Admission and Allocation Policies in Heterogeneous Wireless Networks with Handover

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***Abstract*—In this paper, we deal with a control problem for a new joint admission and resource allocation controller taking into account vertical handover in a heterogeneous wireless network. The controller is dynamic: it uses statistical information on the arrival and sojourn rates of the mobiles to optimize the average performance of the system. To account for multi-objective optimization, we consider the maximization of an objective subject to a set of constraints. We turn this constrained problem into an unconstrained one that we numerically solve using the Semi-Markovian Decision Process (SMDP) framework. We compare the optimal policy to some heuristics for different parameter values.**

I. INTRODUCTION

The increase of wireless internet use exhibits ongoing interest for resource consuming applications such as file transfer, video conference, and streaming which, in turn, imply an exponential increase of the bandwidth needs. To reduce these needs, one tries to get an efficient use of all network resources and an efficient bandwidth allocation between different available wireless technologies. This is allowed by wireless internetworking between technologies such as UMTS, WiMAX, WiFi, LTE and others. In this paper, we consider the optimal decision making process for resource allocation in such *heterogeneous wireless networks* with inter-operating technologies.

For the optimization, network managers are facing two kinds of decisions. Firstly, for each incoming mobile, the system has to decide whether to accept or reject the call. In case of acceptance, the call has to be associated with a given network technology. Secondly, a new technological breakthrough referred to as *soft vertical handover* (SVH), allows mobiles to swap from one technology[1] to another seamlessly for the mobile user. Hence, a network manager has to constantly decide whether or not to reallocate mobiles to cells and if so, to which cell.

The system's objective lies at two levels. On the one hand, for bandwidth consuming applications, the QoS can be measured as the average achieved throughput or delay during the connection. This QoS depends on the technology used, on the system's load during the connection, and on the number of SVH performed, as they induce additional traffic to the system. On the other hand, because of both limited antenna quality and application timeout, there exists a minimum instantaneous throughput needed for the connection to be maintained. This leads to reject some customers in order to insure this requirement. Network operators usually refer to as *rejection rate* the proportion of mobiles whose access to the network cannot be granted. Their goal is then to maximize the average mean connection QoS while maintaining the rejection rate to acceptable levels. From the modeling point of view, we are dealing with a *constrained* optimization problem.

In the existing literature, both the admission and the allocation control problems have been separately tackled, either using static or dynamic criterion. The static approach consists in optimizing the distribution of users according to an immediate global system objective. However, this does not take into account long term performance. This is done by dynamic models that are described by statistics, and whose solutions are often based on stochastic decision processes.

The static allocation problem of mobiles has been studied in [1], [2]. The dynamic admission problem is addressed in [3] for WLAN technology and [4] for WLAN and EDGE technologies. These last works do not consider SVH capabilities: they only focus on admission, and mobiles are definitely associated to a cell once they are connected. The dual approach is treated in [5]: the authors consider SVH swaps in a finite horizon setting. But they do not have any admission concerns. At last, in [6], decisions are splitted between an optimal controller and mobiles that selfishly decide on their assignment. Other lines of research include long term comparisons between static approaches with SVH and dynamic admission approaches without SVH [7]. This underlines the benefits that the SVH can bring. To the best of our knowledge, no dynamic approach considering the joint admission and allocation optimal decision making, to optimize the global users' QoS has been proposed, much less with rejection rate constraints.

In this paper, we address this constrained optimization problem and show how it can be formulated as an equivalent unconstrained Semi-Markovian Decision Process (SMDP) that takes into account the flexibility offered by SVH and their costs. This leads us to design a numerical method that takes as inputs the traffic statistics, the system's topology and technology characteristics. The output is an optimal policy that can be applied on-line when mobiles join and leave the system. Numerical simulations show under which conditions (in terms of SVH costs and rejection rate constraints) our algorithm outperforms classical solutions.

