Optimal Channel Assignment in Mobile Cellular Networks

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ABSTRACT

In this paper, a non-preemptive prioritization scheme for access control in cellular networks is analyzed. Two kinds of users compete for the access to the limited number of frequency channels available in each cell: the high priority ones represent hand-off requests, while the low priority users correspond to new call requests originated within the same cell. It is proved the optimality of the threshold policy within a very wide class, while using an objective function in the form of a linear combination of the blocking probabilities of the two streams of arriving requests.

Keywords: optimal access control, cellular networks, threshold policy, hysteresis policy, randomized policies, hand-off call, originating call, Markov decision processes.

1. INTRODUCTION

A very important result achieved in the field of wireless communication is the capability to support global roaming. The user, no longer tied to a particular fixed station, has ubiquitous access to a wide variety of services from voice communication to data exchange and elaboration, while roaming throughout the whole geographic area covered by the wireless network.

The access control policy should be a trade-off solution between giving high priority service to the hand-off requests, and avoiding the risk of compromising the whole traffic giving not enough weight to the originating calls.

The purpose of this paper is to find the optimal access control policy in a wide class, including well known algorithms such as the threshold [6,15, 20] and hysteresis policies [14,17]. A Markov decision model, representing this wide class, has been formulated under the assumption that there are two different priority arrival streams, related to hand-off and new calls. These streams are generated by Poisson processes and service requirements for both streams are identical and exponentially distributed. The assumption of exponentially distributed holding times has been justified by Guerin[7] and is required for the tractability of the model.

The optimization analysis is carried out in two steps. Linear programming methods permit to discard non stationary and randomized policies from the search for the optimum. The real optimization phase is instead realized through dynamic programming methods.

The main contribution of this work is the analytical proof of the optimality of the threshold policy when the objective function gives higher priority to the hand-off stream. This result has an immediate practical application because the optimal threshold can be easily computed when a few statistic parameters defining the traffic of requests are known. The originality of the results comes from the observation that literature rarely presents comparisons among different policies, which are either based on simulative results without analytical demonstration [14], or limited to few policies [15].

The paper is organized as follows. Section 2 describes the continuous-time Markov model. In Section 3 this model is uniformized and discretized, in order to apply methods and results of the theory of discrete-time processes. Section 4 demonstrates that the threshold policy is optimal when using an objective function which is a linear combination of the blocking probabilities of the two streams of requests. Section 5 presents some numerical results that confirm the analytical results achieved in the previous sections. Section 6 concludes the paper.

2. A GENERAL CLASS OF ACCESS CONTROL POLICIES

The Markov processes describing the threshold [6,15,20] and hysteresis [14,17] policy are shown in fig.1 and fig.2, where λ_H and λ_L are the Poisson rates of the hand-off and originating stream of requests respectively, while μ is the exponentially distributed common service rate. T is the threshold value for the threshold policy, while the two thresholds for the cycle of hysteresis are M and M', with $M<M'$.

The index associated to each state represents its occupancy level, duplicated in the case of the process representing the hysteresis policy, for which the system may behave differently according to its past history in correspondence to the same occupancy level.

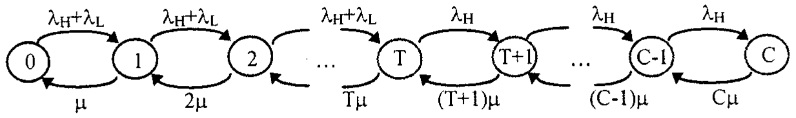

Fig. 1. Transition diagram *(threshold policy)*

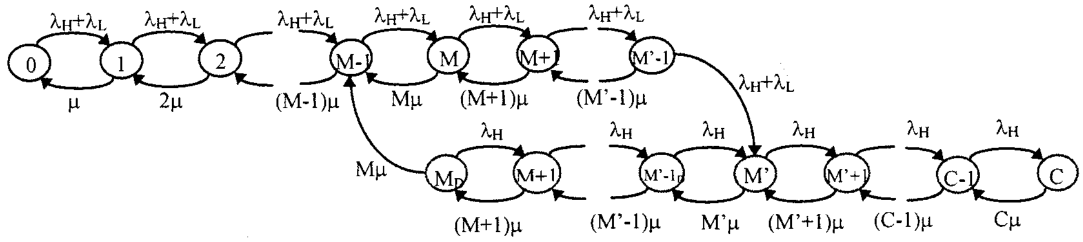

Fig. 2. Transition diagram *(hysteresis)*

These algorithms can be seen as particular instances of the general Markov model we are introducing.

