 s^{-1}

4.1 The Optimal Policy

In order to observe the improvements made by the optimal JCAC policy, we list the optimal policy for each state as the traffic load is changed.

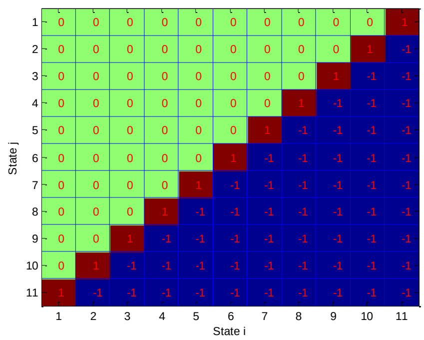

Figure 2. Optimal Decision (λ_n=4, λ_h=2,b=A_n)

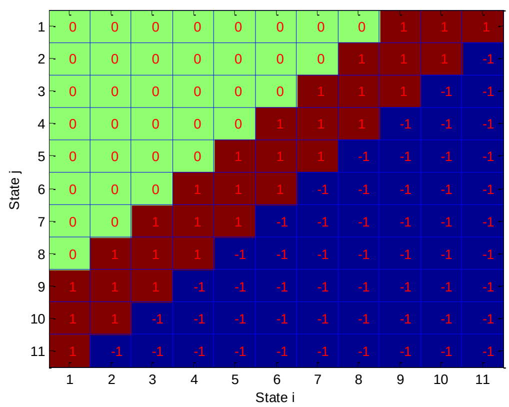

Figure 3. Optimal Decision (λ_n=4, λ_h=2,b=A_h)

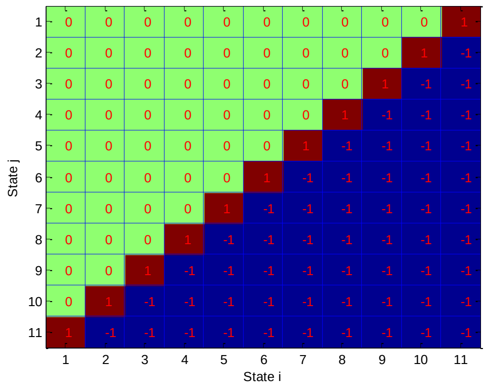

Figure 4. Optimal Decision (λ_n=24, λ_h=12,b=A_n)

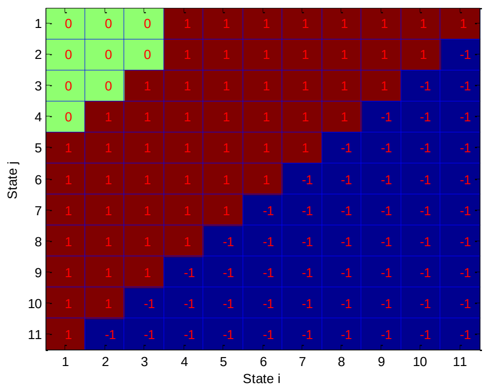

Figure 5. Optimal Decision (λ_n=24, λ_h=12,b=A_h)

Table 3. Total Discounted Expected Reward *V(S)* (Λ_n=4, Λ_h=2)

b=D	$S_h \rightarrow$				
	1.1243	0.8804	0.6365	0.3926	0.1487
	0.9603	0.7165	0.4726	0.2286	-0.0152
	0.7964	0.5525	0.3086	0.0647	-0.1791
	0.6325	0.3886	0.1447	-0.0991	-0.3430
	0.4685	0.2247	-0.0192	-0.2631	-0.5068
$S_n \downarrow$	0.3046	0.0607	-0.1831	-0.4270	-0.6700
	0.1407	-0.1032	-0.3470	-0.5908	-0.8313
	-0.0232	-0.2671	-0.5110	-0.7548	-1
	-0.1869	-0.4311	-0.6769	-1	-1
	-0.3480	-0.5968	-1	-1	-1
	-0.4716	-1	-1	-1	-1
$S_h \rightarrow$					
-0.0951	-0.3390	-0.5827	-0.8251	-1.0578	-1.1942

-0.2591	-0.5028	-0.7458	-0.9827	-1.1740	-1
-0.4229	-0.6662	-0.9050	-1.1077	-1	-1
-0.5865	-0.8270	-1.0401	-1	-1	-1
-0.7486	-0.9715	-1	-1	-1	-1
-0.9020	-1	-1	-1	-1	-1
-1	-1	-1	-1	-1	-1
-1	-1	-1	-1	-1	-1
-1	-1	-1	-1	-1	-1
-1	-1	-1	-1	-1	-1
-1	-1	-1	-1	-1	-1

Table 4. Total Discounted Expected Reward *V(S)* (Λ_n=24, Λ_h=12)

$b=D$	$S_h\rightarrow$				
	6.7249	6.4810	6.2369	5.9929	5.7489
	6.5610	6.3170	6.0730	5.8289	5.5848
	6.3970	6.1530	5.9090	5.6649	5.4207
	6.2330	5.9890	5.7449	5.5008	5.2563
$S_n\downarrow$	6.0690	5.8250	5.5808	5.3364	5.0912
	5.9050	5.6609	5.4166	5.1715	4.9238
	5.7410	5.4967	5.2517	5.0043	4.7471
	5.5767	5.3319	5.0847	4.8280	-1
	5.4121	5.1651	4.9089	-1	-1
$S_n\downarrow$	5.2455	4.9896	-1	-1	-1
	5.0704	-1	-1	-1	-1
$S_h\rightarrow$					
5.5047	5.2604	5.0157	4.7697	4.5202	4.2596
5.3406	5.0959	4.8501	4.6011	4.3411	-1
5.1761	4.9306	4.6819	4.4225	-1	-1
5.0109	4.7626	4.5038	-1	-1	-1
4.8432	4.5850	-1	-1	-1	-1
4.6661	-1	-1	-1	-1	-1
-1	-1	-1	-1	-1	-1
-1	-1	-1	-1	-1	-1
-1	-1	-1	-1	-1	-1
-1	-1	-1	-1	-1	-1
-1	-1	-1	-1	-1	-1