The paper is organized as follows. We first introduce the

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[1]In the following, we interchangeably refer to ”technology” or the ”cell” supporting the given technology.

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model in Section II. Next, we detail how to compute the optimal policy in Section III. Finally, in Section IV, we analyze some case studies before concluding the paper.

II. System Model and Problem Formulation

A. Heterogeneous Wireless Networks modeling

Each area covered by a dedicated radio access technology is called a *cell*. We suppose that cells associated with two different technologies do not interfere. We divide the entire cell into different *rings* in which identical signal characteristics (in terms of interference and attenuation levels) are found. This means that all mobiles in the same ring are assumed to receive the same bit-rate from the cell base station. Now, consider a set of overlapping cells. Since the area covered by each cell is discretized in rings, this yields in geometric intersections of rings, called *zones*. Mobiles in the same zone and associated to the same cell receive identical signal and bit-rate. Notions of cells, rings and zones are summarized in Figure 1.

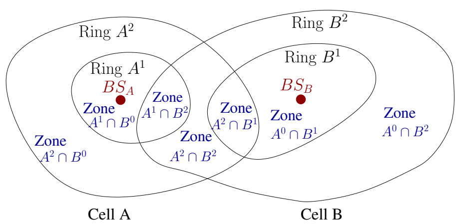

Fig. 1. Example of system with two cells and two rings each. There are $3 * 3 - 1$ zones, with, in this example zone $A^1 \cap B^1$ being empty.

Denote by $\mathcal{Z}$ (resp. Z) the set (resp. the number) of zones in the system. The *load* of any cell c is the number of mobiles in each associated zone. This can be represented by a vector $\ell_c = (\ell_c^1, \ell_c^2 \ldots, \ell_c^Z)$, where ℓ_c^z is the number of mobiles into zone z that are connected to cell c (necessarily equal to zero if the zone is not covered by the cell). We denote by ℓ the vector of the global distribution of mobiles $\ell = (\ell_{c_1}, \ell_{c_2}, \ldots)$. This distribution is called *mobile allocation*.

B. Traffic model

We assume that mobiles join the whole system according to a Poisson process of parameter λ. Arrivals occur in a dedicated zone z with independent probabilities $(p_z)_{z\in\mathcal{Z}}$ such that $\sum_{z\in\mathcal{Z}} p_z = 1$. We consider downlink traffic and we assume that it is elastic: each mobile call is characterized by its size (as opposed to its duration for real-time traffic). We suppose that mobile call sizes follow an i.i.d. exponential distribution with parameter μ. Finally, practical requirements imply that the system guarantees an instantaneous minimum QoS [8], here the throughput, to maintain the communication. If, due to finite capacity, this is not satisfied, then losses occur.

The total cell resources (power, code, time) are shared between active mobiles according to an algorithm defined by the wireless protocol. Here, the resource allocation should only belong to the *Generalized Processor Sharing* type, where resources are allocated according to a state dependent processor sharing policy. Then, the system evolution is markovian with arrival rate λp_z in zone z and each mobile connected to cell c in zone z has a load dependent departure rate $\mu\, d_c^z(\ell_c)$ proportional to its mean throughput $d_c^z(\ell_c)$.

At last, following the general trend in the literature [2], [3], [4], we assume that mobiles remain in their respective zones during the whole duration of their communication.

C. Decision Making Parameters

Network managers can act in different ways:

- Admission decision: should an incoming call in a dedicated zone z be accepted or not? If so, it enters in z.
- Allocation decision: to which technologies active mobiles should be allocated ? Formally, assuming that a zone z is covered by cells c_i and c_j, one has to decide if a mobile in z is connected to cell c_i or c_j. Applying this for all mobiles and zones gives a mobile allocation.