The model represent a single base station with C available channels. Hand-off and originating calls arrive at Poisson rates λ_H and λ_L, and require exponentially distributed service with common rate μ.

The service requirements (channel holding time) for hand-off and new call attempts could be different but an average figure used in the model should be sufficiently accurate.

The memoryless property of all probability distributions in a Markov process makes impossible to represent policies for which the behavior of the system strictly depends on its past history, unless we use several different states to represent the same occupancy level. Each state **s**, belonging to the finite set of states E of the Markov decision process, can be defined through a couple of indexes (i,t), where i represents the number of busy servers, while t is a *state tag*, with $t \in \{1,2, \ldots,k\}$ introduced to allow different decisions in correspondence with the same occupancy level i.

Let us consider the following set of possible actions that can be undertaken at each state of the process:

a_1: accept requests belonging to both streams,
a_2: deny access to originating calls,
a_3: deny access to hand-off calls,
a_4: deny access to both streams of requests.

Given $\mathbf{s} \in E$, $n(\mathbf{s})$ is the occupancy level characterizing the state $\mathbf{s}$. If $\mathbf{s}=(i,t)$, then $n(\mathbf{s})=i$.

Consider now a partition of the set E into classes E_i with the following properties: $E=\bigcup_{i=0}^{C} E_i$, where $E_i=\{\mathbf{s} \in E, n(\mathbf{s})=i\}$.

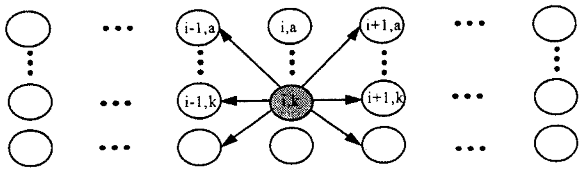

Fig.3. Possible transition from state (i,c)

Starting from the state $\mathbf{s} \in E_i$, the termination of a service brings the system, at rate $i \cdot \mu$, to any state of the class E_{i-1}, denoted by *Prec*($\mathbf{s}$). On the other hand, a new request acceptance leads the system, with rate $\lambda(a)$, to any state of the class E_{i+1}, denoted by *Succ*($\mathbf{s}$).

In particular we have

$$\lambda(a)=\begin{cases} \lambda_H+\lambda_L & \text{if } a=a_1 \\ \lambda_H & \text{if } a=a_2 \\ \lambda_L & \text{if } a=a_3 \\ 0 & \text{if } a=a_4 \end{cases}.$$

The not deterministic choice of the next state among the several states representing the requested occupancy level follows the probability $\pi_{\mathbf{sk}}$, with $\sum_{\mathbf{k} \in Succ(\mathbf{s})} \pi_{\mathbf{sk}} = 1$ and similarly

$$\sum_{\mathbf{k} \in Prec(\mathbf{s})} \pi_{\mathbf{sk}} = 1 .$$

The transition matrix of the process is decision dependent:

$$p_{\mathbf{sk}}^{a}=\begin{cases} \lambda(a)\pi_{\mathbf{sk}} / [\lambda(a)+n(\mathbf{s})\mu] & \text{if } \mathbf{k} \in \text{Succ}(\mathbf{s}) \\ n(\mathbf{s})\mu\pi_{\mathbf{sk}} / [\lambda(a)+n(\mathbf{s})\mu] & \text{if } \mathbf{k} \in \text{Prec}(\mathbf{s}) \\ 0 & \text{otherwise} \end{cases}$$

It is now easy to find the right choice of the parameter $\pi_{\mathbf{sk}}$ and the set of stationary state-decision associations by which to turn our general Markov decision model into the models of fig. 1 and 2.

