Optimal Scheduling of Handoffs in Cellular Networks

Manjari Asawa, *Member, IEEE*, and Wayne E. Stark, *Senior Member, IEEE*

***Abstract*— In this paper, the phenomenon of hard as well as soft handoffs in cellular networks is formulated as stochastic optimization problems. The signals received by a mobile user are treated as *stochastic processes with associated rewards,* which are functions of some measurable characteristics of the received signals, while the handoff is *associated with a switching penalty.* This formulation captures the trade-offs involved in handoffs in a flexible manner and captures many facets of popular cellular communication systems in use currently. Using dynamic programming, necessary and sufficient conditions for determining the optimal base station(s) the mobile should be associated with during each decision epoch are derived. For the cases where the above-mentioned necessary and sufficient conditions fail to determine an optimal decision, "limited lookahead" arguments are used for determining handoff decisions. The decisions are taken in a decentralized manner, which makes its implementation easier compared to centralized algorithms. Simulation results show that for the hard handoffs, performance gain by the proposed algorithm over the simpler threshold algorithms proposed in the literature is small; however, for the case of soft handoffs, the proposed algorithm offers considerable improvement over the algorithm proposed in the IS-95 standard.**

I. Introduction

To accommodate the increasing demand for cellular access and to increase the overall system capacity, cells are being made smaller. Smaller cell sizes, combined with increasing user density and mobility, requires more handoffs to sustain calls to satisfactory completion. Handoffs, in turn, require additional signaling for establishing new set-ups as well as for performing associated database updates. It has been estimated [10] that the additional signaling load generated by handoffs will be 4–11 times greater for cellular networks than for integrated service digital networks (ISDN's) and 3–4 times greater for personal communication networks (PCN) than for the current cellular networks. Hence, the problem of designing efficient handoff algorithms is becoming increasingly important.

Signal strength variations occuring in mobile environment because of the shadowing and fading effects of the surrounding buildings, vehicles and other geographical features, introduce trade-offs in the design of handoff algorithms. Clearly, one does not want the handoffs to be very frequent, as unnecessary handoffs affect call quality and increase the load on the switching network. Hence, it is desirable to minimize the number of handoffs. However, postponing a necessary handoff affects the quality of communication and may result in lost calls, as the signal from the original base station starts to deteriorate. Similarly, if the decisions are made merely by considering the best signal quality, then they can lead to the "ping-pong" effect (constant switching among base stations), thereby considerably increasing the network traffic. Consequently, it is important to have a performance criterion which can capture the above trade-offs in an appropriate manner and allow their simultaneous optimization. Besides designing new algorithms, such a study will also enable the direct comparison of existing methods. To our knowledge, current research work has so far been limited to measurement, simulation, or analysis specific to a particular algorithm (see [7], [11], [14], [17]–[19] and references therein) and does not seek an optimum policy. An exception to this is the recent paper by Rezaiifar *et al.* [12], where the authors have considered a special case of the formulation presented here. However, the concept of a single performance measure which can capture the involved trade-offs in a flexible manner is still lacking.

In this paper, we offer a novel, flexible, and systematic framework within which to view and contrast handoff policies. Our formulation allows both the mobile and the network operator to trade-off the number of handoffs and resource utilization costs versus signal quality. This is achieved by formulating the handoff problem as a stochastic optimization problem, where the objective is to maximize an infinite horizon expected discounted reward obtained by the communicating mobiles minus a cost incurred for handoffs. Signals received by a mobile user are modeled as stochastic processes. The *reward* is a function of some measurable characteristics of the received signal, such as signal strength, carrier to interference power ratios, channel fading, shadowing due to obstructions, propagation loss, power control strategies, traffic distributions, cell loading profiles, channel assignments, etc. The handoffs are modeled as *switching penalties*, that are incurred because of the resources needed for their successful completion.

Depending on the multiple-access techniques used, there are two types of handoffs. In frequency-division multiple access (FDMA) and time-division multiple access (TDMA) based networks, the mobile user can communicate with at most one base station at any time. Consequently, during transition of a mobile user from one cell to its neighbor, communication with the second base is initiated only after terminatination of the communication link with the first base station; thus the term "hard handoff" is used for describing the above handoff. In contrast, in direct sequence code division multiple access

Manuscript received June 6, 1994; revised October 1, 1995; approved by IEEE/ACM Transactions on Networking Editor D. Mitra.

M. Asawa is with the Hewlett-Packard Research Laboratories, Palo Alto, CA 94304-1126 USA (e-mail: manjari@hpl.hp.com).

W. E. Stark is with the University of Michigan, Ann Arbor, MI USA (e-mail: stark@eecs.umich.edu).

Publisher Item Identifier S 1063-6692(96)04295-1.

(DS/CDMA) based networks, due to universal frequency reuse and Rake receivers [5], the mobile can transmit to and receive the same signal from more than one base station at any time. Hence, during transition from one cell to its neighboring cell, the mobile user establishes a communication link with the second base station, while at the same time keeping its communication link with first base station. The first communication link is terminated only after mobile user has firmly established itself in the second cell. Hence, this phenomenon is called "soft handoff." In this paper, we formally derive the properties of optimal policies for hard as well as soft handoff problems.

Our framework captures many facets of popular cellular communication systems currently in use. For instance, during hard handoffs in TDMA-based networks [16], there exists a period of time during which the call is being switched between adjacent base stations wherein the mobile is not being served (due to blank-and-burst control signaling). In our framework, this lack of service is modeled as a cost of switching from the mobile user point of view. There is also a switching penalty corresponding to the bandwidth and resources needed for the signaling and new set-up for the handoff. In DS/CDMA-based networks [15], incorporating soft handoffs, one base-to-mobile switching center (MSC) trunk and one base-to-mobile link are required for every cell involved in the soft handoffs. This affects the ability of the system to support many users, and thereby the ultimate capacity. Hence, the additional use of resources is modeled by extra penalties incurred at each instant of time the mobile communicates with more than one base stations. However, multiple channels enable diversity combining which in turn yields a better quality signal to the user. We account for this by associating a higher reward with the combined signal than can be obtained from the individual signals.

Another feature of our approach to the handoff problems is its decentralized nature, which enables the optimization to be done by distributed controllers using only local measurements. Decentralization is more desirable in the future [6] as centralized control involves added infrastructure, latency and network vulnerability besides placing increasingly greater demands on the processing capability of cellular controllers. Our model, as presented, is most applicable to mobile controlled handoffs [as employed by digital European cordless telephone (DECT), personal access communication systems (PACS), and cellular digital packet data (CDPD)]. However, it can also be used in both network-controlled and mobile-assisted handoffs to determine the need for a handoff. From the point of view of analysis, it is immaterial who makes the handoff decisions. If the mobile makes the decision, the network controller can transmit the value of the switching penalties to the mobile in paging channels. The network controller can decide the appropriate value of the switching penalties based on traffic conditions.

The rest of this paper is organized as follows. In Section II, we describe the model and performance criterion for hard handoffs for the case of two base stations in terms of arbitrary reward processes and switching costs and then derive necessary and sufficient conditions for a handoff decision to be optimal. When the above-mentioned necessary and sufficient conditions fail to determine an optimal handoff decision, a heuristic approach for making handoff decisions, based on lookahead arguments, is proposed. We also discuss some practical considerations and demonstrate how appropriate selections of reward and cost functions yield most of the commonly proposed criteria in the literature. Extensions of the above model to N base stations, finite horizon cost and time-varying, base station dependent switching costs are presented in Section III. In Section IV, the model for soft handoffs in DS/CDMA-based networks and optimality conditions are presented. In Section V, the performance of the policies proposed in Sections II and IV is compared via simulations with the corresponding algorithms commonly proposed in the literature [7], [15], [17]. Finally, conclusions are presented in Section VI.

A few words about notation are in order before we proceed. Random quantities are denoted by upper case letters, while nonrandom quantities are denoted using lower case letters. A random process, i.e., a sequence of random variables indexed by time, is denoted by the same symbol as the corresponding random variables without the time index.

II. The Hard Handoff Model

A. Problem Formulation

In a cellular environment employing hard handoffs, a user (mobile unit) will constantly monitor the signals received from nearby base stations, and at each instant of the decision epoch will select the communication path which provides the mobile with the best signal quality. We model each signal in the system as a Markov process. This is not unrealistic as we can take an n-dimensional state space to account for n-step memory. The signals from different base stations need not be independent. If they are dependent, then knowledge of the joint distribution is assumed to be known, whereas if the signals change independently, then only the marginal distributions need to be known.

Our formulation is in discrete time. At each time slot, measurement of signal quality is made and in the beginning of the next slot, decisions are made as to which base-station the user should be associated with based on these measurements. In the remainder of the paper we use the terms base-station and process and also the terms user and mobile interchangeably. To begin with, we will consider only those two base stations that are closest to the mobile. Hence, the system is comprised of two base stations and a single mobile unit. The mobile unit can observe signals from both base stations simultaneously and at any instant of time can associate with only one of the base stations.