Refusing a call increases the rejection rate but saves some system resources for future incoming calls and allows flexibility in reallocating mobile users. On the other hand, the reallocation requires to perform SVH. These decisions can be taken at any time. They require knowledge on the current system state (load cell and topology) and its forecast (traffic statistics). Simply put, larger amounts of information at the controller allows better decision making, but higher complexity cost. In the absence of traffic statistics, static greedy policies can be developed. For example, maximizing the global instantaneous throughput which belongs to the static optimization class.

D. Problem Formulation

We define a *policy* as being a time sequence of rules $\pi = (\pi_0, \pi_1, \ldots)$ where π_n is a mapping from the information history (past states and actions) to the action set. We aim at finding a policy that minimizes the expected sojourn time of mobiles. This can be viewed as a dynamic control problem where resource sharing in each cell and traffic statistics are given as inputs. Optimal policies are pre-computed, and then on-line applied.

More formally, let S_m^π be the sojourn time of mobile m under policy π. It consists of the service time plus (if any) the additional time induced by performing SVH. Let $\mathcal{A}_T^\pi$ (resp. $\mathcal{R}_T^\pi$) be the set of mobiles that have been accepted (resp. denied access) to the system before time T, and $r_{\max}$ be the fixed maximum rejection rate. The objective is to find a policy π^*, in a given set Π, minimizing the expected sojourn time of mobiles $S^\pi \stackrel{\text{def}}{=} \lim_{T\to+\infty} \frac{1}{|A_T^\pi|} \sum_{m\in A_T^\pi} S_m^\pi$ with guarantee on the expected rejection rate $R^\pi \stackrel{\text{def}}{=} \lim_{T\to+\infty} \frac{|R_T^\pi|}{|A_T^\pi| + |R_T^\pi|}$. This optimization problem can be formulated as

$$(P_\Pi^C) : \qquad \begin{cases} \min_{\pi\in\Pi} S^\pi\,, \\ \text{subject to } R^\pi \leq r_{\max}\,. \end{cases}$$

The set of policies Π depends on the available information and the possible set of actions. In the following section, we detail some possible scenarios and their corresponding set Π.

E. Policy Descriptions

Classical resource *allocation* controllers, like [1], aim at maximizing the instantaneous throughput of the overall system thanks to handover procedures. Yet, such approaches do not secure any time average performance. Neither do they consider the additional time induced by SVH, which can drastically degrade the solution. These resource allocation controllers are, in practice, coupled with admission controllers that aim at optimizing the long term performance while ensuring the required rejection rate. In such a scheme, that we refer as *greedyAlloc* policy, the cost of the handover is not considered by the (greedy) resource allocation controller, but is indirectly taken into account by the admission controller.

To assess the performance of such approach, we compare it to two other dynamic approaches: the optimal one and the one that does not perform any SVH.

We define three policy sets, respectively $\Pi_{\text{adm\&Alloc}}$, $\Pi_{\text{greedyAlloc}}$ and Π_{admOnly}. The corresponding optimal policies solving problem (P_Π^C) are:

- *adm&Alloc*: this is the ideal case where all information is available on-line and both admission and allocation decisions are jointly optimized.
- *greedyAlloc*: the decision is only admission. The admission controller uses as input a static pre-computed mobile allocation scheme that aims at optimizing the instantaneous throughput for each system load.
- *admOnly*: for this policy, no handover is performed. The decision set is reduced to admissions, like in [3], [4].

Obviously, $\Pi_{\text{admOnly}} \subset \Pi_{\text{adm\&Alloc}}$ and $\Pi_{\text{greedyAlloc}} \subset \Pi_{\text{adm\&Alloc}}$: the *adm&Alloc* policy always reaches at least as good performance as the *adm&Alloc* and *admOnly* policies. However, in some cases (see Section IV), the performance of *optimal* and *adm&Alloc* policies are quite similar. The following result gives one configuration for which performance is equal.

