Proactive Radio Resource Management Using Optimal Stopping Theory

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Abstract

In this paper, we focus on proactive radio resource management schemes that retain the quality of the individual connections by pre-reserving the needed resources in a cellular network. We propose a new scheme, which improves older proactive solutions. Typically, in such solutions an improvement in call dropping probability negatively impacts new call blocking probability. We improve this framework by careful, fine-grained time scheduling of the proactive resource management. We adopt optimal stopping theory for our solution. Our findings are quite promising for the broader framework of proactive resource management and mobile computing.

1. Introduction

In this paper we introduce a new proactive radio resource management scheme. The main objective of the proposed scheme is to reduce the dropping or forced termination probability in wireless cellular systems attributed to handovers. This objective is achieved through the pre-reservation of the required resources (e.g., bandwidth) in the most likely to be visited cell of the current neighborhood. Hence, after the occurrence of the handover, the mobile terminal (MT) does not compete for finite network resources but enjoys a pre-arranged configuration and the user does not experience service discontinuation or low service quality. The user (MT) pays a price to the network for this proactive service, so that it compensates for the occupied resources that cannot be offered to another terminal for the pre-reservation time interval. The proposed scheme consists of a path prediction algorithm and the determination of the optimal time instance for the pre-reservation of the required bandwidth. Finally a call admission control scheme is used, if no pre-reservation takes place.

The rest of the paper is organized as follows. In section 2, we describe related prior work in proactive resource management. In Section 3, we discuss optimal stopping theory and, specifically, the parking problem. Section 4 presents our proposed scheme, while Section 5 provides simulation results. Section 6 concludes the paper.

2. Prior work in proactive resource management

In this section, prior work on predicting the movement of a user and pro-actively performing resource management is presented. A general survey of the above topics can be found in [1].

Many authors have proposed schemes that are based on guard channels. According to these schemes a portion of the bandwidth is intended for handed-over sessions. In [6], a simple scheme assuming a fixed amount of guard bandwidth is introduced whereas in [4], a simple call admission control (CAC) algorithm which takes advantage of guard channels is used. In [5] other adaptive reservation schemes based on guard resources are discussed. A new proactive QoS provisioning technique is introduced in [3]. This technique involves requesting network resources ahead of time as the mobile host moves from one cell to another.

In [2], the authors use the shadow cluster concept, which can be used to estimate future resource requirements and perform call admission decisions in wireless networks. The framework of a shadow cluster system can be viewed as a message system where MTs inform the base stations (BSs) in their neighborhood about their requirements. With this information, BSs predict future demands and can reserve resources accordingly.

Finally in [7], a scheme for the proactive allocation of network resources to mobile users, based on a pricing framework is proposed. The future BS, where resources have to be a-priori secured, is determined by a path prediction algorithm. The network receives a fee for providing the advance reservation service to the user while the exact price is determined after a sequential bargaining procedure, modeled as a two person

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non-cooperative game between the mobile user and the network.

It is obvious that, even though the proactive resource management has attracted significant research efforts, this problem has not been studied yet to further improve the efficiency of the various solutions.

3. Optimal stopping theory – Parking problem

Optimal stopping theory is concerned with the problem of choosing the best time instance to take a decision to perform a given action based on sequentially observed random variables in order to maximize the expected payoff or minimize the expected cost. There are many problems whose solutions may be effectively evaluated by this method, as we can see in [9]. The most famous of these are the secretary problem and the parking problem. The scheme introduced in this paper is based on the parking problem.

In the original parking problem, a person (the decision-maker) drives a car along a straight highway towards his destination and is looking for a parking place. When he finds a parking place, he can either park or continue driving. Parking places are assumed to occur along the highway at random and they constitute a Bernoulli distribution. If the decision maker has not parked by the time he reaches his destination then he continues driving until he finds the first parking place thereafter and parks there. Once he parks somewhere, the decision-maker must walk to his destination, which corresponds to the cost (loss) he has to pay.

The extension of the original problem, in which we base our proposed scheme, was presented in [10]. According to this modified problem, parking places do not follow a Bernoulli distribution, but they are assumed to occur along the highway according to a Poisson process. In contrast with the original problem where the decision-maker is assumed to know the exact location of his destination, it is supposed that the distance between the starting point and the destination is not known in advance but is a positive random variable with given probability distribution. Considering this we can find a policy, which minimizes the expected cost that is the distance to his destination.

4. Model for proactive resource management

In this section we discuss in more detail the proposed proactive resource management scheme.

