Traffic Studies for DSA Policies in a Simple Cellular Context with Packet Services

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***Abstract*—DSA (Dynamic Spectrum Allocation) techniques are very challenging when the quality of service has to be guaranteed in a flexible spectrum situation. In this paper, we present and analyze DSA policies for packet services in cellular context. A centralized model, where a *meta-operator* shares a common spectrum among different operators, is considered. We focus on two criteria for the policies design: the total welfare (sum of operators' rewards), and the blocking probability. We go through two steps to pass from the actual FSA (Fixed Spectrum Allocation) situation into DSA. First, DSA algorithms depend on the arrival rates. Second, DSA algorithms depend on both the arrival rates as well as the number of active users. Targeting the reward maximization shows to be inefficient when the blocking probability has to be guaranteed. However policies targeting a blocking probability threshold, achieve greater rewards then FSA rewards. We also present a heuristic DSA algorithm that takes into consideration: the arrival rates, the number of active users and the blocking probability. The algorithm gives a very close blocking probability to the one achieved using FSA, while the obtained reward significantly exceeds the FSA reward.**

I. Introduction

The actual spectrum crowd situation and the rapid evolutions of the SDR (Software Defined Radio) techniques, provoke the development of cognitive radio and DSA systems. Existent spectrum allocation process, denoted as FSA (Fixed Spectrum Allocation), is inflexible and shown to be inefficient [1].

In [2], the spectrum management models are divided into four main axis: command and control, exclusive-use, primary/secondary usage, and commons. The exclusive-use model presents the actual cellular operator case where the operators own exclusively the rights to use the spectrum band for decades. DSA algorithms are being investigated as new promising techniques to overcome this inflexible situation which has leaded to resources limitation problem.

In the cellular context two main axis of resource management exist. The JRRM (Joint Radio Resource Management) axe, in which one operator manages jointly his networks (or Radio Access Technology) making benefit of his own licensed bands [10]. The second axe: *operator sharing DSA*, (or *Inter-operator DSA*) in which the competition and/or the cooperation aspects between different operators are explored. Competition aspects are referred to the costs and revenues partitioned among the operators as a result of spectrum sharing.

Several researchers have worked on DSA for cellular networks. For instant in reference [3], the authors introduce an inter-vendor spectrum sharing technique where a spectrum allocation server dynamically assigns the unused spectrum from a vendor to another. The authors in [7], made use of a Darwinian algorithm for DSA in WCDMA networks, the algorithm has been proposed to assign the minimum number of carriers to the cells while satisfying the required demands. In [6], authors propose a coordinated DSA system where a pool of resources (CAB "Coordinated Access Band") is shared and controlled by a central entity (the regional spectrum broker).

Most of the works related to DSA in cellular networks are based on centralized architecture, due to its practical impact [4]. We believe the success of a centralized DSA network model depends on to the proper design of the centralized entity (meta-operator). In this paper we focus on the DSA algorithms for the cellular networks in a spectrum sharing context. We present and evaluate DSA strategies (policies) for the meta-operator.

Talking about sharing the spectrum argues the consideration of the pricing aspects. As cellular operators pay high prices for the license, hence their main interest in sharing the spectrum lies behind the expected benefits [8]. Many references considered the pricing issue while studying DSA techniques. In [9], the authors analyze a network model where the base stations of the service providers are sharing a common amount of spectrum. A distributed DSA algorithm is proposed where each user maximizes his utility (bit rate) minus the payment for the spectrum. The revenue maximization in a spectrum auction framework has been studied also in [5].

In [4], the authors propose a dynamic auction approach to allocate the spectrum to competing base stations. The base stations are sharing a common spectrum band controlled by a *spectrum broker*. The broker assigns the spectrum to the base stations to maximize its revenue, without violating the interference constraint.

Most of the works dealed with DSA in cellular networks have supposed the demands (in terms of spectrum) are already given [7], [3], [6], and [4]. We are focusing in this paper on the traffic and dimensioning study. The target of our study is to determine how much spectrum the operators need to buy. Authors in [9] have performed a similar study, however (unlike this paper) they presented a distributed algorithm for the end-users. The authors in [9] did not consider the impact on the blocking probability.