Theorem 1. *If there is only one zone in the system, every solution π^* of Problem (P_Π^C) with $\Pi = \Pi_{\text{adm\&Alloc}}$ is such that $\pi^* \in \Pi_{\text{greedyAlloc}}$.*

Proof: (sketch) The result is based on the study of the underlying Markov chain. In the one-zone case, this chain is uni-dimensional. One can show that the stationary distribution of the *greedyAlloc* policy maximizing the instantaneous global throughput, is stochastically lower than every stationary distribution obtained by a policy in $\Pi_{\text{adm\&Alloc}}$. It follows that, whatever the constraint on the expected rejection rate, the minimal cost is reached with the *greedyAlloc* policy. ■

One can find examples showing that this result cannot be extended as soon as there is more than a single zone, even if the global cells throughput has strong monotonic structure.

III. Optimal Policy Computation

In this section, we detail the computation of the policies solving (P_Π^C). To this end, the optimization problem is first turned into an unconstrained control problem by introducing Lagrangian multipliers (Section III-A). Then, we propose an efficient method for finding the optimal policy (Section III-B).

First note that, without loss of efficiency, the two following restrictions can be made (see *e.g.* [9]):

- Decisions are taken only at changes of the system state that are arrival or departure or mobiles;
- Decisions only depend on the current state regardless of the past history of the system, *i.e.* there exists an optimal markovian stationary policy.

A. From Constrained Optimization to Classical Methods

Constrained optimization problems can often be reduced to an unconstrained one by the introduction of variables, called *Lagrangian multipliers*, associated to each constraints. Here, Problem (P_Π^C) can be turned into the unconstrained problem:

$$(P_\Pi^U): \qquad \min_{\pi\in\Pi}\max_{K\geq 0} S^\pi + K(R^\pi - r_{\max}), \tag{1}$$

where $K \geq 0$ is the Lagrangian multiplier.

If a strictly feasible policy exists, *i.e.* if $\exists \pi,$ s.t. $R^\pi < r_{\max}$, then the dual problem defined by $\max_{K\geq 0}\min_{\pi\in\Pi} S^\pi + K(R^\pi - r_{\max})$ has the same value than (1). Denote

$$J_\Pi(K) = \min_{\pi\in\Pi} J_\Pi(\pi, K) \quad \text{with} \quad J_\Pi(\pi,K) = S^\pi + KR^\pi. \tag{2}$$

The dual problem can be written $\max_{K\geq 0} J_\Pi(K) - Kr_{\max}$. It is known (see [10]) that $J_\Pi(K) - Kr_{\max}$ is a concave function of K and goes to $-\infty$ when $K \to \infty$. Then its maximal value, attained at K^*, can be computed using a dichotomy algorithm.

For a given K, and set Π, we denote by $\pi_\Pi^*(K)$ the optimal policy:

$$\pi_\Pi^*(K) \in \arg\min_{\pi\in\Pi} J_\Pi(\pi, K)). \tag{3}$$

Theorem 2.8 of [10] claims that the policy solving the constrained problem (P_Π^C) is the policy $\pi_\Pi^*(K^*)$ modified at, at most one state, where the decision is randomized between two actions. Consequently, solving Problem (P_Π^C) amounts to find K^*, and then to compute $\pi_\Pi^*(K^*)$. Finally, computation of $\pi_\Pi^*(K)$ is the main point for solving the constrained problem. This is detailed in the next section.

B. SMDP formulation

We now detail the computation of the *adm&Alloc* policy for solving the unconstrained Problem (3), by mean of Semi Markov Decision Processes (SMDP) methods [9]. In the following, we present the main aspects of the formulation of the SMDP to find $\pi^*_{\Pi_{\text{adm\&Alloc}}}(K)$, where K is the Lagrangian multiplier.

The two other policies (*greedyAlloc* and *admOnly*) follow a similar approach but their SMDP are different. Indeed, compared to existing works [4], the treatment of SVH requires to express a new SMDP in which the decision set as well as the decision epoch set should be enlarged. In particular, in order to model all the reallocation possibilities, one defines the concept of *class* of a mobile allocation as the set of all mobile allocations that can be reached using SVH. We denote by $\bar{\ell}$ the class of the mobile allocation ℓ.