When a MT enters a new cell, the path prediction algorithm (PPA) is invoked and its output vector indicates the most likely cell for the next handover. We assume the use of the PPA reported in [8]. After the next cell is determined, MT makes a request for bandwidth pre-reservation to this cell. Henceforth, the initial problem boils down to an optimal stopping problem. Therefore, we should determine the optimal time instance to commit a request for resource pre-reservation, in order to minimize the cost incurred by the MT.

This problem can be modeled as a modified parking problem, based on Tamaki's work [10]. At first, we assume that the critical variable in our model is time (time to handover) and not space (distance to a given destination). The MT is considered to be the "car driver" (i.e., the decision-maker) moving toward the destination. In our scheme, the destination is considered to be the handover time instant. The objective of the MT is to "park" before it reaches the destination, that is to pre-reserve the required bandwidth before the handover (after the handover, the MT contents - equally - with other MTs). We consider that the MT pays a price to the BS of the corresponding cell in proportion to the time interval of the pre-reservation. Consequently the cost incurred by the MT decreases for shorter prereservation periods and is given by:

$$L = p \cdot BW_{required} \cdot \Delta t \qquad (1)$$

where $\Delta t = t_{HO} - t$ (time interval until handover), t_{HO}: time of handover, p: price per bandwidth unit per time unit (m.u.[1]/(Kb/s)) that the MT pays and $BW_{required}$: the required bandwidth.

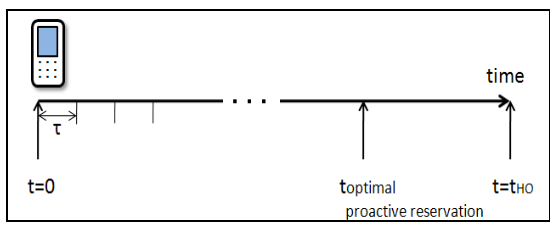

Figure 1. Representation of the proposed model

After the occurrence of the handover, the term pre-reservation has no meaning. For this reason, we consider that the MT cannot "park" after the handover time instant, and we assume that the respective cost is very high.

Regarding the empty parking places, they represent the time instances when the available bandwidth of BS exceeds the required bandwidth, that is to say:

[1] m.u. is monetary units.

$$\begin{cases} BW_{free}(t) - BW_{required}(t) \geq 0 \leftrightarrow \text{"Empty parking place"} \\ BW_{free}(t) - BW_{required}(t) < 0 \leftrightarrow \text{"Full parking place"} \end{cases}$$

From t=0 and afterwards, MT queries the BS every τ time intervals, trying to determine the availability of "free parking places" (free bandwidth) (see Figure 1). If the MT finds available bandwidth, it can either "park" (request for pre-reservation) or continue, considering that it can find another "parking place" with smaller cost. The time instant of the handover is not known in advance and is treated as a random variable t_{HO} that follows a Gamma distribution with probability distribution function $F(t_{HO})$. This can be justified if we take into account that the cell residence time of MT can be approximated well by a Gamma distribution [11]. Furthermore, we assume that as the MT moves, the "free parking places" are Poisson distributed with parameter λ. This is a reasonable assumption if we take into account the fact that "free parking places" are the cumulative effect of connections handed-over, initiated and terminated in the considered cell.

The time instances when the BS has available bandwidth constitute a $\{T_k\}$ Markov chain, whose values can be $\{T_k=t\}$ if the handover has not yet occurred and the MT finds the k^{th} "parking place" at t, and $\{T_k=[t,t_{HO}]\}$ if the handover has occurred at t_{HO} and the MT finds the k^{th} "parking place" at t ($t>t_{HO}$). Based on Tamaki's work [10], it can be easily seen that the expected cost if the pre-reservation occurs in time t is given from the following equations:

$$V_1(t) = \int_t^{\infty} p \cdot BW_{required}(t_{HO} - t)dF(t_{HO} \mid t) = \\ = p \cdot BW_{required} \frac{T_F(t)}{\overline{F}(t)} \qquad (2)$$

where $\overline{F}(t) = 1 - F(t)$, $F(t)$ is Gamma probability distribution function and

$$T_F(t) = \int_t^{\infty} (t_{HO} - t)dF(t_{HO})$$

In case that the MT does not make a request and a handover occurs, the cost is very high:

$$V_1(t, t_{HO}) = k \cdot p \cdot BW_{required} \cdot (t - t_{HO}) \quad (3),$$

where k is a large value.