The threshold policy can be obtained by selecting $\pi_{\mathbf{sk}}$, with $\mathbf{s}=(i_s,j_s)$ and $\mathbf{k}=(i_k,j_k)$, in the following way: $\pi_{\mathbf{sk}}=1$ if $j_s=j_k=fixed\_tag$, for any *fixed_tag* else $\pi_{\mathbf{sk}}=0$, and taking the decision a_1 for all the state $\mathbf{s}$ with i_s lower than the threshold T, the decision a_2 if $T \leq i_s < C$ and the decision a_4 if $i_s=C$.

The hysteresis policy can be obtained selecting two different tags *tag1* and *tag2*; $\pi_{\mathbf{sk}}=1$ if $j_s=j_k=tag1$ and i_s lower than the threshold M', $\pi_{\mathbf{sk}}=1$ if $j_s=j_k=tag2$ and i_s higher the threshold M, $\pi_{\mathbf{sk}}=1$ if $\mathbf{s}=(M'-1,tag1)$ and $\mathbf{k}=(M',tag2)$ or if $\mathbf{s}=(M,tag2)$ and $\mathbf{k}=(M-1,tag1)$ and else $\pi_{\mathbf{sk}}=0$, and taking the decision a_1 for all the state $\mathbf{s}$ with $j_s=tag1$, the decision a_2 for the states with $j_s=tag2$ and $i_s<C$ and the decision a_4 in the state (C, *tag2*) as shown in fig. 4.

It has to be noted that the generality of the defined model consists not only in the shape of its transition diagram, but also in its including both pure stationary and not stationary policies of the randomized kind.

3. DISCRETIZATION TECHNIQUE

The Markov chain {X(t)} related to the process described above is continuous-time. The dwell time of the process in each state is exponentially distributed and not uniform, but decision dependent. The set of rates which characterizes the process is bounded by $C\mu+\lambda_H+\lambda_N$, hence we conclude the process is uniformizable. Adding dummy transitions from states to themselves, a uniform Poisson process can be constructed which governs the epochs at which transitions take place. The uniformization technique transforms the original continuous-time Markov chain with not identical transition times into an equivalent continuous-time Markov process in which the transition epochs are generated by a Poisson process at uniform rate. The uniformized Markov process $\{\hat{X}(t)\}$ is probabilistically identical to the continuous-time $\{X(t)\}$.

The theory of discrete Markov processes can be used to analyze the discrete-time embedded markov chain of the uniformized model.

Let us assume uniform rate $\Lambda = C\mu+\lambda_H+\lambda_N$. The transition probabilities of the uniformized process are:

$$\hat{p}^a_{\mathbf{sk}} = \begin{cases} [\lambda(a)\pi_{\mathbf{sk}}]/\Lambda & \text{if } \mathbf{k}\in \mathrm{Succ}(\mathbf{s}) \\ [n(\mathbf{s})\mu\pi_{\mathbf{sk}}]/\Lambda & \text{if } \mathbf{k}\in \mathrm{Prec}(\mathbf{s}) \\ [\Lambda-\lambda(a)-n(\mathbf{s})\mu]/\Lambda & \text{if } \mathbf{s}=\mathbf{k} \\ 0 & \text{otherwise} \end{cases} \qquad \textbf{(3-1)}$$

If access is denied to a call, the system is forced to pay a penalty, which will be higher (H) in case of hand-off refusal rather than in case of refusal of an originating call (L). Referring to the uniformized process, we can define the cost function in the following way:

$$\hat{r}(\mathbf{s},a) = \begin{cases} 0 & \text{if } a=a_1 \\ L\cdot\lambda_L/\Lambda & \text{if } a=a_2 \\ H\cdot\lambda_H/\Lambda & \text{if } a=a_3 \\ (L\cdot\lambda_L/\Lambda)+(H\cdot\lambda_H/\Lambda) & \text{if } a=a_4 \end{cases} \qquad \textbf{(3-2)}$$