1) State space: The state space first consists of the mobile allocation, and secondly, of the system event: either a departure, or an arrival in one of the zones. Henceforth the state space, denoted by $\mathcal{X}$, is such that $\mathcal{X} \ni x = (\ell, z)$, with $z \in \{0, 1, \ldots, Z\}$ (0 corresponds to a departure, and $z > 0$ to the arrival zone).

2) Set of actions: Let $\mathcal{A}(x)$ be the set of actions (depending on the state x) of a policy in $\Pi_{adm\&Alloc}$. Notice that, in each state, actions are *mobile allocations*. If $x = (\ell, 0)$ (departure case), $\mathcal{A}(x)$ is the set of all elements of class $\bar{\ell}$. If $x = (\ell, z)$ (arrival in zone z), $\mathcal{A}(x)$ is the set of all elements of class $\bar{\ell}$ (when rejecting the incoming mobile) plus the set of all elements of class $\bar{\ell}'$ after acceptance of the mobile in zone z. In case of arrival in a partially full system (due the minimum QoS requirement), $\bar{\ell}'$ may be empty.

3) Transition probabilities and transition time: Given state x and action $a \in \mathcal{A}(x)$, $\mathbb{P}\left(y|(x,a)\right)$ is the probability to switch to state y and $\Lambda(x, a)$ is the rate of the exponential distribution of the transition time. This rate is the sum of all possible event rates: $\Lambda(x,a) = \lambda + \mu \sum_{c,z} d_c^z(a_c)$. If y is a state corresponding to an arrival in zone z, $\mathbb{P}\left(y|(x,a)\right) = \lambda p_z / \Lambda(x,a)$. In case of a departure in zone z of cell c, $\mathbb{P}\left(y|(x,a)\right) = \mu d_c^z(a) / \Lambda(x,a)$.

4) Instantaneous and Average Cost: We aim at minimizing the expected sojourn time of mobiles. Yet, for implementation purposes, it is more convenient to minimize the expected number of mobiles, which, by Little law, gives the same optimal policy. The corresponding instantaneous cost $c(x, a, K)$ in state x with decision a consists of three terms: (i) the total number of mobiles in the system after decision, (ii) the cost induced by the Lagrangian multiplier K and (iii) the cost induced by each handover. The cost associated to one handover is denoted by K_H. By Little law, $K_H = \lambda T_H$, where T_H is the additional time needed to perform the vertical handover (that we assume independent of the technology) [2].

The time average cost of policy π with initial state x_0 is:

$$C_\pi(x_0, K) \stackrel{\text{def}}{=} \lim_{N\to\infty} \frac{1}{N} \mathbb{E}_\pi \left[\sum_{k=1}^{N} c(X_k, a_k, K) | X_0 = x_0 \right],$$

where X_k is the (random) state and a_k the action, at epoch of the k^{th} transition of the system under policy π. Since every state can be reached from every other state, this function does not depend on the initial state x_0 (the SMDP is *unichain*), which we omit in the rest of the paper.

5) Optimal Policy as a Fixed Point of Bellman Equation: The solution $\pi^*_\Pi(K)$ of the unconstrained problem, as defined in Eq. (3), is such that $\pi^*_\Pi(K) \in \mathrm{argmin}_{\pi\in\Pi} C_\pi(K)$. Let $C_\Pi(K) \stackrel{\text{def}}{=} \min_{\pi\in\Pi} C_\pi(K)$ be the minimal cost value.