Consider two parallel and possibly nonhomogeneous (as a mobile channel is in general time-varying) Markov Processes X_1 and X_2 denoting the signals received by the mobile from each base station. Each process X_j, $j \in \{1, 2\}$ is characterized by its state process $\{X_j(t), t = 0, 1, 2, \cdots\}$, where $X_j(t)$ represents the state of the process X_j at time t. The state space of X_1 and X_2 need not be countable. The state $X_j(t)$ of process X_j, $j = 1, 2$ evolves according to a Markov transition rule (which may be nonhomogeneous) independent of past and present actions taken in the system. At each instant of time, the mobile user observes the states of both processes and can associate with only one of them. Denote by $m(t)$ the process with which the mobile associates at time t. If $m(t) = i$, i.e., the mobile is associated with process X_i at time t, then the mobile user acquires an immediate expected reward of $R_i[X_i(t)]$. We will assume that the rewards are uniformly bounded, i.e.,

$$r \leq R_i\left[X_i(t)\right] \leq R \quad \forall i \in 1, 2, \quad \forall t$$

where r and R are finite constants, and may be negative. If $m(t) \neq m(t-1)$, then a switching cost K, $K < \infty$, is incurred at time t, i.e., a switching cost is incurred at each instant of time the mobile associates with a base station different from the one previously associated with.

Rewards are discounted in time by a fixed discount factor β, $0 < \beta < 1$. Given that the call duration is geometrically distributed with parameter β, the introduction of the discount factor takes into account the probability that a call is not terminated by the user. The assumption of geometric (exponential) call distribution is a standard assumption in queueing theory, when call duration is discrete (continuous) [8]. Philosophically, the discount factor accounts for the fact that the present is more important than the future but the future cannot be neglected completely. The problem is how to switch between base stations sequentially in time, so as to maximize the total expected discounted reward minus the handoff costs over the infinite horizon.

To formally formulate the problem, let us define the state of the system at time t by $[X_1(t), X_2(t), p(t)]$, where $p(t)$ is the base station the user was associated with at time $t-1$, i.e., $p(t) = m(t-1)$. For convenienece in notations, we also define $X(t) = [X_1(t), X_2(t)]$, and hence, the state can also be expressed as $[X(t), p(t)]$. An admissible policy π over an infinite horizon is defined as an infinite sequence of functions $m(0), m(1), m(2), \cdots\cdots$ where $m(t)$ maps state $\{[X(l), p(l)], l \leq t\}$ into the control action $u(t) \in U = \{1, 2\}$. The control action $u(t) = 1(2)$ corresponds to the user associating with process $X_1(X_2)$ at time t. Let Π be the set of admissible policies, and $I(\cdot)$ denote the indicator function. The handoff scheduling problem can now be formally stated as follows:

Problem: Find an optimal policy $\pi^* \in \Pi$ that for a given initial state (x_0, p_0), maximizes the expected discounted reward

$$F(x_0, p_0) := E\left\{\sum_{t=0}^{\infty} \beta^t \{R_{m(t)}[X_{m(t)}(t)] - K.I [m(t) \neq m(t-1)]\} \mid [x(0), p(0)] = (x_0, p_0)\right\}. \tag{1}$$

The first term in the right-hand side (rhs) of (1) is the reward obtained from the signal received from the base station with which the mobile is associated at time t, and the second term is the cost incurred at each instant of time a handoff is made.

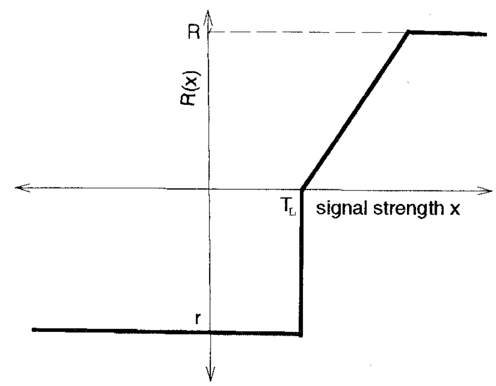

Fig. 1. Reward function to minimize probability that the received signal strength is below a certain threshold.

The presence of a reward which increases as the quality of the received signal improves provides the user with an incentive to associate with the base station with the best signal. On the other hand, the introduction of a switching cost incurred at each instant of handoff discourages frequent handoffs. Thus, the overall reward function captures the fundamental tradeoff between signal quality and frequent switching involved in handoff problems.

B. Motivation

We now motivate the above formulation by showing how an appropriate selection of reward and cost functions yield the various performance criteria proposed in the literature. One of the performance measures of interest is the probability of unnecessary handoffs. This can be achieved by making K large, $R(\cdot)$ a slowly increasing function with signal strength and $\beta \approx 1$ in (1). Minimizing the probability of unnecessary handoffs is now equivalent to maximizing (1). Another figure of merit for a handoff algorithm is to minimize the probability of outage, i.e., the probability that the signal level falls below the minimum value, say T_L, required for satisfactory call performance. This, too can be achieved by selecting $R(\cdot)$ a function as shown in Fig. 1, K small and $\beta \approx 1$. Similarly, the objective to maximize the signal quality, i.e., to maximize the signal strength received by the mobile at all times, can be captured by (1) by making $R(\cdot)$ a linear function of the signal strength, $\beta \approx 1$ and K small.

Thus, designers can select in a unified fashion appropriate reward functions and switching penalties to achieve the desired balance between the various performance criteria of interest to them. Typically, such selection can be based on either measurements in the field or simulations. Furthermore, it can be done in a centralized manner by taking into account the traffic conditions in different cells. For instance, during high load in the signaling network a higher value of switching cost K can be used. Likewise, when there is local congestion in a few cells, it is possible (and often necessary) to discourage users from associating with base stations in those cells by simply reducing rewards obtainable from those base stations (e.g., reward obtained = signal strength $-L$, where L is large if the cell is congested, and small otherwise). Similarly, the case when no channel is available for handoff can be accounted by making the reward from the corresponding cell to be smaller than r. These parameters may change at a slower rate than the rate at which handoff decisions are made.

For the case $K = 0$, the problem of finding an optimal policy is trivial, viz. it is optimal for the user to associate with the base station with the highest value of reward at each instant of time. This is because the evolution of the processes X_1 and X_2 is not affected by the mobile's actions and handoffs are free. However, when $K \neq 0$, there is a *conflict* between *future switching costs incurred* and *current reward obtained*, and it is not obvious as to what constitutes an optimal policy. In the following subsection we will derive qualitative properties of an optimal policy when $K \neq 0$. In particular, we will derive a necessary condition and a sufficient condition that can determine when it is optimal for a mobile to switch between processes.

C. Analysis

To derive properties of an optimal policy, we begin by formulating the handoff problem as a Markov decision problem. Denote the maximal expected value of the reward $F(x_t, p_t)$ conditional on the state $(x_t, p_t) = (x, p) = [x_1(t), x_2(t), p(t)]$ by $\Psi_t(x, p)$. Then, Ψ_t is the unique bounded solution [13] of the dynamic programming equation

$$\Psi_t = \max_i L_i \Psi_t \quad \forall t \tag{2}$$

where $L_i \Psi_t(x, p)$ is the expected reward obtained over an infinite horizon if in state (x, p) the user associates with base station i and proceeds optimally from the new state reached; i.e.,

$$L_i \Psi_t(x, p) = R_i[x_i(t)] - I[i \neq p(t)]K + \beta E\{\Psi_{t+1}[X(t+1), i] \mid (x, p)\}. \tag{3}$$

In the problem under consideration, the reward per step and cost per step are bounded. Furthermore, the control set U is composed of only two elements for any value assumed by the state variable. This ensures that there exists an optimal Markov policy for the above problem in the set Π of admissible policies [13]. Furthermore, if $\Psi_t(\cdot, \cdot)$ is known, then an optimal Markov policy is one which in state $(x, p) = [x_1(t), x_2(t), p(t)]$, selects the action that maximizes the rhs of (2). The difficulty, however, is that in general, $\Psi_t(\cdot, \cdot)$ is not known. The following lemma gives the relationship between $\Psi_t(x, p)$ and $\Psi_t(y, q)$ when $x = y$ but $p \neq q$.

Lemma 2.1: For $i, j \in \{1, 2\}$ $i \neq j$, we have

$$|\Psi_t[x(t), i] - \Psi_t[x(t), j]| \leq K \quad \forall t. \tag{4}$$

Proof: If the user is in state $[x(t), i] = [x_1(t), x_2(t), i]$, then by paying a switching penalty of K, the user can always associate with process X_j and obtain a total reward of $\Psi_t[x(t), j]$. Hence, the maximal expected reward obtainable from state $[x_1(t), x_2(t), i]$ is greater than or equal to the maximal expected reward obtainable from state $[x_1(t), x_2(t), j]$, minus the switching cost. Therefore, $\Psi_t[x(t), i] \geq \Psi_t[x(t), j] - K$. Reversing the role of i and j, we get $\Psi_t[x(t), j] \geq \Psi_t[x(t), i] - K$. The last two inequalities yield (4). □

Since at any time instant handoff may be the optimal decision, the bound in the above lemma is tight. Using the above bound we can prove the following theorem.