Using the previous notation and denoting with $N(T)$ the number of transitions being completed at time T, and with X_n the state of the system at the time of the n-th transition, the average cost objective function can be written as

$$\lim_{T\to\infty} E\left\{\sum_{n=0}^{N(T)} r\left[X_n, u_n(X_n)\right]\right\} / T$$

We refer to [9] for the proof that the optimization procedures can be applied directly to the discrete-time Markov process described by the embedded Markov chain of the uniformized one. The optimal policy will be the same for the initial, the uniformized and the discretized process, while the optimal values of the objective functions only differ in a constant factor.

4. OPTIMAL POLICY WITHIN THE GENERAL CLASS

It can be proved, by means of linear programming methods that it exists an optimal deterministic stationary policy, i.e. not randomized, for which the decision chosen in correspondence to each state is always the same, independently of the particular instant of time. Observing the shape of the transition diagram in fig.3, it can be affirmed, without loss of generality, that our general model can be restricted to the only processes with no transient states and with only one communicating class of states, i.e. to the only unichain models. The unichain assumption, together with the finiteness of *C*, implies the existence of a unique stationary distribution which is independent of the initial state of the process.

The optimal solution can thence be expressed through a vector $\underline{\mathbf{D}}^*$ whose generic component D_{sa}^* represents the stationary probability that in correspondence to the state **s**, the system takes the decision *a*.

$D_{sa}=P\{a_n=a|\ s_n=\mathbf{s}\}$,

$D_{sa}\geq 0$ and

$\sum_{a\in A_s} D_{sa} = 1 \qquad \mathbf{s} \in E,$

where A_s is the set of all actions that can be taken in state **s**.

Having observed that the optimal policy is a stationary one, we can interpret our objective functions as a linear combination of some QoS parameters consisting in the two blocking probabilities of the two streams of requests.

The expected value of the cost function can now be expressed in the form

$$z = \sum_{(\mathbf{s},a)\in C} D_{sa}\cdot p_{\mathbf{s}}\cdot \hat{r}(\mathbf{s},a), \qquad \textbf{(4-1)}$$

where p_s represents the stationary probability that the system is in state **s**, and the product $D_{sa}{\cdot}p_s$ represents the joined probability for the system to be in state **s** and contemporaneously to take the decision *a*.

As we have seen before, $\hat{r}(\mathbf{s},a)$ is the product between the penalty related to the decision *a* and the probability of the outer event correspondent to the arrival of the request refused under the application of such decision.

Through the application of the total probability theorem, we conclude that the average cost function we have defined through the expressions (4-1) consists in:

z=P(hand-off-block)$\cdot H$+P(originating call-block)$\cdot L$.

Furthermore analyzing the topology of our transition diagram, we can also notice the total absence of transient states that, together with the unichain assumption gives a particular shape to the set of constraints of the linear programming problem related to our optimization procedure.

Denoting $x_{sa} \triangleq D_{sa}\lambda_s$, $(s,a) \in C$, and recalling that $D_{sa} = \frac{x_{sa}}{p_s} = \frac{x_{sa}}{\sum_{j \in A_s} x_{ja}}$, $a \in A_s$, the linear programming problem becomes:

Maximize $\quad \sum_{(s,a) \in C} r(s,a) x_{sa}$

constrained to

$x_{sa} \geq 0 \quad (s,a) \in C$

$$\sum_{(s,a) \in C} x_{sa} = 1 \qquad (4-2)$$

$$\sum_{a \in A_j} x_{ja} = \sum_{(s,a) \in C} p_{sj}^{a} x_{sa} \quad j \in E.$$

Proposition 1:

The linear programming problem (4-2) has an optimal solution which does not belong to the randomized kind, for which $D_{sa} \in \{0,1\}$, i.e. is not fractionary.