We present a network model where different operators are sharing a common pool of resources (a CAB) inspired by the idea of resources sharing proposed in [3] and [6]. We address the pricing and reward issue. We define a model for the operators reward that takes into consideration: (1) the spectrum price as a function of demand, and (2) the end-user satisfaction as a function of the achieved throughput. We study the traffic aspects for dynamic spectrum sharing policies on a simple system model. A compromise level has to be found between the spectrum price and the revenues. Our studies of DSA policies has been undertaken using simulations. In this paper we extend our work presented in [13] to more realistic scenarios. A SMDP (Semi Markov Decision Process) framework for DSA in cellular networks is proposed in [13].

The paper is organised as follows: Section II presents the network model in terms of system model, traffic model, the reward model, and the principle of DSA operation. The DSA policies are presented in sections III, IV and V. Conclusion is finaly given in section VI.

II. Network model

A. System model

We intend to study DSA among different operators on the cell level. Our system is based on a centralized architecture, inspired from [4], [3] and [6], where a central unit (i.e. meta-operator, government agency, or regulator) is the system core. The *meta-operator* owns and manages a common pool of spectral resources (the CAB) in a specific region. The CAB is shared between different numbers of operators. In this paper each operator operates one RAN (Radio Access Network).

The operators (RANs) do not own the spectrum but rather share the CAB controlled by the meta-operator. According to the load variations of the RANs, the meta-operator dynamically attributes frequency blocks to the operators (section II-D).

Operators are assumed to use frequency reuse 1 (all cells use the same band leased by the meta-operator from the CAB); the cellular network is supposed to be regular; propagation and traffic are considered to be homogeneous. Based on these assumptions, all cells of an operator statistically behave the same way, we can thus focus on a single cell per operator.

The CAB is subdivided into m_{max} elementary spectrum bands (blocks) where a number of blocks m_i is allocated momentarily (from the CAB) to cell i. Fig. 1 gives the general schema of our system model. Parameters $n_i,\ i = 1, 2$ are the number of active users in cell 1 and cell 2.

On one hand, revenue is assumed to be proportional to the satisfaction of the users. On the other hand, it is supposed that spectrum cost follows the 'law' of supply and demand (section II-C). We are interested in the design of the meta-operator DSA policies that assign bandwidth to the operators.

Our model could be coherent with SOFDMA (Scalable Orthogonal Frequency Division Multiple Access) cellular networks (i.e. WiMAX, 3GPP-LTE), where the bandwidth of the system is scalable [11]. In these systems, the operator has

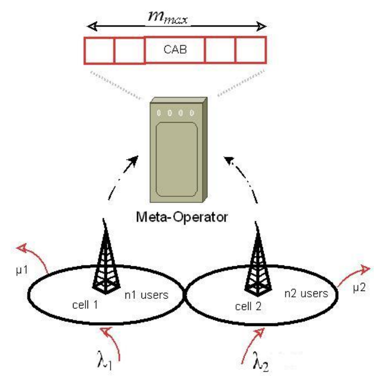

Fig. 1. System model: two operators access to a CAB

indeed an additional flexibility in resource allocation through the possibility of scaling the bandwidth.

B. Traffic

We consider a bursty packet traffic, such as web browsing or file downloading on the downlink: a user alternates between packet calls (several packets are transferred in a very short time) and reading times (there is no transfer). In this paper, we focus on the packet call level and so we neglect the details of the packet level. An illustration of the traffic model is shown in Fig. 2.

We assume Poisson arrivals of user downlink packet calls with rate λ_i in cell i. Traffic is supposed to be elastic: the packet call size is exponentially distributed with mean X_{ON} bits in both cells and so the service rate depends on the available cell throughput. We assume a fair share of resources between users of a given cell. For cell i let D_i be the data rate (in bits/s) accessible with one spectrum block. Then the service rates can be written as:

$$\mu_i = \frac{m_i D_i}{X_{ON}}.$$

Each user has a maximum throughput that can not exceed R_{max}, where R_{max} presents the physical capability of the mobile terminal. We assume that the average data rate accessible by users in a cell is proportional to the bandwidth allocated to the cell and is equally divided among all users of the cell.