Theorem 2.1: Suppose the user associates with process X_i at time $t-1$. Then at time t, a necessary condition for handoff from process X_i to X_j to be optimal is

$$R_j[x_j(t)] \geq R_i[x_i(t)] + (1-\beta)K \tag{5}$$

and a sufficient condition for such a handoff to be optimal is

$$R_j[x_j(t)] \geq R_i[x_i(t)] + (1+\beta)K. \tag{6}$$

Proof: By the optimality (2) and (3), switching from process X_i to X_j is optimal if and only if

$$R_j[x_j(t)] - K + \beta E\{\Psi_{t+1}[X(t+1), j] \mid [x(t), i]\} \geq R_i[x_i(t)] + \beta E\{\Psi_{t+1}[X(t+1), i] \mid [x(t), i]\}. \tag{7}$$

Since the state process evolution is independent of the past and present actions of the mobile, the above expression is equivalent to

$$R_j[x_j(t)] - K + \beta E\{(\Psi_{t+1}[X(t+1), j] - \Psi_{t+1}[X(t+1), i]) \mid x(t)\} \geq R_i[x_i(t)].$$

By Lemma 2.1, if the above condition is satisfied, then it must be true that $R_j[x_j(t)] - K + \beta(K) \geq R_i[x_i(t)]$ which is equivalent to (5). Similarly, (7) is equivalent to

$$R_j[x_j(t)] - K \geq R_i[x_i(t)] + \beta E\{\Psi_{t+1}[X(t+1), i] - \Psi_{t+1}[X(t+1), j] \mid x(t)\}.$$

By Lemma 2.1, the above inequality yields

$$R_j[x_j(t)] - K \geq R_i[x_i(t)] + \beta(K)$$

which is equivalent to the sufficient condition of (6). □

The conditions given by Theorem 2.1 guide the search for an optimal policy. If at any time t, the necessary condition is not satisfied, then switching cannot be optimal, whereas if the sufficient condition is satisfied then switching is optimal. The conditions given in the above theorem are intuitive. Since switching at time t is more expensive than switching at time $t+1$ by an amount $K(1-\beta)$, switching can only be optimal if the instantaneous reward obtained by switching at time t is greater than the reward obtained without switching by at least an amount $K(1-\beta)$. Similarly, switching to process X_j at time t and then switching back to process X_i at time $t+1$ costs $K(1+\beta)$. Hence, if the instantaneous reward obtained from process X_j is more than the instantaneous reward obtained from process X_i by an amount greater than or equal to $K(1+\beta)$, then switching must be optimal. Furthermore, the above conditions are simple to implement since at each instant of time the user only has to compare the rewards obtainable from both processes.

If at a decision epoch the necessary condition is met whereas the sufficient condition is not, then the above conditions are unable to determine an optimal action. At such an uncertain epoch, a natural question to ask is "can one determine further tighter necessary and sufficient conditions by using k-step lookahead arguments" [3]. Unfortunately, use of lookahead arguments in this problem turns out to be difficult. The reason is that we are dealing with a stochastic system, and the arguments similar to those of Theorem 2.1 would require the comparison of a possibly uncountable number of handoff (closed-loop) policies. Hence, we have chosen to proceed with a heuristic scheme that takes into account the future evolution of the state and reward processes. In this scheme, the lookahead arguments are restricted to policies which are open-loop at next time instant. Determination of the proposed algorithm proceeds as follows: Define π_{uv}, $u, v \in \{1, 2\}$, as the policy that associates with process X_u at time t, associates with process X_v at time $t+1$, and proceeds optimally from time $t+2$ onwards. Starting at time t, only the four policies which are open-loop at time $t+1$ are possible. They are π_{ii}, π_{ij}, π_{ji}, and π_{jj}. Denote by $V_t(\pi)$ the total expected discounted reward obtained by policy π from time t onwards, conditional on the state $[x(t), i]$. Then

$$\begin{aligned} V_t(\pi_{ii}) = {} & R_i[x_i(t)] + \beta E\{R_i[X_i(t+1)] \mid x(t)\} \\ & + \beta^2 E\{\Psi_{t+2}[X(t+2), i] \mid x(t)\} \end{aligned} \tag{8}$$

$$\begin{aligned} V_t(\pi_{ij}) = {} & R_i[x_i(t)] + \beta E\{R_j[X_j(t+1)] \mid x(t)\} \\ & - \beta K + \beta^2 E\{\Psi_{t+2}[X(t+2), j] \mid x(t)\} \end{aligned} \tag{9}$$

$$\begin{aligned} V_t(\pi_{jj}) = {} & R_j[x_j(t)] - K + \beta E\{R_j[X_j(t+1)] \mid x(t)\} \\ & + \beta^2 E\{\Psi_{t+2}[X(t+2), j] \mid x(t)\} \end{aligned} \tag{10}$$

$$\begin{aligned} V_t(\pi_{ji}) = {} & R_j[x_j(t)] - K + \beta E\{R_i[X_i(t+1)] \mid x(t)\} \\ & - \beta K + \beta^2 E\{\Psi_{t+2}[X(t+2), i] \mid x(t)\}. \end{aligned} \tag{11}$$

By (8)–(11) and assumption that the necessary condition (5) of Theorem 2.1 is satisfied but the sufficient condition (6) is not, we get

$$V_t(\pi_{ii}) - V_t(\pi_{ji}) = R_i[x_i(t)] - R_j[x_j(t)] + K(1+\beta) > 0$$

and

$$V_t(\pi_{ii}) - V_t(\pi_{ji}) = R_i[x_i(t)] - R_j[x_j(t)] - K(1-\beta) > 0.$$

Hence, we can disregard policies π_{ij} and π_{ji}. Now, policy π_{jj} is at least as good as policy π_{ii} if and only if $V_t(\pi_{jj}) \geq V_t(\pi_{ii})$, i.e.,

$$\begin{aligned} & R_j[x_j(t)] - K + \beta E\{R_j[X_j(t+1)] \mid x(t)\} \\ & \quad + \beta^2 E\{\Psi_{t+2}[X(t+2), j] \mid x(t) \\ & \geq R_i[x_i(t)] + \beta E\{R_i[X_i(t+1)] \mid x(t)\} \\ & \quad + \beta^2 E\{\Psi_{t+2}[X(t+2), i] \mid x(t)\}. \end{aligned} \tag{12}$$

As in Theorem 2.1, by Lemma 2.1 and the assumption that process dynamics are independent of the control actions, if the above condition is satisfied, then it must be true that

$$\begin{aligned} & R_j[x_j(t)] + \beta E\{R_j[X_j(t+1)] \mid x(t)\} \geq \\ & R_i[x_i(t)] + \beta E\{R_i[X_i(t+1)] \mid x(t)\} + (1-\beta^2)K. \end{aligned} \tag{13}$$

Similarly, if

$$\begin{aligned} & R_j[x_j(t)] + \beta E\{R_j[X_j(t+1)] \mid x(t)\} \geq \\ & R_i[x_i(t)] + \beta E\{R_i[X_i(t+1)] \mid x(t)\} + (1+\beta^2)K \end{aligned} \tag{14}$$

then by Lemma 2.1 (12) must be true.

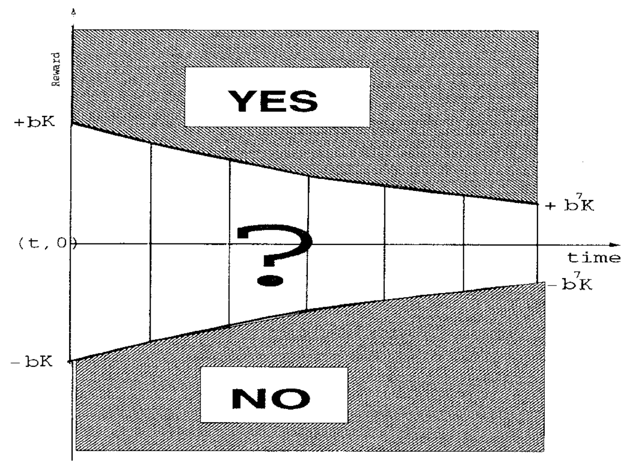

Fig. 2. Decision region for hard handoffs (discounted objective function). [If $m_{t-1} = i$, then the decision depends on $\sum_{l=t}^{t'} E\{\beta^{l-t} R_j[X_j(l)]\} - \sum_{l=t}^{t'} E\{\beta^{l-t} R_i[X_i(l)]\} - K$ as shown above.]

Thus, the main idea of the above algorithm for determining a handoff decision at any time t can be summarized as follows: Denote the process with which the user is associated at time $t-1$ by X_i. Compute the reward obtainable from both processes X_i and X_j at time t. If the necessary condition of Theorem 2.1 is not satisfied at time t, then continue association with process X_i. If the sufficient condition of Theorem 2.1 is satisfied at time t, then handoff to process X_j. If the necessary condition of Theorem 2.1 is met but the sufficient condition is not, then continue association with process X_i if the necessary condition (13) is not satisfied. If the sufficient condition of (14) is satisfied, then handoff to process X_j. Note that the conditions (13) and (14) are tighter than those of Theorem 2.1, and it is possible for them to determine an action at time t, when the conditions of Theorem 2.1 could not. Thus, the combination of Theorem 2.1 and conditions (13) and (14) guide the search for a decision by first looking just at the current state and then "one step ahead."