From figure 2 and figure 3, we can see that deterministic stationary decision rule of optimal policy for each state. Using the improved Value Iteration Algorithm, we get the values of v(s), which are shown in table 3 and table 4. ‘0’ means to accept the call and ‘1’ means to reject the call and ‘-1’ means that state does not exist. If we change the traffic load, which would make the system in a heavier traffic load, the action values can be seen from figure 4 and figure 5. Compared with the figure 3, the decision to accept the new call is smaller, this is because the system is in a heavier traffic load.

4.2 System Performance

The network cost represents the performance of a system. Complete Sharing (CS) policy refers to the admission policy where a call is always allowed access to the network if there is sufficient bandwidth on the link available. This is a greedy algorithm since the policy does no control at all to choose accept/reject the call arrivals. We compare the optimal policy with the CS policy shows how effective the control algorithm is.

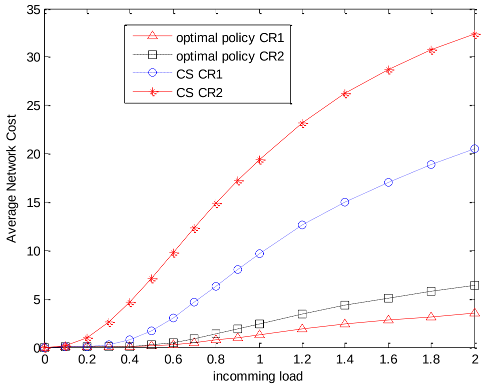

Figure 6. Optimal and CS Policy Network Costs Versus Traffic Load

Figure 6 shows the result of this comparison for two different cost vectors of, $CR_1 = \{5,3,45,10,25\}$ and $CR_2 = \{5,3,15,10,15\}$. The average network cost is computed for each cost vector. The network cost in optimal policy is lower than the same cost setting under a CS policy. Therefore, CS policy cannot provide a controlled service differentiation among users with different needs. Consequently, the global optimal objective function is hard to obtain. The optimal policy consider the reward of accepting a request and the long-term expected reward, make the resource utilization effective and reduce the average cost. The larger is the difference between the average network cost induced by the optimal and CS policies. The reason is that under the optimal policy the blocking and dropping probabilities are adaptively changing to achieve the minimum average network cost. Again, Figure 7 shows the QoS performance of new call blocking probability with the load increased.

Figure 8 shows the results under increasing user mobility rate. It can be observed that the new arrivals blocking probabilities and dropping probabilities for calls of type 3 and 4 are increasing, that reason is the increase of total incoming load. The change in dropping probability for calls of type5 are monotonic, the increasing part shows the handovers from underlay try to handover to the underlay.

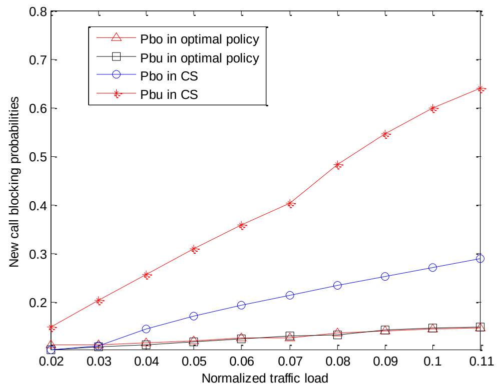

Figure 7. New Call Blocking Probabilities for Optimal and CS Policy

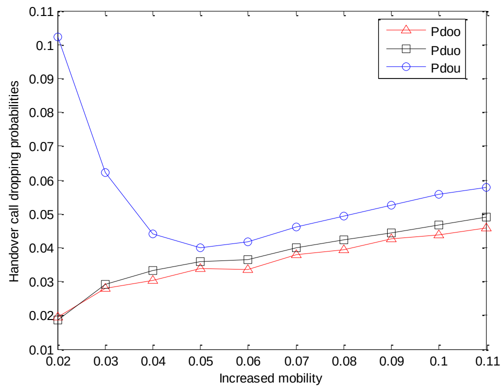

Figure 8. Handover Call Dropping Probabilities for Increased Traffic Load

5. Conclusions

In this paper, an optimal JCAC policy for HWNs is considered. We have proposed an optimization model based on SMDP, which considered the efficient value iteration algorithm and the long-term expected reward. System performance on the optimal average network cost for a two-type HWN architecture is presented The proposed method is a new adaptive framework for JCAC in HWNs.

Experiments show that improved VIA is reliable and effective. Firstly, the proposed optimal policy in much less computational load compared to conventional numerical methods. Also, the simulation confirms that the optimal policy is effective in maintaining high QoS performance.

In this paper, we have worked with new call and handover traffic classes (horizontal and vertical), for forthcoming analysis, we will consider the multimedia traffic in JCAC, which will lead to much better and realistic optimal policies.

Acknowledgements

This work was supported by Beijing Natural Science Foundation （No：4110001） and Scientific Research Common Program of Beijing Municipal Commission of Education （No：KM201010005011）.

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