Based on the presented model, we can see that each cell behaves as M/M/1/n_i^{max} system, where n_i^{max} is the maximum number of users the cell accepts (according to the Connection Admission Control configuration). The network traffic load $\rho_i = \lambda_i/\mu_i$.

C. Reward model

The challenging issue in DSA techniques for the operator lies in the trade-off between the cost paid for the spectrum and the revenues obtained from the satisfied users: more spectrum per cell means a higher cost for the operator but also means higher throughputs for the end-users. Based on this principle we define a reward model that takes into account both the user throughput as well as the spectrum price.

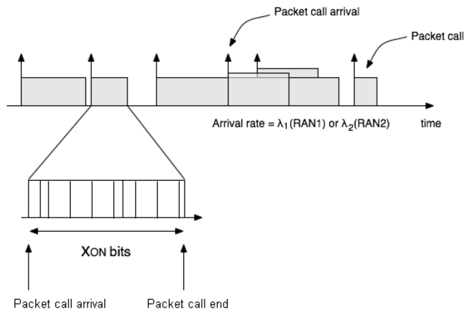

Fig. 2. Assumed traffic model.

Different from [4] and [5], where the target was the maximization of the central unit's revenues, in this paper, we are interested in the total social welfare of the operators (the sum of their rewards).

The reward function depends on the revenue expected by the operators. The higher the satisfaction of users, the higher the operator revenue. The revenue obtained from a given customer in cell i increases with its satisfaction:

$$\phi_i(n_i, m_i) = K_u(1 - \exp(-\mu_i/n_i\mu_{com})),$$

where K_u is a constant in euros per unit of satisfaction, μ_{com} is a constant called comfort service rate, and the satisfaction is an increasing function of the user data rate (without unit) [12]. Thus the total revenue obtained by the operators in tuple (n_1, m_1, n_2, m_2) is:

$$g_1 = n_1\phi_1(n_1, m_1) + n_2\phi_2(n_2, m_2).$$

As the spectrum price depends on the market demand, the price increases when the amount of free spectrum decreases. The total price paid by both operators can be given as:

$$g_2 = K_B(m_1 + m_2)\exp\left(-\frac{m_{max} - m_1 - m_2}{m_{com}}\right),$$

where m_{com} is a constant that controls the variation of the price and K_B is a constant in euros per block. If m_{com} is high, the exponential function is close to 1 whatever the state. If m_{com} is small, there is a high discount when the CAB is free. Note that the price paid by the operator for a given elementary band varies with the occupation of the CAB. The global reward function per time unit can thus be written:

$$g = g_1 - g_2.$$

D. Dynamic spectrum allocation

In this paper, a DSA policy is a strategy (algorithm) that dynamically attributes spectrum blocks from the CAB to the operators. We consider a periodical assignment of spectrum portions: every allocation period T_{alloc}. At the DSA decision instant, the *meta-operator* is supposed to attribute a number of blocks to each cell according to the load variations. The *meta-operator* is aware of the operators situations such as: number of users, maximum cell throughput, the arrival rates, etc... As the CAB size is limited and as spectrum cost increases with increasing demand, there is a strong interaction between the operators. We assume that at least one spectrum block is always available to each cell, so that starvation is not possible.

We are now interested in defining the DSA policies and evaluating their performances. In the coming sections we will present policies that envisage the maximization of the total welfare (sum of the rewards obtained by the operators), and others that envisage not exceeding a pre-defined blocking probability threshold. Finding a compromise between the revenues, costs and the blocking probability is essential for the DSA operation.

III. Total welfare maximization policy

We begin by illustrating the first criteria. In this policy the spectrum assignment decision is based only on the arrival rates of the cell. Hence the steady state analyses of the M/M/1/n_i^{max} system can be used.

Formally, the algorithm allocates (m_1,m_2) band blocks such that:

$$\sum_{i=1}^{2}\sum_{n_i=0}^{n_i^{max}} \pi_{n_i}(\lambda_i)n_i\phi_i(n_i, m_i) - g_2(m_1, m_2),$$

is maximized, where the $\pi_{n_i}(\lambda_i)$, $i \in \{1, 2\}$, $n_i \in \{0, ..., n_i^{max}\}$ are the steady state probabilities of a M/M/1/n_i^{max} with arrival rate λ_i and service rate μ_i.

$$\pi_{n_i} = \rho_i^{n_i}\left(\frac{1 - \rho_i}{1 - \rho_i^{n_i^{max}+1}}\right),$$

and $\pi_{n_i} = 1/(n_i^{max} + 1)$, if $\rho_i = 1$.