It is still possible that the necessary condition of (13) is met but the sufficient condition of (14) is not satisfied. Then extension of the above scheme by "looking n steps ahead" ($n \geq 2$), to obtain further tighter necessary and sufficient conditions for a handoff can be achieved by restricting attention to policies that are open loop from time $t+1$ till time $t+n$. The necessary and sufficient conditions obtained by looking "n steps ahead" in the above fashion differ by $2\beta^{n+1}K$ which converges to zero as n increases. Thus, using the proposed policy, a general approach for determining a handoff decision would be to employ first the "current state look policy," then "one step lookahead" and so on until either a necessary condition is not met or a sufficient condition is met, thereby specifying an action at time t. The decision region resulting from this scheme is as shown in Fig. 2. In this algorithm, future rewards affect the present handoff decision; thus it is important to obtain good estimate of future rewards as closely as possible (i.e., a good predictor is important).

We conjecture that the performance of a policy that computes decisions by the above algorithm, will be close to optimal. Computation of bounds on the maximum deviation from the optimal performance as well as determination of conditions under which the above policy will be close to optimal, are topics of future investigation.

Remark: In this section, we have assumed that the mobile's actions have no influence on the signal strength or the evolution of future rewards. This is an approximation because the network has many users. A user's action affects the signal quality of other users (through interference, power control etc.) and they in turn act to optimize their own performance, which in turn affects the signal quality of the first user. Hence, a user's action indirectly affects the evolution of its own reward process. Inclusion of this effect greatly complicates the formulation. Furthermore, if the number of users is large, effect of an individual user's actions on the evolution of its own reward pattern can be very small, thereby making the above a reasonable assumption. With the simplified model of this paper, we have been able to develop an approach for determining an optimal action at any time t and it may be possible to use the insight gained from this approach to determine properties that a good handoff policy should have in practice.

III. Extensions to the Hard Handoff Model

A. Extension to N ($N \geq 2$) Base Stations

The problem formulation for N base stations ($N \geq 2$) is similar to that of two base stations. The state space needs to be extended to all base stations $1, \cdots, N$ and $p(t) \in \{1, 2, \cdots, N\}$. For the following, we define $x(\cdot) = [x_1(\cdot), \cdots, x_N(\cdot)]$ and $X(\cdot) = [X_1(\cdot), \cdots, X_N(\cdot)]$. With this notation, the optimality equation is

$$\Psi[x(t), p(t)] = \max_i \{R_i[x_i(t)] - I[i \neq p(t)]K + \beta E\{\Psi[X(t+1), i] \mid x(t), p(t)\}\}.$$

The rhs of the above expression is equivalent to

$$\max\{R_{p(t)}[x_{p(t)}(t)] + \beta E\{\Psi[X(t+1), p(t)] \mid x(t)\} \\ \max_{i \neq p(t)} \{R_i[x_i(t)] - K + \beta E\{\Psi[X(t+1), i] \mid x(t)\}\}\}.$$

Hence, we can select the best candidate for handoff and then compare it with the present base station to find if performing a handoff is optimal or not. The selection of the best candidate for handoff is done according to the following:

Theorem 3.1: A necessary condition for the handoff to base station i, $i \neq p(t)$ to be better than the handoff to base stations j, $j \neq i, j \neq p(t)$ is

$$R_i[x_i(t)] + \beta K \geq R_j[x_j(t)].$$

A sufficient condition for the handoff to base station i, $i \neq p(t)$ to be better than the handoff to base stations j, $j \neq i$, $j \neq p(t)$, is

$$R_i[x_i(t)] \geq R_j[x_j(t)] + \beta K.$$

Proof: Follows by arguments similar to that of Theorem 2.1 and hence is omitted. □

If the above necessary condition is satisfied, but sufficient condition is not, then one has to "look further into the future" to determine which one of the base stations i and j is the best candidate for handoff. Arguments similar to those in Section II-C can be used for the "looking further into the future."

Using the above methodology for pairwise comparisons of all the candidate base stations, one can determine the best base station k, $k \neq p(t)$ for the handoff. Then by using Theorem 2.1, and its extension to compare the current base station $p(t)$ with base station k, one can determine whether a handoff should be performed or not. The whole process requires N pairwise comparisons of base stations.

B. Extension to the Undiscounted Finite Horizon Problem

It is possible to obtain results similar to that of the previous section for the undiscounted finite horizon version of the objective function of (1). This objective function is applicable to situations where the finite call termination instant is known to the mobile. This is generally the case in packet switched data calls, where due to fixed packet lengths the finite transmission completion instant can be easily precomputed.

The problem formulation is similar to that of the infinite horizon discounted version. As the reward and switching penalties are bounded, and the horizon is finite, the objective function is well defined. The problem is to find the policy that maximizes

$$F(x_0, p_0) := E\left\{\sum_{t=0}^{T} \{R_{m(t)}[X_{m(t)}(t)] - I[m(t) \neq m(t-1)]K\} \mid [x(0), p(0)] = (x_0, p_0)\right\}.$$

The optimal policy still satisfies the optimality Equation (2). Equation (3), Lemma 2.1, and Theorem 2.1 remain valid with $\beta = 1$ until time $T - 1$. When the necessary condition of Theorem 2.1 is met, but the sufficient condition is not, it is possible to derive a heuristic policy similar to that in Section II. The necessary and sufficient conditions of this heuristic till time $T - 1$ can be obtained by the corresponding conditions of Section II with $\beta = 1$. However, at time T, the necessary and sufficient conditions become identical. In this case, the decision region is as shown in Fig. 3.

C. Extension to Time Varying, Base Station Dependent Switching Cost

In the case of a heterogeneous cellular environment (e.g., mobile moving from a cellular region served by microcells to regions served by macrocells, from AMPS to D-TDMA networks, etc.), it might be true that the handoff from one cell to another requires a different set-up than that in the reverse direction. Furthermore, due to changes in traffic conditions, the handoff costs themselves may be time-varying. Formally

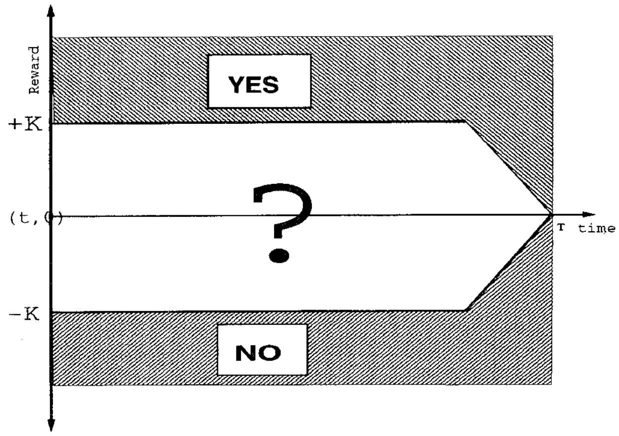

Fig. 3. Decision region for hard handoffs (undiscounted objective function). [If $m_{t-1} = i$ and for $t \le t' \le T$, $\sum_{l=t}^{t'} E\{R_j[X_j(l)]\} - \sum_{l=t} t'$ $E\{R_i[X_i(l)]\} - K$ is in the region YES, then a handoff is performed, and if it is in the region NO, then the mobile remains with the current base station.]

stated, the handoff cost to base station i at time t is given by $K_i(t)$, and the problem is to find the policy π that maximizes

$$V(x_0, p_0) := E\left\{ \sum_{t=0}^{\infty} \{\beta^t R_{m(t)}[X_{m(t)}(t)] - I[m(t) \ne m(t-1)]\, K_{m(t)}(t)\} \mid [x(0), p(0)] = (x_0, p_0) \right\}.$$

The basic results of Section II (Theorems 2.1 and 3.1) with the necessary and sufficient conditions appropriately modified remain valid provided $K_i(t) < A$, for all i and for some finite constant A. Handoff decisions can also be determined by the same procedure. As the problem is conceptually similar to the one considered before, we omit the details.

IV. The Soft Handoff Model

A. Problem Formulation

In networks employing soft handoffs, the network operator must make a careful tradeoff between the network overhead and the diversity advantage of soft handoffs by properly engineering the handoff phenomenon for a given operational environment. Our model for soft handoffs is similar to the model for hard handoffs presented in Section II, except that now during a call at any instant of time a user may associate with both processes and must associate with at least one of them. If the user associates with only process X_i at time t, then the user acquires an immediate expected reward of $R_i[x_i(t)]$ and if associates with both processes, then the instantaneous reward obtained is a function $R_{1,1}[x_1(t), x_2(t)]$ of the individual instantaneous states of the processes. We assume that $R_{1,1}[x_1(t), x_2(t)] \ge R_i[x_i(t)]$, $i \in \{1, 2\}$, for all x_1, x_2. This is realistic, as by diversity combining, signal quality would be at least as good as the individual signal quality. To simplify notation, we also define $R_{1,0}[x_1(t), x_2(t)] := R_1[x_1(t)]$ and $R_{0,1}[x_1(t), x_2(t)] = R_2[x_2(t)]$. Furthermore, for the purpose of analysis we assume that the rewards are uniformly bounded, i.e.,

$$r \le R_{i,j}[X_1(t), X_2(t)] \le R \quad \forall i, j \in \{0, 1\}, \quad \forall t$$

where r and R are finite (possibly negative) constants.