Proof:

Thanks to the absence of transient states we conclude that the optimal solution $\underline{\mathbf{x}}^{o}$ has the following property: $\sum_{a \in A_s} x_{sa}^{o} > 0, \quad \forall s \in E$. Thence $\underline{\mathbf{x}}^{o}$ has at least |E| strictly positive variables. Summing up all their related equations deriving from the set of positiveness constraints, we again find the equation $\sum_{(s,a) \in C} x_{sa} = 1$. We conclude the redundancy of one among the |E|+1 remaining constraints. The operations research applied to linear programming problems demonstrates the existence of an optimal base solution containing a number of positive variables at most equal to the number of non redundant constraints.

Without loss of generality we can suppose that $\underline{\mathbf{x}}^{o}$ has this property. So we conclude that $\underline{\mathbf{x}}^{o}$ contains at most |E| positive variables. Having stated before that the number of positive variables is at least |E| and at most |E|, and that $\sum_{a \in A_s} x_{sa}^{o} > 0, \quad \forall s \in E$, we conclude that for all $s \in E$ there will be exactly a decision a for which $x_{sa}^{o} > 0$. This leads to conclude a very important result which is the existence of a pure stationary optimal policy. This result gives us the possibility to further restrict our consideration to policies for which $D_{sa} \in \{0,1\}$, excluding policies belonging to the randomized kind. ❑

The proof that the threshold policy is optimal among all the policies included in the general model can be summed up as follows:

- The existence of an optimal policy for which the optimal decision does not depend on the state tag, but depends on its occupancy level only, is proved by means of dynamic programming methods.
- The optimality of the threshold policy is proved through the analysis of structural properties of the optimal cost function.

Equivalence theorems between a continuous time process and its uniformization allow us to exploit discrete-time optimization methods analyzing the discretization of the initial continuous-time Markov decision process. A first step towards the optimization of the average cost for the infinite horizon problem is the evaluation of the N-step optimal total discounted cost $\mathrm{V}^{\alpha}(\mathbf{s},N)$ which can be calculated with the following dynamic programming equation:

$\mathrm{V}^{\alpha}(\mathbf{s},N)=\min_{a\in A_s}\left\{\hat{r}(\mathbf{s},a)+\sum_{\mathbf{k}\in E}\alpha\hat{p}^{a}_{\mathbf{sk}}\cdot \mathrm{V}^{\alpha}(\mathbf{k},N-1)\right\}$, where $\alpha=\Lambda/(\eta+\Lambda)$, and η is the discount factor of the original continuous time model.

By induction on the number of steps K, in [2] we prove that $\forall\mathbf{s}$ and $\mathbf{z}$, such that $n(\mathbf{s})=n(\mathbf{z})$, $\mathrm{V}^{\alpha}(\mathbf{s},K)=\mathrm{V}^{\alpha}(\mathbf{z},K)\ \forall K\in\mathrm{N}$.

This means the best decision does not depend on the particular state in which the system is, but on its occupancy level only. For this reason it can be defined the function $\mathrm{W}(\cdot,\cdot)$ on the domain $\{0,1,\ldots,C\}\times\mathrm{N}$, with the following property: $\mathrm{V}^{\alpha}(\mathbf{s},K)=\mathrm{V}^{\alpha}(\mathbf{z},K)=\mathrm{W}^{\alpha}(n(\mathbf{s}),K)$.

The following dynamic programming equation is obtained for the total discounted cost for the infinite horizon problem:

$$\mathrm{W}^{\alpha}(i)=\lim_{k\to\infty}\mathrm{W}^{\alpha}(i,k)$$

$$=\frac{i\cdot\mu}{\Lambda+\eta}\cdot \mathrm{W}^{\alpha}(i-1)+\frac{C-i}{\Lambda+\eta}\cdot\mu\cdot \mathrm{W}^{\alpha}(i)+\frac{\lambda_H}{\Lambda+\eta}\cdot\min\{H+\mathrm{W}^{\alpha}(i);\mathrm{W}^{\alpha}(i+1)\}+$$

$$+\frac{\lambda_L}{\Lambda+\eta}\cdot\min\{L+\mathrm{W}^{\alpha}(i);\mathrm{W}^{\alpha}(i+1)\}.$$

The structural properties of monotony and convexity of $\mathrm{W}^{\alpha}(i)$ demonstrated in [2] imply the following proposition.