A. Parameters

Hereafter we define the paremeters we used to illustrate the DSA policies. The CAB is assumed to have a size of 10 MHz, the elementary band (m_i = 1 block) has a size of 100 KHz, and m_{com} = 3 MHz. For the sake of simplicity, we assume that both cells have the same characteristics. The average cell data rates D_i are considered to be 1250 Kbps, $X_{ON} = 3$ Mbits, $\lambda_1 = \lambda_2 = \lambda$, $n_1^{max} = n_2^{max} = 8$, and R_{max} is set to 2 Mbps. The pricing constants are fixed as follows: $K_u = 100$ euros, $K_B = 1$ euro, and $\mu_{com} = 0.0167$ s^{-1}.

B. Results

The evaluation of the DSA policies is performed using event-based simulator. Three event types exist according to our system model: arrival of packet call, departure (end) of packet call, and DSA decision instant (band attribution instant to the cell performed by the *meta-operator*).

Fig. 3 gives the obtained reward as well as the blocking probability using DSA policy applying criteria one (referred to as *reward-max DSA*) and FSA respectively. It is clear the obtained reward is much higher than the one obtained using FSA. However the blocking probability shows a severe degradation with respect to FSA.

DSA strategies are succeseful if, and only if, they could use less spectrum (less cost for the operator) while still providing

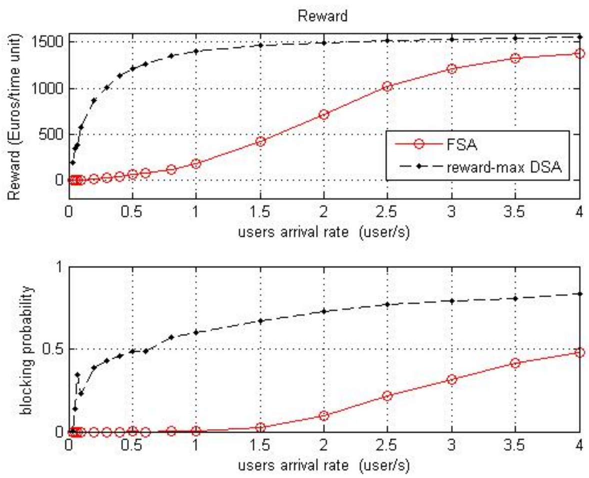

Fig. 3. Total reward and blocking probability obtained with FSA, and DSA policy applying criteria one (total welfare maximization).

an acceptable satisfaction level for the end-users. The obtained high blocking probability using *reward-max DSA* policy makes us think an adaptive CAC (Connection Admission Control) is needed. This conclusion will lead us to envisage the blocking probability while designing the DSA policies for the meta-operator.

IV. Blocking probability threshold policy

Hereafter we will illustrate the second criteria. The criteria envisages achieving a blocking probability that does not exceed a pre-defined blocking probability threshold. At each allocation instant, the *meta-operator* allocates a number of spectrum blocks to each cell in order to achieve a blocking probability $P_b < P_{thrs}$, where P_{thrs} is the pre-defined threshold. We go through two steps;

A. Long term DSA

In the first step, DSA decisions depend only on the arrival rate λ_i of the cell i, hence the blocking proabability can be calculated at the steady state of the M/M/1/n_i^{max} system. Formally, the algorithm allocates a number of band blocks to each cell, such that the blocking probability is less than the threshold:

$$P_b(\lambda_i, m_i) = \rho_i^{n_i^{max}} \left(\frac{1-\rho_i}{1-\rho_i^{n_i^{max}+1}} \right) < P_{thrs}.$$

In case the CAB size does not allow satisfying the blocking proabability condition for both cells, then the CAB is divided equaly between the cells (FSA situation). We refer to this algorithm as *long term DSA*, in the rest of the paper.