At each instant of time the user associates with both processes, a cost C is incurred to penalize the extra resources used. Every time a new association is established or an existing connection is terminated, a "set-up" cost S or a "tear-down" cost T, respectively, is incurred.[1] Let $n_i(t)$ denote whether or not the user is associated with process X_i, $i \in \{1, 2\}$ at time t. If the user is associated with process X_i at time t, then $n_i(t) = 1$ and 0 otherwise. The state of the system at time t is $[X(t), q(t)] = [X_1(t), X_2(t), q_1(t), q_2(t)]$ where $q_i(t) = n_i(t-1)$. An admissible policy (over an infinite horizon) is a sequence of functions $\pi = \{\pi(0), \pi(1), \cdots\}$ where for every t, $\pi(t) : \{[X(l), q(l)], l \le t\} \to U$ and $U = \{[1, 0], [0, 1], [1, 1]\}$. The set of all admissible policies is denoted by $\tilde{\Pi}$. Rewards are additive and discounted in time by a fixed discount factor β, $0 < \beta < 1$. The problem can now be formally stated as follows:

Problem: Find an optimal policy $\pi^* \in \tilde{\Pi}$ that for a given initial state (x_0, q_0), maximizes the net expected reward $\tilde{F}(x_0, q_0)$, given by

$$\begin{aligned}\tilde{F}(x_0, q_0) := E\Bigg\{ \sum_{t=0}^{\infty} \beta^t \{ & R_{m(t)}[X_1(t), X_2(t)] \\ & - I[m_1(t) = m_2(t) = 1]\, C \\ & - I[m_1(t-1) = 0, m_1(t) = 1]\, S \\ & - I[m_2(t-1) = 0, m_2(t) = 1]\, S \\ & - I[m_1(t-1) = 1, m_1(t) = 0]\, T \\ & - I[m_2(t-1) = 1, m_2(t) = 1] T \\ & \mid [x(0), q(0)] = (x_0, q_0) \Bigg\}.\end{aligned}$$

The first term in the summation is the reward obtained from the signals received from the base stations. The second term is the cost incurred whenever connections to both base stations are active. The third and fourth terms represent the costs incurred when new connections are established, and the last two terms are the cost incurred when existing connections are terminated. As in Section II, by suitable choice of the reward functions and costs different performance criteria proposed in the literature can be captured in this framework. Notice that while the problem formulation proposed in this section captures the fundamental tradeoff between the diversity advantage of soft handoff and the increased infrastructure load due to use of additional channels, it does not capture the multi-user aspect of the spread spectrum system.

[1] In the model for soft handoffs we need to have separate set-up and termination costs, since it is not necessary to terminate the previous connection whenever a new connection is established. In the model for hard handoffs, as the mobile can associate with at most one base station at any time, whenever a new connection is established the previous one has to be terminated. Hence, in the model for hard handoffs, one can combine the set-up and termination costs into one "switching cost" $K = S + T$.

For the case $C = S = T = 0$, the above problem is trivial. By our assumption $R_{1,1}[x_1(t), x_2(t)] \geq R_i[x_i(t)]$, $i \in \{1, 2\}$, $\forall x_1, x_2$; the optimal policy in this special case is to always associate with both the processes. However, when C, S, and T are nonzero, then it is not obvious what an optimal policy should be. In the following subsection, we present necessary and sufficient conditions that may determine optimal actions at each instant of time. Since, the derivation of these conditions is similar to that for the hard handoffs, we omit the details. Interested readers may refer to [2].

Theorem 4.1: Suppose the user is associated with only process X_i at time $t-1$. Then at time t:

1) a necessary condition for a soft handoff to process X_j (i.e., now the call will be carried by both base stations) to be optimal is

$$R_{1,1}[x_1(t), x_2(t)] - R_i[x_i(t)] \geq C + (1-\beta)S$$

and

$$R_{1,1}[x_1(t), x_2(t)] - R_j[x_j(t)] \geq C - T - \beta S \quad (15)$$

and a sufficient condition for soft handoff to process X_j to be optimal is

$$R_{1,1}[x_1(t), x_2(t)] - R_i[x_i(t)] \geq C + S + \beta T$$

and

$$R_{1,1}[x_1(t), x_2(t)] - R_j[x_j(t)] \geq C - (1-\beta)T. \quad (16)$$

2) a necessary condition for completely switching (hard handoff) from process X_i to X_j ($j \neq i$), to be optimal is

$$R_j[x_j(t)] - R_i[x_i(t)] \geq (1-\beta)(S+T)$$

and

$$R_{1,1}[x_1(t), x_2(t)] - R_j[x_j(t)] \leq C - (1-\beta)T \quad (17)$$

and a sufficient condition for the above handoff to be optimal is

$$R_j[x_j(t)] - R_i[x_i(t)] \geq (1+\beta)(S+T)$$

and

$$R_{1,1}[x_1(t), x_2(t)] - R_j[x_j(t)] \leq C - T - \beta S. \quad (18)$$

Part i) of the above theorem gives the necessary and sufficient conditions for a soft handoff initiation to be optimal. The following theorem gives the corresponding conditions for a soft handoff termination to be optimal.

Theorem 4.2: Suppose the user is associated with both processes X_1 and X_2 at time $t-1$. Then at time t, a necessary condition for the continuation of association with process X_i, $i \in \{1, 2\}$ and the termination of association with process X_j, $j \in \{1, 2\}$, $j \neq i$ to be optimal is

$$R_i[x_i(t)] \geq R_{1,1}[x_1(t), x_2(t)] - C + (1-\beta)T$$

and

$$R_i[x_i(t)] \geq R_j[x_j(t)] - \beta(S+T) \quad (19)$$

and the corresponding sufficient condition is

$$R_i[x_i(t)] \geq R_{1,1}[x_1(t), x_2(t)] - C + T + \beta S$$

and

$$R_i[x_i(t)] \geq R_j[x_j(t)] + \beta(S+T). \quad (20)$$

The above results guide the search for an optimal policy and are intuitive. At any time t, if any of the necessary conditions for the optimality of a certain action is not satisfied, then that action cannot be optimal; if both the sufficient conditions for the optimality of a certain action are satisfied, then that action is optimal. The first part in the necessary condition of (15) follow from the fact that in our model, establishment of a new connection at time t is more expensive than at time $t+1$ by an amount $(1-\beta)S$. To intuitively understand the second part of the necessary condition, notice that after some algebra, the second part is equivalent to the relation $R_{1,1}[x_1(t), x_2(t)] - C - S \geq R_j[x_j(t)] - S - T - \beta S$. Given that at time $t+1$ it is optimal to associate with both base stations i and j, the left hand side of the above relation denotes the reward obtainable by the soft handoff at time t, and the rhs denotes the reward obtainable by hard handoff at time t. Other conditions can be interpreted similarly.

As for the hard handoffs, it can happen that at a decision epoch the necessary conditions are satisfied whereas sufficient conditions are not. In such a situation, the mobile has to "look further into the future" to determine the optimal action. Again due to the difficulties discussed in Section II, an explicit determination of conditions by "looking ahead" will be complicated. However, a heuristic policy for handoffs, as in Section II, can be derived.

There is one special case where the Theorems 4.1 and 4.2 specify an optimal policy completely, as the following corollary, which is a direct consequence of Theorems 4.1 and 4.2, illustrates:

Corollary 4.1: Suppose $S = T = 0$ and the user is associated with only process X_i at time $t-1$. Then, a hard handoff to process X_j is optimal if and only if

$$R_j[x_j(t)] \geq R_i[x_i(t)]$$

and

$$R_{1,1}[x_1(t), x_2(t)] \leq R_j[x_j(t)] + C$$

and a soft handoff to processes (X_i, X_j) is optimal if and only if

$$R_{1,1}[x_1(t), x_2(t)] \geq R_i[x_i(t)] + C$$

and

$$R_{1,1}[(x_1(t), x_2(t)] \geq R_j[x_j(t)] + C.$$

Similarly, during soft handoff it is optimal to switch completely to process X_i if and only if

$$R_{1,1}[x_1(t), x_2(t)] \leq R_i[x_i(t)] + C$$

and

$$R_i[x_i(t)] \geq R_j[x_j(t)].$$

Remark: If we let $C = R - r$ in our formulation for soft handoffs, we essentially discourage soft handoff from ever happening, and the optimal policy will be the same as the optimal policy for the hard handoff model with $K = S + T$.

B. Extension to N ($N \geq 2$) Base Stations

In general, during soft handoffs it is possible to communicate with any nonempty subset of $\{1, 2, \cdots, N\}$ base stations. Hence, soft handoff gives flexibility in determining not only the base station(s) with whom the mobile can communicate, but also their number. The problem formulation for the case of more than two base stations is similar to the case of the two base stations and the notations are similar to that of Section III-A. However, the problem of determining the optimal policy becomes much harder. As each $n_i(t)$ can take a value of 1 or 0, and each possible combination of 1's and 0's (except all 0's) denotes a feasible communicating set, the number of possibilities in the optimality equation for each possible state of the system is $2^N - 1$. Hence, unlike the problem of hard handoff (Section III) where the complexity increases linearly with N, now the complexity increases exponentially with N.