One can characterize $C_\Pi(K)$ as the solution of a fixed point equation (known as Bellman equation). One searches $C_\Pi(K)$ and the vector $h_\Pi : \mathcal{X} \to \mathbb{R}$ such that, $\forall x \in \mathcal{X}$:

$$C_\Pi(K) + h_\Pi(x) = \min_{a\in\mathcal{A}(x)} \Big(c(x,a,K) + \sum_{y\in X} \mathbb{P}(y|(x,a)) h_\Pi(y) \Big).$$

[2] Strictly speaking, in the rest of the paper, all variable functions should include the dependence in K_H (e.g. $C_\Pi(x_0, K)$ should be read $C_\Pi(x_0, K, K_H)$). Yet, for sake of readability, we omit them.

The unique solution $(C_\Pi, h_\Pi)(K)$ is computed by using dynamic programming. The optimal decision (hence policy $\pi^*_\Pi(K)$) is obtained, for all $x \in \mathcal{X}$, by taking action $a \in \mathcal{A}(x)$ that achieves the minimal value.

IV. Numerical Comparisons of Policies

A. Scenario Description

We use the model and numerical values of [4]. We consider the downlink traffic in a system in which a WLAN cell c_1 and a HSDPA cell c_2 superimpose perfectly with 2 rings. The minimum throughput requirement is $d_{min} = 0.7$ Mbit/s corresponding to a maximum of 18 mobiles. The CSMA/CA algorithm is approximated by a fair scheduling in throughput. The throughput of the WLAN cell is $d^z_{c1}(\ell_{c_1}) = \left(\sum_z \frac{\ell^z_{c_1}}{D^z_{c1}}\right)^{-1}$ where $D^z_{c_1}$ is the nominal data rate of the WLAN technology in zone z. The HSDPA share is assumed as a fair scheduling in time. The throughput for the HSDPA cell is $d^z_{c_2}(\ell_{c_2}) = \frac{D^z_{c_2}}{\sum_z \ell^z_{c_2}}$, with $D^z_{c_2}$ the nominal rates of HSDPA.

B. Comparisons with other SVH algorithms

None of the methods given in the survey [11] consider the rejection rate as a criteria to optimize. Thus, none of them can be used to solve our constrained problem and no relevant comparisons with previous works can be made at this time. However, according to [11], the SMDP we consider here belongs to the category of *cost function* methods. Without any rejection constraints, such methods perform better than simpler ones based on RSS or bandwidth (for *AdmOnly*, [7] found 20% of improvement).

C. Simulations

1) Performance comparisons: We compare the performances (expected sojourn time) of the 3 constrained policies defined in II-D when the load varies. Figures 2 shows that *greedyAlloc* and *adm&Alloc* have close performances. The benefits that the SVH brings is around 30% whatever the load is. Furthermore, SVH allows to enlarge the range in which the rejection constraint is satisfied.

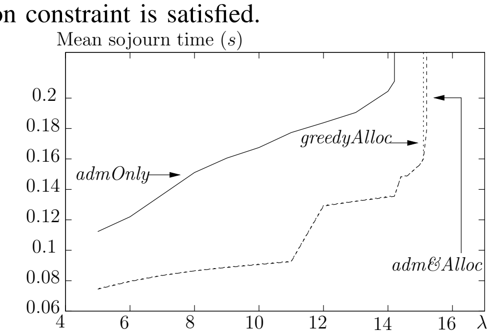

Fig. 2. Performance of the policies ($\mu = 3$, $K_H = 0$, $r_{\max} = 15.5\%$) as a function of the arrival rate λ. An infinite value means that the constraint cannot be satisfied.

We now compare the performances when the rejection rate varies. On Figure 3 policies *greedyAlloc* and *adm&Alloc* are also quite similar and they significantly outperform *admOnly* when the rejection rate constraint is tight (*i.e.* $r_{\max}$ is low). Policy *greedyAlloc* improves the average sojourn time of the mobiles up to 44% (attained for $r_{\max} = 20\%$). When the constraint is relaxed (*i.e.* $r_{\max}$ is high), the handover capabilities of the system appear to be of little use and simple *admOnly* policies are well adapted. Indeed, in this case, the best action to trigger is the rejection of mobiles arriving in zones far away from the antenna, for which negligible gain can be obtained through reallocation.