B. Short term DSA

In the second step, we consider the spectrum allocation depends on the arrival rate as well as on the number of the active users at the allocation instant n_i. Here we make use of the transient analysis of the M/M/1/n_i^{max} system. In this algorithm (we refer to as *short term DSA*), the meta-operator allocates a number of the spectrum blocks to each cell such that:

$$\bar{P}_b(\lambda_i, m_i, T_{alloc}, n_i) < P_{thrs},$$

where $\bar{P}_b(\lambda_i, m_i, T_{alloc}, n_i)$ is the mean blocking probability calculated over the allocation period T_{alloc}. In case the CAB size does not allow satisfying the blocking proabability constraint for both cells, then the CAB is divided equaly between the cells (FSA situation).

The transient regime analysis is based on:

$$\pi_t = \pi_0 \exp(Qt),$$

where π_t is the probabilities vector at instant t, π_0 is a vector presenting the number of active users at the allocation instant, and Q is the infinitesimal generator of the Markov chain. Integrating both sides of the equation over the period T_{alloc} gives,

$$\bar{\pi}(\lambda_i, m_i, T_{alloc}, n_i) = \frac{\pi_0}{T_{alloc}} \int_0^{T_{alloc}} \exp(Qt)dt,$$

where $\bar{\pi}(\lambda_i, m_i, T_{alloc}, n_i)$ is the mean probabilities vector over the period T_{alloc}. Thus $\bar{P}_b = \bar{\pi}_{n_i^{max}}(\lambda_i, m_i, T_{alloc}, n_i)$.

C. Results

In this section, we give the results obtained using the second criteria, and we compare FSA, *long term DSA*, and *short term DSA*. We show the effect of the allocation period T_{alloc} on the network performance.

It worth mentioning that the operators would be mostly interested in the arrival rate values $0 < \lambda \leq 2$ users/s for the considered set of parameters, however for an asymptotic study we have performed our simulations for higher arrival rate values.

Fig. 4 gives the CAB utilization and the blocking probability, while Fig. 5 gives the total reward and the obtained mean user throughput, for T_{alloc} = 1 min, and 3 sec. P_{thrs} is set to 20%. Fig. 6 gives the total reward and the blocking probability for P_{thrs} = 10%.

We can see from Fig. 4 a considerable spectrum conservation using the presented DSA algorithms with respect to FSA.

We can notice also that DSA algorithms targeting a pre-defined blocking probability threshold achieve gain over FSA in terms of operators-reward (Fig. 5), while providing a blocking probability less than P_{thrs} ($0 < \lambda < 2$). The advantage of performing DSA based on both the arrival rate and the number of active users (*short term DSA*), over performing DSA based only on the arrival rate (*long term DSA*), is conditioned by the proper choice of the allocation period T_{alloc}.

In other words, if $T_{alloc} >> T_{call}$, where T_{call} is the packet call duration, including n_i in the DSA decision does not have a significant impact. However if $T_{alloc} \approx T_{call}$ (same order of magnitude) we can gain through conserving the spectrum by taking n_i into consideration. Note that the spectrum saving is the major target behind DSA.

Obviously, we can see from Fig. 4 that less blocking probability is achieved using *short term DSA* than the one achieved using *long term DSA*, when T_{alloc} = 3 sec.

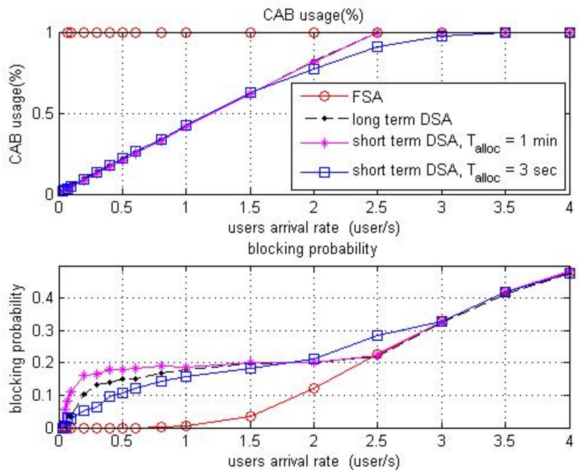

Fig. 4. CAB usage and blocking probability obtained using FSA, *long term DSA* and *short term DSA* for two T_{alloc} values. P_{thrs} is set to 20%.