Let $V(t)$ be the expected loss under an optimal policy given that the decision-maker is at t. Then, by the principle of optimality, we compare the return for stopping, namely $V_1(t)$, with the return we expect to be able to obtain by continuing and using the optimal rule for the next stages through the destination, which is $PV_1(t)$. Thus, we obtain the functional equation:

$$V(t) = \min\{V_1(t), PV_1(t)\} \quad (4)$$

Where the operator P is introduced to represent

$$PV_1(t) = \int_0^{\infty} V_1(t+s)p\{t+s \mid t\}ds + \\ + \int_0^{\infty}\int_t^{t+s} V_1(t+s, t_{HO})p\{[t+s, t_{HO}] \mid t\}dt_{HO}ds \quad (5)$$

where $p\{t_{HO} \mid t\} = \Pr\{T_{k+1} = t_{HO} \mid T_k = t\}$

Let

$$G = \{t \mid V_1(t) \leq PV_1(t)\} \quad (6)$$

be the set of states derived from the application of the one-stage look ahead (OLA) policy. G can be interpreted as the set of states for which the immediate stop is at least as good as continuing exactly for one more transition and then stop. If we define the OLA policy as one, which indicates to stop as soon as the state enters G, then it can be proven that the OLA policy is optimal [10].

Straightforward calculations derive:

$$PV_1(t) = \int_0^{\infty} p \cdot BW_{required} \frac{T_F(t+s)}{\overline{F}(t+s)} \lambda e^{-\lambda s} \frac{\overline{F}(t+s)}{\overline{F}(t)} ds + \\ + \int_0^{\infty}\int_t^{t+s} k \cdot p \cdot BW_{required}(t+s-t_{HO})\lambda e^{-\lambda s} \frac{f(t_{HO})}{\overline{F}(t)} dt_{HO}ds = \\ = V_1(t) + \frac{2}{\lambda} \cdot \left((k+1) \cdot p \cdot BW_{required}\right) \cdot \int_t^{\infty} e^{-\lambda(t_{HO}-t)} dF(t_{HO} \mid t) - \\ - \frac{1}{\lambda} \cdot (p \cdot BW_{required}) \qquad (7)$$

So if we let

$$g(t) \equiv \int_t^{\infty} e^{-\lambda(t_{HO}-t)} dF(t_{HO} \mid t) \qquad (8)$$

then

$$G = \{t \mid g(t) \geq 1/(2(k+1))\} \quad (9)$$

The function $g(t)$ is the conditional probability that no "parking place" (free bandwidth) has been located by the time the handover occurs, given that the MT is at state t. $g(t)$ must be non-decreasing in t, so that G is an optimal stopping region. If g(t) is non-decreasing in t then G can be written as $G = \{t \mid t \geq t^*\}$ where t^* may be infinity.

As it has been mentioned before, the time until the next handover is considered to be Gamma distributed with distribution function as follows:

$$F(t_{HO}) = 1 - e^{-\mu t_{HO}} \left[\sum_{j=0}^{n-1} \frac{(\mu t_{HO})^j}{j!} \right], \\ 0 \leq t_{HO} < \infty, n \geq 1 \quad (10)$$

So, we have

$$g(t) = \left(\frac{\mu}{\lambda+\mu}\right)^n \left[\sum_{j=0}^{n-1} \frac{((\lambda+\mu)t)^j}{j!} \bigg/ \sum_{j=0}^{n-1} \frac{(\mu t)^j}{j!} \right] \quad (11)$$

g(t) can be proven to be non-decreasing by the fact that if we let $u(t)=\sum_{j=0}^{n} a_j t^j$, $\upsilon(t)=\sum_{j=0}^{n} b_j t^j$ then $u(t)/\upsilon(t)$ is non-decreasing in the interval $(0, \infty)$ so far as α_j, $b_j \ge 0$ and α_j/b_j is non-decreasing in j. Since $g(0)=(\mu/(\lambda+\mu))^n$ and $g(\infty)=(\mu/(\lambda+\mu))$, t^* is the unique positive root of the equation $g(t)=1/(2(k+1))$ if $(\mu/(\lambda+\mu))^n \le 1/(2(k+1)) \le (\mu/(\lambda+\mu))$, otherwise $t^*=0$ or ∞ according as $1/(2(k+1)) \le (\mu/(\lambda+\mu))^n$ or $(\mu/(\lambda+\mu)) \le 1/(2(k+1))$.

Consequently with the entrance of MT in *G* state, it has to stop and request for pre-reservation. This will be the optimal policy.