Proposition 2:

The threshold policy is optimal within the class of policies described in section 2 of this paper under the total discounted cost criterion, for the infinite horizon problem.

Proof:

The optimal policy chooses the best action to take in each state with the following rule:

$$u(i)=\begin{cases}1 & \text{se } \mathrm{W}^{\alpha}(i+1)-\mathrm{W}^{\alpha}(i)\le L\\ 0 & \text{otherwise}\end{cases}$$

where $u(i)$=1 and $u(i)$=0 imply respectively the acceptance or the refusal to service an originating call, and

$$u(i)=\begin{cases}1 & \text{se } \mathrm{W}^{\alpha}(i+1)-\mathrm{W}^{\alpha}(i)\le H\\ 0 & \text{otherwise}\end{cases}$$

for what concerns with the hand-off stream of requests.

Since $W^{\alpha}(i)$ is monotone and convex, the term $W^{\alpha}(i+1) - W^{\alpha}(i)$ is non-decreasing, thence two integers values i_L and i_H can be found such that

$i_L = \arg\min \{ W^{\alpha}(i+1) - W^{\alpha}(i) > L \}$,

$i_H = \arg\min \{ W^{\alpha}(i+1) - W^{\alpha}(i) > H \}$,

where since $H>L$, it results that $i_L < i_H$.

Therefore the optimal policy regarding the decision to accept or refuse to serve requests of the originating call stream is: $u(i)=1$ if $i<i_L$ and $u(i)=0$ for $i \geq i_L$, i.e. a threshold policy.

The same kind of policy is optimal for what concerns with the acceptance of hand-off calls, but it can happen that $i_H > C$, leading to some channels being idle, because $i_L < i_H$, with underemployment of the system resources. Thus the best solution is that of reserving $(C- i_L)$ channels to the hand-off requests never denying service to them.

The theorems of equivalence between a continuous-time Markov decision process and its discretization permit to conclude that the threshold policy based on the parameter i_L is optimal also for the initial continuous-time problem with discount factor η. ❑

The result obtained for the total discounted cost problem is extensible to the average cost optimization problem. The finiteness of the set E and the fact that the Markov chain related to the application of any policy in the general class described in section 2 belongs to the unichain kind, imply that $W^{\alpha}(i)$- $W^{\alpha}(0)$ is uniformly bounded. This hypothesis implies that the optimal policy, following the average cost criterion, satisfies the optimality equation shown below:

$$g+f(i)=\frac{i\cdot\mu}{\Lambda}\cdot f(i-1)+\frac{C-i}{\Lambda}\cdot\mu\cdot f(i)+\frac{\lambda_H}{\Lambda}\cdot\min\{H+f(i);f(i+1)\}+\frac{\lambda_L}{\Lambda}\cdot\min\{L+f(i);f(i+1)\}$$

where g is a constant value $g = \lim_{\alpha\to 1}(1-\alpha)W^{\alpha}(0)$,

and $f(i) = \lim_{r\to\infty}\left[W^{\alpha_r}(i) - W^{\alpha_r}(0)\right]$ for any sequence $\alpha_r \to 1$.

The function $f(i)$ now defined has the same structural properties of the function $W^{\alpha}(i)$. With analogous method to that used to demonstrate that the threshold policy is optimal for the total discounted cost criterion, notice that the term $(f(i+1)$-$f(i))$ is not decreasing so an integer i_L can be found such that the threshold policy with threshold i_L is optimal within the general class represented by the model described in section 2.

The proof that the optimal policy belongs to the threshold class dramatically decreases the feasible region of the optimization problem. This allows a relevant reduction of the number of iterations for the solution with the most common algorithms like the simplex or the policy improvement.