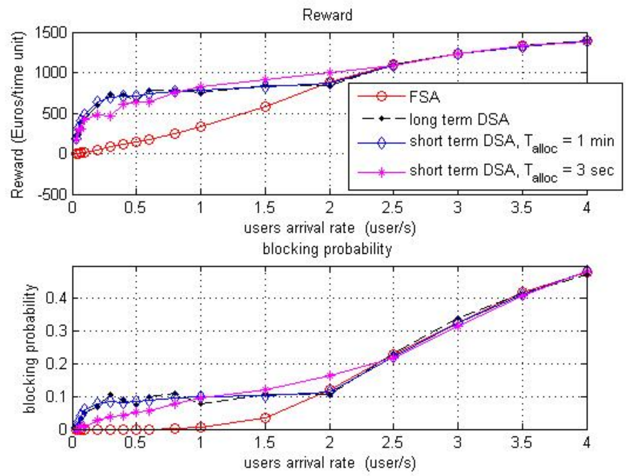

Fig. 6. Total reward and blocking probability obtained for T_{alloc} = 1 min and 3 sec. P_{thrs} is set to 10%.

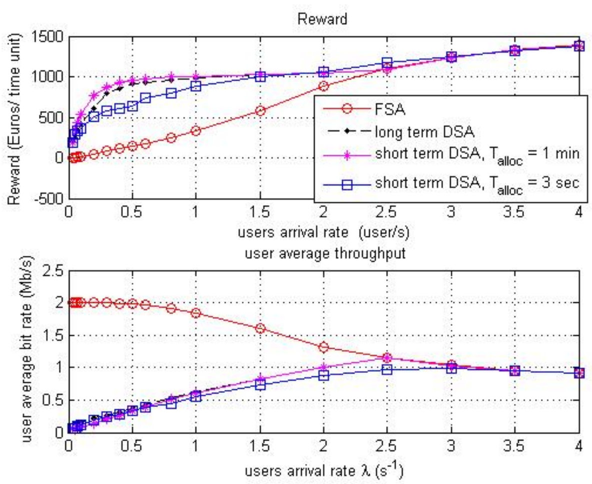

Fig. 5. Total reward and average user throughput obtained using FSA, *long term DSA* and *short term DSA* for two T_{alloc} values. P_{thrs} is set to 20%.

The spectrum saving in DSA and the gain in reward with respect to FSA, is obtained at the price of the reduced mean user throughput. Nevertheless that does not necesserly mean the unsatisfaction of the users in our model, as the gain in the operators rewards include inherently an acceptable level of satisfaction.

As the CAB utilization is not showing a remarkable changes with respect to T_{alloc} (this reflects a fixed spectrum cost situation), and as the mean user throughput slightly decreases with the decrease of T_{alloc}, consequently the obtained reward increases with the increase of T_{alloc}.

From Fig. 6 we can notice that lower blocking probability can be obtained at the price of a reduced reward.

V. Heuristic DSA algorithm

In this section we propose a synthetic DSA policy that takes into consideration: the arrival rates, the number of active users and the blocking probability. In the synthetic algorithm we make use of the steady state analysis, while still taking the number of active users at the allocation instant n_i into consideration. Hereafter, we give the details.