V. NUNERICAL RESULTS

A. Preliminaries

In this section, we discuss the numerical results obtained by using computer simulations for a wide range of parameters. First, we establish some of the modeling techniques used. For the simulations, our model is similar to [17]. We assume that the distance D between the two base stations is 2000 m and the mobile is moving from base station 1 to base station 2 along a straight line with constant speed. The length of a decision slot is 2 m, and the measurements of signal strengths are averaged using an averaging window of one slot length.[2] The measured value (in dB) is the sum of two terms: one due to path loss and the other due to lognormal (shadow) fading. As Rayleigh fading has a short correlation distance relative to that of shadow fading at the time scale under consideration, it is averaged out and can be neglected.[3] Thus, the signal strengths $x_1(d)$ and $x_2(d)$ (in decibels), received from base stations 1 and 2 when the mobile is at a distance d meters from base station 1 are given by

$$x_1(d) = K_1 - K_2 \log(d) + u(d)$$

and

$$x_2(d) = K_1 - K_2 \log(D - d) + v(d), \quad d \in (0, D)$$

respectively. The parameters K_1 and K_2 account for the path loss. The value of K_1 depends on the power levels under consideration and is technology dependent. Nature of the results presented here does not depend on its absolute value. In this paper, we have selected $K_1 = 82.1$ dBm. This value corresponds to an average signal strength of $-$ 7.9 dBm at the cell boundary. For the urban mobile environment, a typical value of K_2 is 30 dB [17]. The shadow fading processes $\{u(d)\}$ and $\{v(d)\}$ are assumed to be zero mean stationary Gaussian processes, independent of each other, and having the exponential autocorrelation function, i.e.,

$$E\{u(d_1)\,u(d_2)\} = E\{v(d_1)\,v(d_2)\} = \sigma_s^2 \exp\left(-\frac{|\,d_1 - d_2\,|}{d_0}\right).$$

The parameter d_0 determines how fast the correlation decays with distance. (Equivalent time functions can be obtained by the transformation $d = vt$.) The shadowing standard deviation of $\sigma_s = 6$ dB and the exponential autocorrelation parameter of $d_0 = 10$ m is assumed (this corresponds to an autocorrelation of 0.1 between two points with distance 46 m away). Since we are mainly interested in the performance in the handoff region, the simulation is started when the mobile is at a distance of 300 m from base station 1, and travels with a constant speed toward the base station 2. We have taken $\beta = 0.995$, which implies that the average call duration is $2/(1-\beta) = 2/0.005 = 400$ slots.

The Reward Function is Equal to the Signal Strength in Decibels. With this choice of reward function, reward is a concave monotonic increasing function of absolute signal strength. While we have chosen this particular reward function for numerical computations, in practice the reward can be a suitable function of any measurable characteristics of the received signal such as carrier-to-interference ratio (CIR), bit-error rate (BER), etc. [20]. Since we have chosen reward to be equal to the signal strength measured in decibels, switching penalties and additional channel use cost are also represented in decibel units.

For both the hard and soft handoff models, in the worst case the algorithms of Sections II and IV, respectively, may require prediction of expected signal strength (conditioned on the present and past signal strength) an arbitrarily large number of steps ahead. For implementation purposes, we assume that the mobile can estimate signal strength for only the next three steps ahead. In order to avoid dependence of our results on estimation algorithms, we present results for the case when signals can be estimated perfectly and also plot the behavior as a function of estimation error N. The estimation error is measured in dB with respect to signal strength. Hence, an error of 2 dB correspond to 58% error in estimation of true signal strength. If at a certain decision epoch, say n, the proposed algorithm is unable to determine a handoff decision with the current and predicted values of the signal strength, then the expected discounted rewards obtainable between step n and step $n+3$, from base stations 1 and 2 are compared. Handoff occurs if the reward obtainable by handoff exceeds the reward obtainable without handoff by an amount T_h. In the numerical results we have taken T_h to be halfway between the thresholds for the necessary and sufficient conditions obtained by looking three steps ahead. Since we restrict ourselves to only three steps ahead, the reward obtained by the implemented algorithm is a lower bound to the best reward obtainable by the proposed algorithm.

[2] Handoffs because of random fast fading is avoided in all known mobile systems by averaging. Some of the factors which merit further investigation are the optimal choice of decision rates and averaging methods [4].

[3] The correlation distance of Rayleigh fading is proportional to the wavelength of signals used. At the frequencies of interests ($\geq$500 MHz), the correlation distance is much less than the slot length.

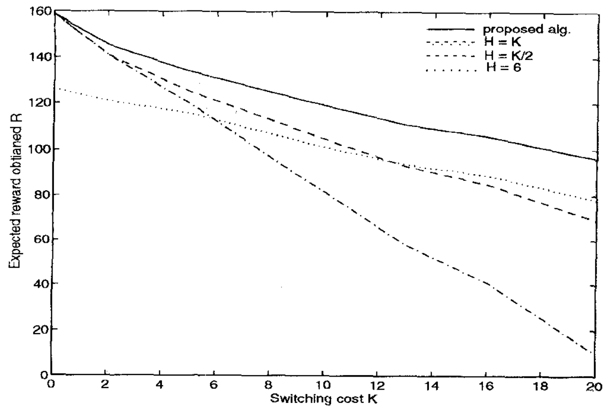

Fig. 4. Expected reward obtained versus switching cost for the hard handoff model (perfect estimation).

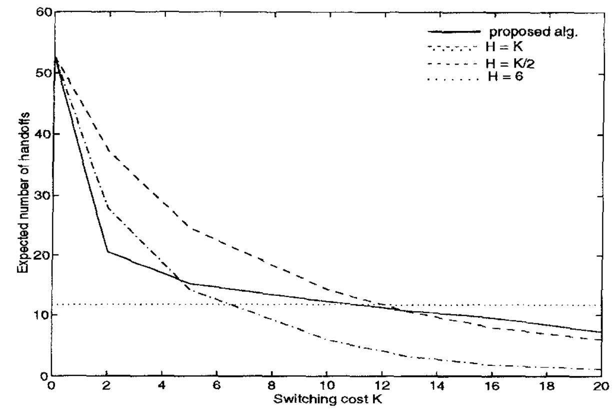

Fig. 6. Expected number of handoffs for the hard handoff model (perfect estimation).

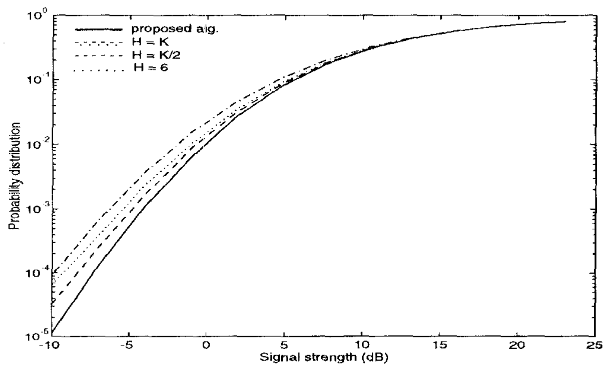

Fig. 5. Probability distribution of received signal strength for the hard handoff model ($K = 10$, perfect estimation).

B. Results for Hard Handoff

For the hard handoff model, we now compare the policy proposed in Section II with the commonly used difference threshold policy in literature [7], in which a handoff is made when the signal level from the new base station exceeds the signal level from the current base station by a certain value H. In particular, we have considered the case $H = K$, $H = K/2$, and $H = 6$ (an arbitrary but reasonable value). Fig. 4 plots the total discounted reward obtained as a function of switching cost K, for the above and for the implemented version of the algorithm of Section II for the case of perfect estimation.

It can be seen that the performance of the threshold algorithms varies considerably with switching cost and thresholding values. In particular, $H = K$ does better at low values of K, but performs poorly at larger values, whereas $H = 6$ does poorly at low values and better for higher values of K. The implemented algorithm proposed in this paper performs uniformly better for all values of K. The probability distribution of the received signal strength by the mobile during its travel from base 1 to base 2 when $K = 10$ dB is plotted in Fig. 5 and the expected number of handoffs as a function of switching cost K is plotted in Fig. 6.

From the relatively small tail of the distribution function at low values of signal strength, we can conclude that the implemented algorithm yields a smaller probability of outage[4] and hence fewer calls can be expected to be dropped. Note that the starting offset depends on the value of K_1, whose selection depends on signal strengths appropriate for the particular application.