It is mentioned that if MT has not "parked" (has not request for pre-reservation) and the handover occurs, then the conventional call admission control has to decide if BS will accept the call or not.

5. Simulations and results

The proposed scheme has been simulated using Matlab. Specifically, we compared our model with a non-proactive scheme, and a simple proactive scheme in which the users can pre-reserve resources right after their entrance in the previous cell.

5.1 Simulation model

We consider a multi-cell system with 7 BSs (see Figure 2) while the capacity of each BS is 2000 bandwidth units. Cells are considered neighbors if they share one common side.

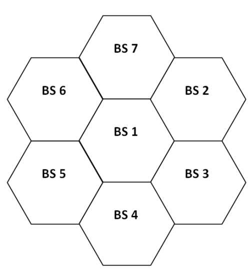

Figure 2. Plan of the simulation area

We assume that a MT can successfully predict the next cell. Modern PPAs yield a success probability close to 0.95. The handling of the PPA failures is an open issue left for future work.

Furthermore, we assume a simple traffic model with four types of applications. Their specific characteristics are shown in Table 1. We consider that each user can execute only one application each time. Application types are randomly invoked. The duration of application sessions is exponentially distributed with mean value as indicated in Table 1 while the arrivals of new sessions are Poisson distributed. Moreover, the cell residence time of each user is modeled as a random variable that follows the Gamma distribution as in [11].

Table 1. Characteristics of Application Types

Application	Requested Bandwidth (kb/s)	Mean session duration (s)	Arrival rate (sessions/h)
Voice	64	120	4
FTP	128	300	2
HTTP	64	6	40
Video	512	320	1

5.2 Simulation results

In this section, we initially compare the probability of blocking a new application (P_{block}) and the probability of dropping an existing one (P_{drop}) in our scheme with the same probability measures in a non-proactive scheme. Specifically, P_{block} is the ratio of blocked application sessions against the total count of application sessions and P_{drop} is the ratio of dropped sessions (due to handovers) against the total count of sessions. Our simulation involves 700 users that are initially uniformly distributed in the considered area.

In Figure 3, we notice that our scheme has succeeded to reduce significantly the dropping probability for all types of applications.

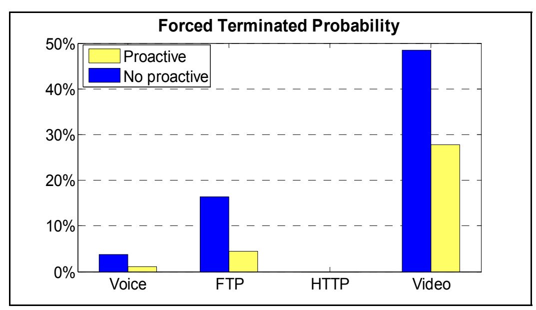

Figure 3. Dropping probability

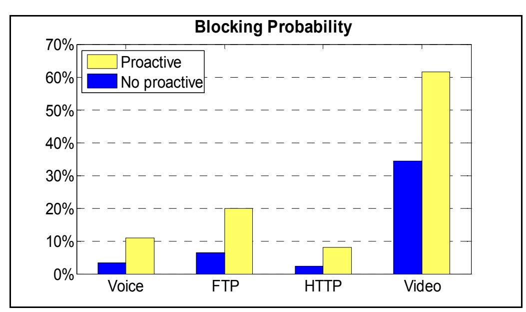

Figure 4. Blocking probability

On the contrary, as we can see in Figure 4, the blocking probability is higher in our scheme. In the proposed scheme a portion of the network bandwidth is reserved for handed-over sessions, resulting in less available bandwidth for the new sessions and, thus, in higher blocking probability.

Comparing the proposed model with the simple proactive model, we observe that the proposed model has lower blocking and dropping probabilities independently of the number of users, as we can see in Figures 5 and 6. This is reasonable since the proposed model performs a careful time management of the proactive scheme. Users cannot preserve resources right after their entrance in the previous cell as they are charged for the service. They need to rationalize their proactive requirements. The network, on the other side, can exploit the unreserved resources in order to accommodate other sessions with very specific, immediate requirements. As an example of the rationalization of the proactive resource management we mention that 25% of the active connections terminated in the current cell despite the fact that they proactively reserved resources in the future cell.