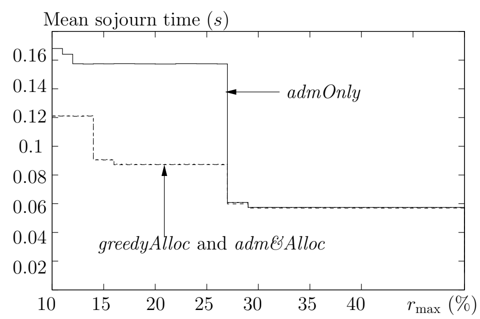

Fig. 3. Performance of the policies ($\lambda = 10$, $\mu = 3$, $K_H = 0$) as a function of the rejection rate constraint. The performance of *greedyAlloc* policy coincides with the optimal policy.

Hence, *greedyAlloc* is a suitable solution to the optimization problem since, thanks to handover, it largely outperforms *admOnly* while having a similar policy set Π.

2) Influence of the handover cost: In practice, SVH adds supplementary traffic to the system. Thus, the sojourn time of mobiles should now include the actual communication time plus the time induced by the handover procedure. Such an additional time T_H is modeled by a cost K_H in the SMDP (hence, in Figure 4, an handover cost of 1 corresponds to $T_H = 0.1s$).

We now study the influence of the handover latency and we compare, for the 3 policies, the influence of the handover cost K_H on the average sojourn time for a given rejection rate constraint. For the three policies, the mean sojourn time is non decreasing with the handover cost. As the policy *admOnly* does not perform any handover, its performances are constant. We see that for high values of the handover cost (for $K_H > 1.5$), *adm&Alloc* and *admOnly* have similar sojourn time, suggesting that the policies are nearly identical. This is natural since the handover cost inhibits the potential performance gain of handover.

Concerning *greedyAlloc*, its optimization allocation mechanism does not take into account the handover cost although this cost is charged during reallocation. This degrades the performance of the policy when the handover time is high. However, for low handover costs ($K_H < 1$), *greedyAlloc* is not much affected. Indeed, with our rate constraint ($r_{\max} = 10\%$), the admission controller has little flexibility on rejecting mobiles, especially these ones having many handovers during their communication. In this case, handovers have negligible impact and *greedyAlloc* has nearly optimal performance.

V. Conclusion

We proposed a general framework for solving the problem of optimizing the time average QoS of mobiles, while ensuring

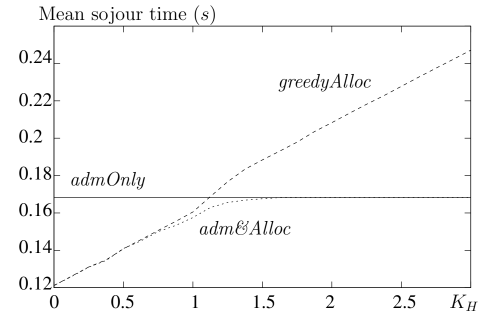

Fig. 4. Mean sojourn time of policies as a function of the handover cost K_H ($\lambda = 10$, $\mu = 3$ and $r_{\max} = 10\%$).

an acceptable rejection rate. Adding a rejection rate constraint in the objective function should prove to be very useful for operators that have to deal with several criteria: mobiles QoS, rejection or blocking rates, etc. Such a method can be thus included as an optimization toolbox in simulators containing the network topology of metropolitan or national area in the performances assessments for deployment and sizing purposes.

We also illustrated that, when handover can be performed quickly, greedy algorithms, with low complexity, may achieve reasonable performance compared to solutions with full control and full information on the system. Additional features (e.g. considering operator total revenues) could be modeled with a more complex cost function without any further changes. Moreover, our dynamic programming approach could be seen as a first step for decentralized similar models since dynamical games are studied by mean of competitive SMDP.

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