When $K = 0$, handoffs are free and the best thing to do is to always associate with the base station with highest signal strength. Hence the number of handoffs in this case is large. As handoffs become more expensive, the obtainable reward decreases. Note that at $K = 10$, the threshold algorithm with $H = K$ yields about half the number of handoffs compared with the implemented algorithm, but the probability of outage is about a decade higher. The threshold algorithm with $H = 6$ has about the same number of handoffs, but again the probability of lost calls due to bad signal quality is again considerably higher. The threshold algorithm with $H = K/2$ has more handoffs and the quality of call is also worse. If H is selected to be very small, it is possible that the quality of signal obtained with the threshold algorithm is better than the implemented algorithm, but there will be considerably more handoffs. The implemented algorithm does not always yield the least number of handoffs or the best quality of call. The reason for this is that the objective function is not selected to minimize the number of handoffs or to maximize the received signal quality, but rather to optimize the tradeoff between received signal quality and the number of handoffs, as discussed before.

The results for the case of imperfect estimations are plotted in Figs. 7–11. As expected the performance of the proposed algorithm deteriorates with the increase in the estimation error. However, even for prediction errors as high as 2 dB (i.e., 58% error in estimation of absolute signal strength), the proposed algorithm outperforms the threshold algorithm.

C. Results for Soft Handoff

For soft handoffs, we compare the policy proposed in Section IV with the policy proposed in the IS-95 standard [15], [19]. In the later policy, a user adds all those channels

[4]For our purposes, we define a call outage to be a dropped call due to bad signal quality, i.e., low received signal strength.

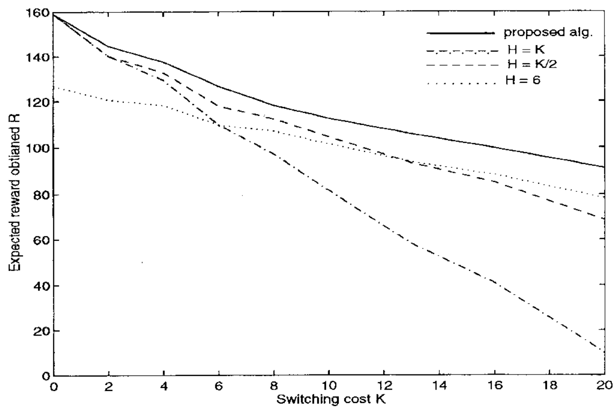

Fig. 7. Expected reward obtained versus switching cost for the hard handoff model (estimation error $N = 2$ dB).

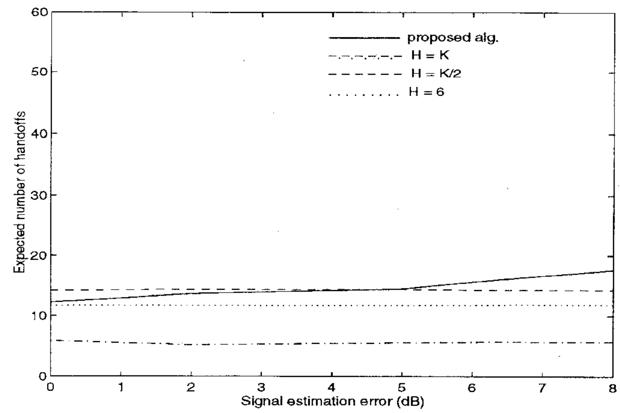

Fig. 10. Expected number of handoffs versus estimation error for the hard handoff model ($K = 10$).

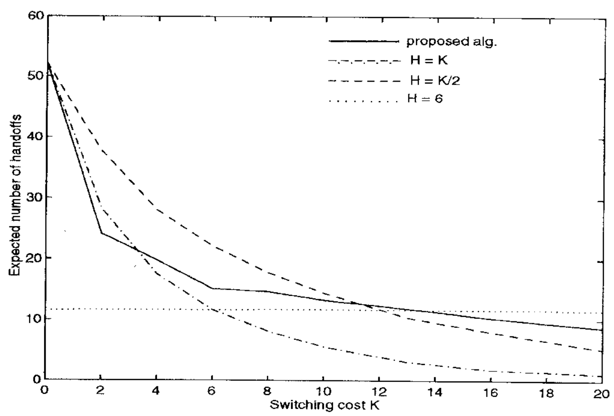

Fig. 8. Expected number of handoffs versus switching cost for the hard handoff model ($N = 2$ dB).

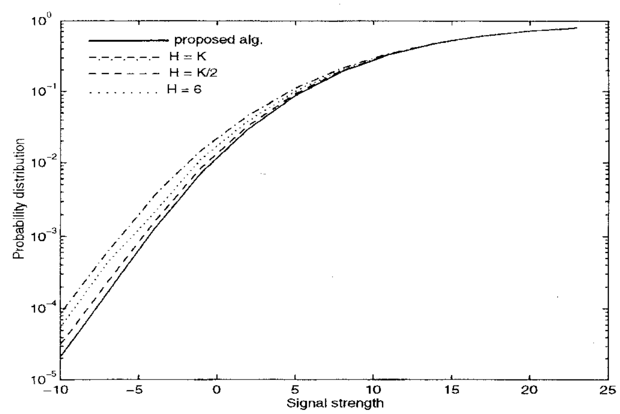

Fig. 11. Probability distribution of received signal strength for the hard handoff model ($K = 10$, $N = 2$ dB).

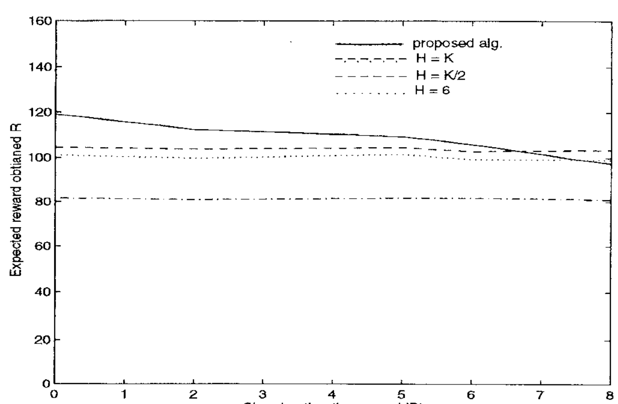

Fig. 9. Expected reward obtained versus estimation error N for the hard handoff model ($K = 10$).

with signal strength greater than a certain threshold, say T_{add}, to the communicating set and deletes all those channels with signal strength less than a certain threshold, say T_{drop} ($T_{\text{drop}} < T_{\text{add}}$), from the communication set. The results for the case of perfect estimation are plotted in Figs. 12–15. In particular, we have considered two cases, i) $T_{\text{add}} = K_1 - K_2 \log(D/2) + C + 2$, $T_{\text{drop}} = K_1 - K_2 \log(D/2) + C - 1$; and ii) $T_{\text{add}} = K_1 - K_2 \log(D/2) + C + 3$, $T_{\text{drop}} = K_1 - K_2 \log(D/2) + C - 2$. These values are reasonable compared to the mean signal strength of $K_1 - K_2 \log(D/2)$ at the cell boundary. For comparison purposes, we have also plotted the reward obtained by a simplified algorithm. This algorithm is obtained from Theorems 4.1 and 4.2 by assuming $\beta = 0$. Hence, this algorithm is able to make a decision by just looking at the current step and uses the same information as the algorithm proposed in the IS-95 standard [15]. Note that the choice of K_1 has only an offset effect on the performance curves of Fig. 12, and have no effect on the curves of Figs. 13–15. Similarly, for a fixed value of T_{add} and T_{drop}, the performance curves for the algorithm in the IS-95 standard depend directly on the value of C only in Fig. 12.

Since the values of T_{add} and T_{drop} as selected depend on the value of C, the plots obtained in Figs. 12–14 also show the change in performance of the IS-95 algorithm with change in values of T_{add} and T_{drop} (since C varies in these plots). The performance of the IS-95 algorithm does not seem to change significantly with different values of T_{add} and T_{drop}. As discussed before, when $C = 0$, once a connection is set up, it is optimal to never terminate the connection. This is because

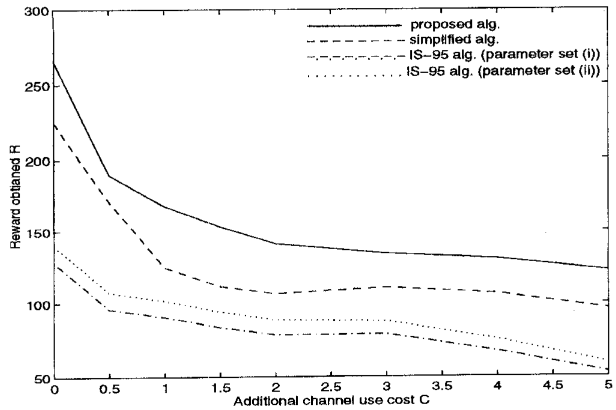

Fig. 12. Expected reward obtained versus additional channel use cost C for soft handoff model ($S = 7$, $T = 0.7$).

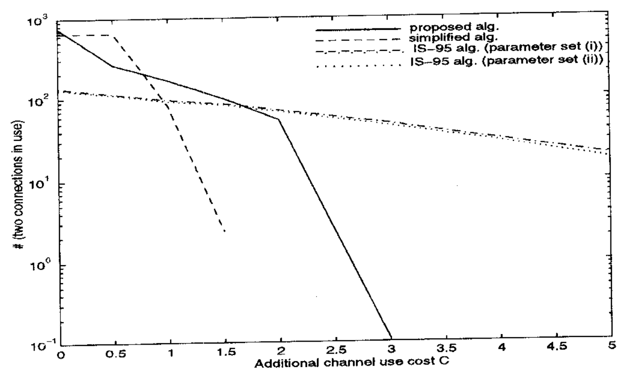

Fig. 13. Expected number of times connections to both base stations are used versus additional channel use cost C for soft handoff model ($S = 7$, $T = 0.7$).