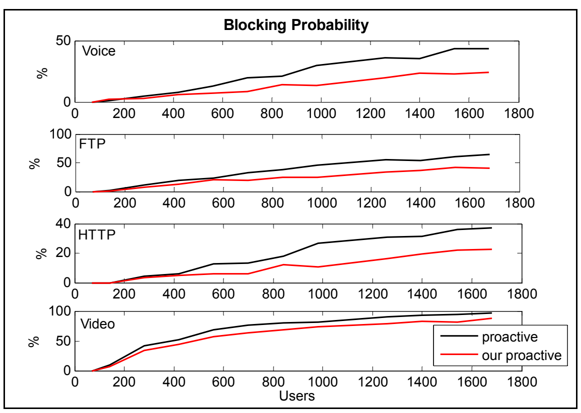

Figure 5. Blocking Probability - Comparison between the proposed model and a simple proactive model

An optimal stopping scheme reduces this unwanted resource consumption, increases the efficiency of the network as it may accommodate other users and reduces the monetary cost incurred by users. That means that our model leads to a more rational resource management as it reduces the time interval of the pre-reservation. Contrary to this scheduling framework, the simple proactive method does not exploit properly the available resources, resulting in high blocking and dropping probabilities.

Subsequently, we study the effect of our scheme in the revenues of the network and the cost per user. In our model, it has been considered that the users who want to pre-reserve bandwidth in a cell should pay a higher price than those who are already in the cell. Specifically, we consider that the prices for a user are $p_{cell} = 10^{-4}$ m.u. (per bandwidth unit per time unit) and $p_{proactive}=1.5 \cdot 10^{-4}$ m.u. (per bandwidth unit per time unit). Consequently, another factor that is important for further study is the network income.

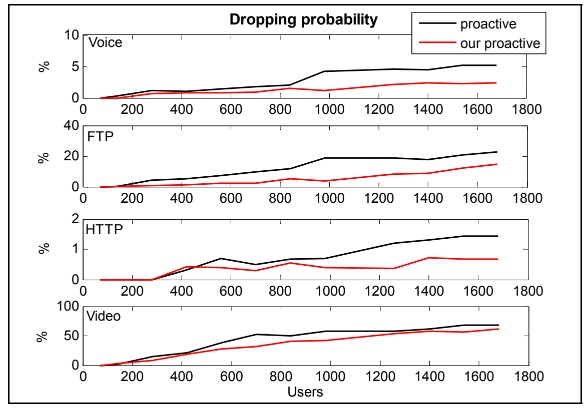

Figure 6. Dropping Probability - Comparison between the proposed model and a simple proactive model

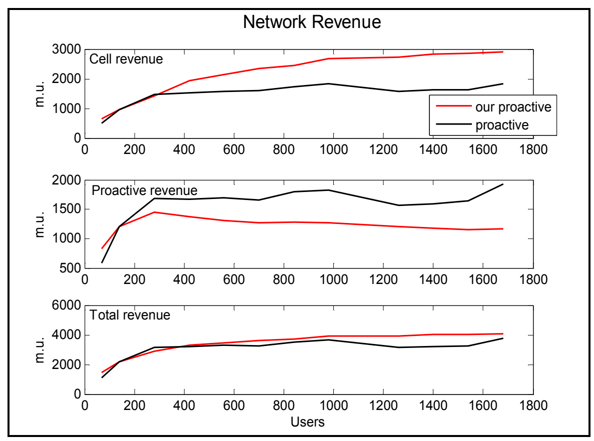

Figure 7. Network Revenue - Comparison between the proposed model and a simple proactive model

Initially, we compare the results regarding cell revenue in the proposed model and those of a simple proactive model. As it appears from Figure 7, below a certain number of users, the total network income is the same for the two models. However, for more users, the proposed model leads to higher income. In particular, the income from users that are already in the cell is higher in the proposed model. This can be explained if we take into account that our model leads to a smaller blocking probability than the simple model. On the contrary, the income due to pre-reservation is higher in the simple proactive model as the MTs reserve the required bandwidth for more time than in the proposed model. This, however, leads to higher cost per user in the simple model, which is, surely, not desirable (Figure 8).