5. NUMERICAL RESULTS

In the previous sections it is proved the optimality of the threshold policy for a general model including also the well known hysteresis policy. Given the number of channels C, the traffic parameters λ_H, λ_L and μ, we can find the *optimal hysteresis policy* searching for the values M and M' (with $M<M'$) for which a hysteresis model such as the one depicted in fig. 2 reaches the minimum cost.

In accordance with the results demonstrated in Section 4, fig. 4 shows, for different values of $\gamma = \lambda_H / (\lambda_H + \lambda_L)$, that the cost of the optimal hysteresis policy is always higher than that of the optimal threshold policy. Numerical values in fig. 4 are obtained with C=10, λ=4, μ=6, L=5 and H=5600.

The threshold policy based on the threshold value i_L reserves a fixed number of frequency channels (C-i_L) to the hand-off stream of requests. In [2] we demonstrate the intuitive result that the threshold value and, consequently the number of reserved channels, depends on the ratio H/L. The number of reserved channels grows with the ratio H/L as we can see in fig. 5 for different values of the handoff fraction γ and with C=10, λ=4, μ=6.

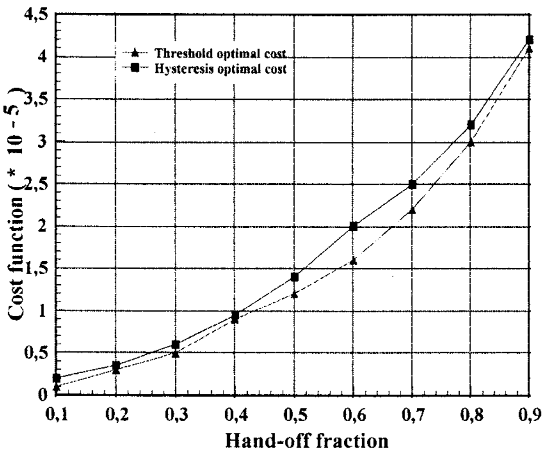

Fig. 4

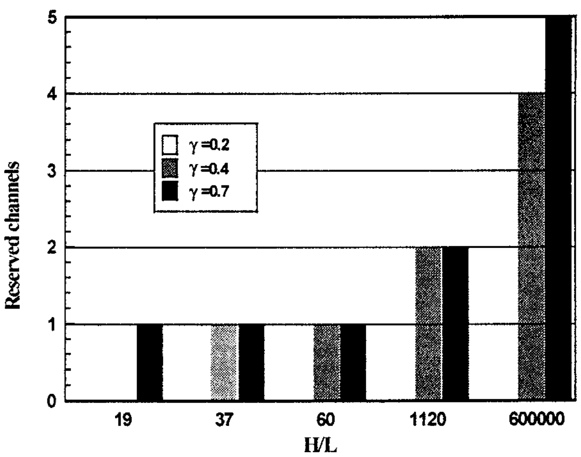

Fig. 5

6. CONCLUSIONS

In this paper an optimization method of channel assignment is proposed. The model is based on a cost function which gives higher priority to hand-off requests than to originating calls. The cost function has been studied through a decision Markov model characterized by a great generality. This model is able to represent both not stationary policies and randomized fractional policies. Moreover, thanks to the particular shape of its transition diagram, it allows us to study policies of great interest such as the threshold policy and algorithms with one or more cycles of hysteresis. The optimization analysis is carried out in two steps. Linear programming methods permit to discard non stationary and randomized policies from the search for the optimum. The real optimization phase is instead realized through dynamic programming methods. We analytically demonstrate that if the objective function is the total discounted cost function, or the average cost function applied to the infinite horizon problem, the threshold policy always reaches the best performance.

ACKNOWLEDGMENTS

The work described in this paper is a part of the author's graduation thesis undertaken at the University of Rome"Tor Vergata". Many thanks are due to V. Grassi for his indispensable contribution, and to M. Colajanni and S. Tucci for their careful review of the manuscript.

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