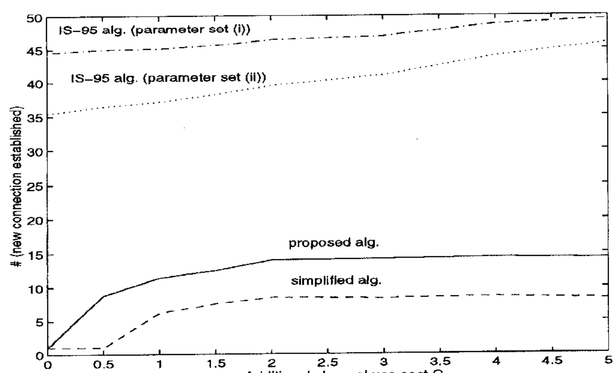

Fig. 14. Number of connections are established (terminated) versus additional channel use cost C for soft handoff model ($S = 7$, $T = 0.7$).

due to diversity combining, an existing connection cannot be harmful, and termination is costly. Both the proposed and simplified algorithms have this property, whereas the algorithm in the standard does not. The IS-95 algorithm for the second set of values adds a connection later than with the first set of values, but also drops a connection later. Hence, the amount of time the mobile user associates with both base stations is

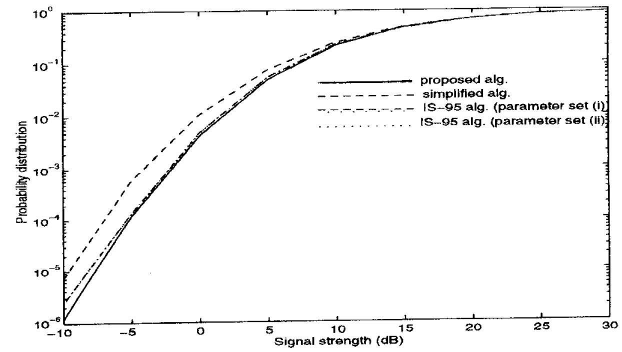

Fig. 15. Probability distribution of received signal strength for soft handoff model ($S = 7$, $T = 0.7$, $C = 2$).

almost the same for both sets of parameters. Similarly, with the second set of parameters there is less inclination to add a connection (due to higher T_{add}) and hence fewer connections are established than with the first. In terms of signal strength and the number of times new connections are set up, the performance of the simplified algorithm is not too far from the proposed algorithm, though it has less inclination to use both signals as C increases.

From the figures, it is clear that even when it is not possible to obtain a good estimation of expected signal strength from the next step onwards, it is probably better to use the simplified algorithm instead of the algorithms proposed in the standard [15]. One possible reason for the simplified algorithm's better performance might be that it takes into account the benefit obtainable and cost incurred by using the additional channel. In other words, the decision is based on the joint reward obtainable, instead of just the individual rewards obtainable. This is unlike the IS-95 algorithm which makes decisions based only on the rewards obtainable from individual signals. Note that the simplified algorithm has some extreme optimality properties: namely, it is optimal when $\beta = 0$, or when $S = T = 0$.

For the completeness, we plot the performance of soft handoff algorithm with changes in the noise level in Fig. 16. Since the proposed simplified algorithm does not use any future estimation, its performance is unaffected by signal estimation error.

D. Comparison of Hard and Soft Handoffs

Note that for $K = S + T = 7.7$, the reward obtainable from the algorithm proposed for the hard handoff model is approximately 125. The reward obtainable from the algorithm proposed for the soft handoff model varies with C. In particular, it is about 260 for $C = 0$, and settles down to about 125 for higher values of C. This is to be expected, as the model of soft handoff has one extra degree of freedom, namely a user is allowed to associate with both base stations. This extra degree of freedom is not allowed in the hard handoffs. This is in accordance with the results reported in [18]. For high values of C, a user very rarely exercises this extra degree of freedom, as the penalty to exercise is too high, and hence the reward obtained by both hard and soft handoffs are almost

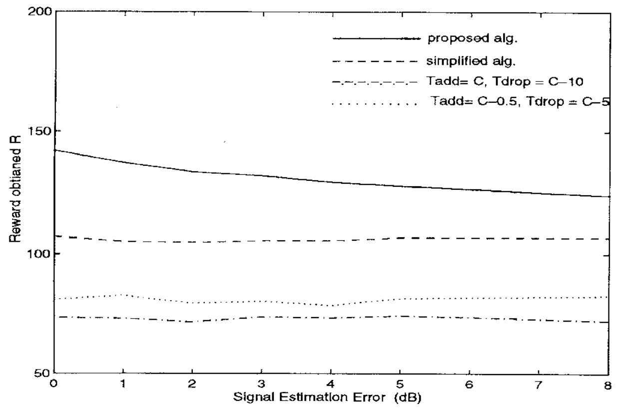

Fig. 16. Expected reward obtained versus estimation error C for soft handoff model ($S = 7$, $T = 0.7$, $C = 2$).

equal. For small values of C, this extra degree of freedom with soft handoffs allows for the possibility of much greater advantage to the user than with the hard handoffs. This leads to the conclusion that the soft handoff is beneficial only when the additional channel use cost is not too high. Note that, in our model, the reward obtainable by hard handoff with $K = S+T$, will always be less than or equal to that obtained by soft handoff, as a hard handoff is a special case of a soft handoff.

It can be seen from Fig. 12 that for the typical mobile environment model used, the proposed algorithm for soft handoff (and even a simplified version of it) offers a significant improvement in performance compared to the algorithms proposed in [15]. While, in the case of hard handoff, a threshold algorithm does reasonably well (provided the threshold is optimally selected), for the soft handoff model the algorithms proposed in the standard [15] did not perform well. Note that for $\beta = 0$, the threshold algorithm is indeed the optimal for the hard handoff model, whereas it is not the case for the algorithm of [15] and the soft handoff model.

VI. Conclusion

In this paper, models for hard handoffs (as applicable to FDMA- and TDMA-based networks) as well as soft handoffs (as applicable to DS/CDMA-based networks) were presented. The handoff problem was formulated as an optimization problem, and necessary and sufficient conditions for determining optimal handoff decisions were derived. Furthermore, an approach based on "limited lookahead arguments" for determining handoff decisions was developed for the cases where the above-mentioned necessary and sufficient conditions fail to determine an optimal handoff decision. The proposed policy takes into account the possible future evolution of the mobile's signal process. Since, prediction of future evolution is also required in many predictive load-sharing and channel allocation policies [9], this information may be already available. The handoff decisions can be made in a decentralized online manner, and the parameters of the objective function can be manipulated by either the mobile user or the network provider to achieve different performance criteria, individually or in conjunction with each other. It was shown that by appropriate choice of reward and cost functions, one can achieve different performance criteria proposed in the literature on handoff problems. Hence, the formulation presented in this paper provides a unified framework for handoff problems and gives further insight into the fundamental trade-offs involved in the design of the handoff problems.

Acknowledgment

The authors will like to thank the anonymous reviewers for their careful evaluation of the paper, Prof. J. Holtzman for his comemnts on the initial draft of the paper, and Prof. D. Teneketzis for bringing a technical error in the earlier draft of the paper to our attention.

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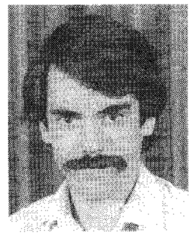
Manjari Asawa (M'95) received the Ph.D. degree in electrical engineering-systems from the Universiy of Michigan, Ann Arbor in 1995, and the M.E. degree from the Indian Institute of Science, Bangalor, India in 1990.

From May–November 1995, she was a post-doc researcher at the University of California, Berkeley. Currently, she is a member of technical staff at the Hewlett-Packard Laboratories, Palo Alto, CA. Her research interests are primarily in the modeling, performance analysis and control of stochastic systems with emphasis on applications to wireless communication systems and high-speed networks.



Wayne E. Stark (SM '94) received the B.S. (with highest honors), M.S., and Ph.D. degrees in electrical engineering from the University of Illinois, Urbana in 1978, 1979, and 1982, respectively.

Since September 1982, he has been a faculty member in the Department of Electrical Engineering and Computer Science at the University of Michigan, Ann Arbor. From 1984–1989, he was Editor for Communication Theory of the IEEE TRANSACTIONS ON COMMUNICATIONS in the area of Spread-Spectrum Communications. He was involved in the planning and organization of the 1986 International Symposium on Information Theory which was held in Ann Arbor, MI. His research interests are in the areas of coding and communication theory, especially for spread-spectrum and wireless communication networks.

Dr. Stark was selected by the National Science Foundation as a 1985 Presidential Young Investigator. He is a member of Eta Kappa Nu, Phi Kappa Phi, and Tau Beta Pi.