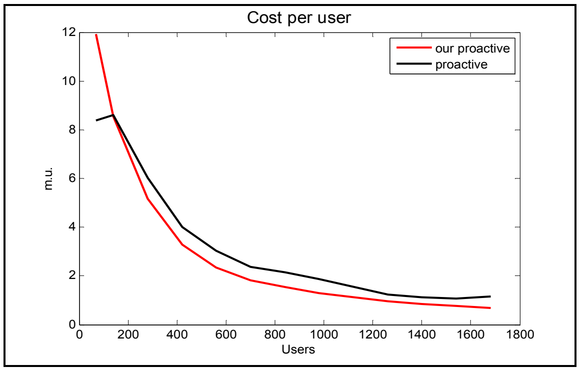

Figure 8. Comparison between the proposed model and a simple proactive model in terms of cost per user

Finally, we compare the proposed model with a non-proactive model in terms of network income. As it can be seen from Figure 9, network income is higher in the proposed model. That means that the revenue that the network earns because of the pre-reservation is higher than its loss because of the increased blocking probability.

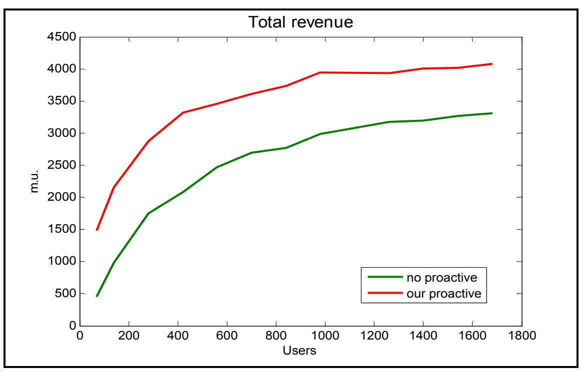

Figure 9. Network Revenue - Comparison between the proposed model and a non-proactive model

6. Conclusion

This paper presents a new proactive resource management scheme for the pre-reservation of network resources. The objective of our model is to reduce the handover dropping probability in wireless cellular systems and guarantee an acceptable QoS. The proposed scheme adopts optimal stopping theory and, specifically, the parking problem to determine the optimal time of committing the request for resource pre-reservation, in order to minimize the cost incurred by the MT. This delayed preservation yields the extra benefit of allowing the network to optimally exploit the resources, which would otherwise be committed to a possibly unneeded pre-reservation.

Different simulation experiments of the proposed scheme are also presented. The results show that the proposed scheme succeeds to reduce the dropping probability while at the same time increases the total revenues of the network. In the future, we plan to adjust other problems of optimal stopping to solve radio resource management issues.

7. References

[1] I. Priggouris, E. Zervas, and S. Hadjiefthymiades, "Location Based Network Resource Management", *Handbook of Research on Mobile Multimedia (Ed. Ismail Khalil Ibrahim)*, Idea Group Reference, May 2006.

[2] D. Levine, I. Akyildiz and M. Naghshineh, "A Resource Estimation and Call Admission Algorithm for Wireless Multimedia Networks Using the Shadow Cluster Concept", *IEEE/ACM Trans. Networking*, Vol. 5, No 1, 1997.

[3] A. Lakas, F. Sallabi, M. Boulmalf, K. Shuaib and H. Elsayed, "A Proactive Resource Management in 3G Networks", Proc. 7th IFIP International Conference on Mobile and Wireless Communication Networks, Morocco, 2005.

[4] Y. Zhang and D. Liu, "An Adaptive Algorithm for Call Admission Control in Wireless Networks", *Proc. IEEE Globecom*, San Antonio, TX, 2001.

[5] C. Oliveira, J. Kim and T. Suda, "An Adaptive Bandwidth Reservation Scheme for High-speed Multimedia Wireless Networks", *IEEE JSAC*, Vol. 16, No 6, 1998.

[6] R. Guerin, "Queuing-blocking system with two arrival streams and guard channels", *IEEE Trans. Commun.*, Vol. 36, No.2, 1988.

[7] G. Alyfantis, S. Hadjiefthymiades, and L. Merakos, "Proactive Resource Management for the Mitigation of Service Discontinuation in Mobile Networks", Proc. *ICCCN 2006*, Washington DC, USA, October, 2006.

[8] M. Kyriakakos, S. Hadjiefthymiades, N. Frangiadakis and L. Merakos, "Enhanced Path Prediction for Network Resource Management in Wireless LANs", *IEEE Wireless Communications Magazine*, Vol.10 No 6, December 2003.

[9] T.S. Ferguson, "Optimal Stopping and Applications", Available online at: http://www.math.ucla.edu/~tom/Stopping/Contents.html

[10] M. Tamaki, "An Optimal Parking Problem", *Journal of Applied Probability*, Vol. 19, No 4, Dec. 1982.

[11] M. Zonoozi and P. Dassanayake, "User Mobility Modeling and Characterization of Mobility Patterns". *IEEE JSAC*, Vol. 15, No 7, 1997.