1) We define the *operational arrival rate* $\lambda_{op}(m_i)$ as the maximum arrival rate for which P_b (calculated at the steady state) $< P_{thrs}$ when m_i blocks are assigned to operator i. Note that $\lambda_{op}(m_i) = m_i \lambda_{op}(1)$.
2) On the long term when $T_{alloc} >> T_{call}$, and for a given arrival rate λ_i, the number of blocks to be alloacted (under the blocking probability constraint) to operator i is thus:
$$m_i = \lceil \lambda_i / \lambda_{op}(1) \rceil,$$
because $\lambda_i \leq \lambda_{op}(m_i)$, hence $m_i \leq \lambda_i / \lambda_{op}(1)$.
3) When $T_{alloc} >\sim T_{call}$, we then take into consideration the number of active users at the allocation instant n_i, by defining a dimensioning arrival rate λ_i^{dim}.
Formally, the number of allocated blocks m_i becomes,
$$m_i = \lceil \lambda_i^{dim} / \lambda_{op}(1) \rceil,$$
where λ_i^{dim} is denoted as:
$$\lambda_i^{dim} = \lambda_i + (n_i - \bar{n_i})a,$$
where $\bar{n_i}$ is the mean number of users in the system at $\lambda_{op}(m_i)$ (both calculated at the steady state), and a is a constant set to $\lambda_i/4$ in the rest of the paper. The term $(n_i - \bar{n_i})a$ represents the margin to be added to λ_i in the dimensioning process.
If at the allocation instant, $n_i = 0$ users and $\lambda_i = 0.03$ users/s, the margin equals to -0.028. That gives $m_i = 1$ (no more blocks are needed). However if $n_i = 7$ (the cell is almost in a blocking situation), we add a margin of 0.0545. That gives $m_i = 2$. Note that parameters $\bar{n_i}$ and $\lambda_{op}(1)$ equal to 3.7 users and 0.04 s^{-1} respectively, for the system parameters defined in section III.

4) In case the CAB size does not allow satisfying the blocking proabability condition for both cells, then the CAB is divided equaly between the cells (FSA situation).

A. Results

We give hearafter the results obtained using the proposed heuristic DSA algorithm, and we compare with *long term DSA*, *short term DSA*, and FSA policies. Fig. 7 and Fig. 8 compare the algorithms in terms of: CAB utilization, the blocking probability, the obtained total reward, and the user mean throughput respectively. Both *long term DSA*, and *short term DSA* algorithms are performed with T_{alloc} = 3 sec.

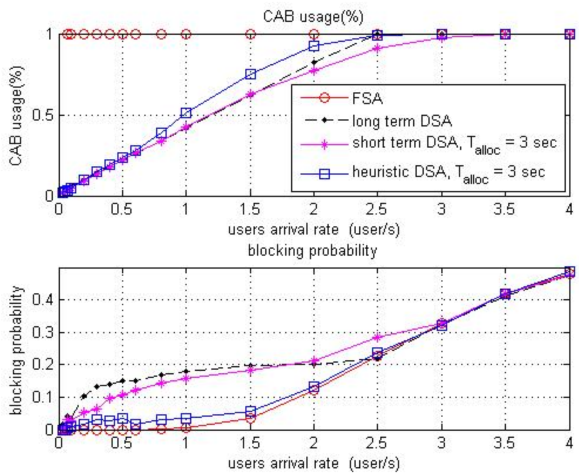

Fig. 7. CAB usage and blocking probability obtained using *long term DSA*, *short term DSA*, heuristic DSA and FSA. T_{alloc} = 3 sec. P_{thrs} is set to 20%.

We can see, the heuristic algorithm gives higher reward than the FSA case for all values of simulated λ. The heuristic algorithm gives also higher reward than the reward obtained using *short term DSA* for arrival rate values $0 < \lambda \leq 0.5$ users/s, while less reward for values $0.5 \leq \lambda < 4$ users/s but still acceptable (higher than the FSA).

The synthetic algorithm uses a bit more spectrum from the CAB than both *long term DSA* and *short term DSA* policies (Fig. 7), consequently the achieved average user throughput is higher (Fig. 8). The synthetic algorithm shows a very close blocking probability behaviour to the FSA case.

VI. Conclusion

In this paper, we have presented and evaluated DSA policies for cellular networks. We have studied a centralized network model where a *meta-operator* shares and controls the spectrum attribution to the operators. The spectrum assignment is performed on periodical basis. We have focused on two main criteria for the designing of DSA algorithms: the total welfare maximization and the blocking probability minimization. We have presented DSA policies based on the knowledge of users arrival rates, and policies based on the knowledge of both arrival rates as well as on the number of active users. All the presented DSA algorithms show to use less spectrum than the FSA case, and achieve higher reward compared to FSA. There is a clear trade-off between the amount of used spectrum, the blocking probability, and the obtained reward. We also presented a DSA heuristic algorithm that gives a very low blocking probability, while saves the spectrum and achieves higher reward than FSA.

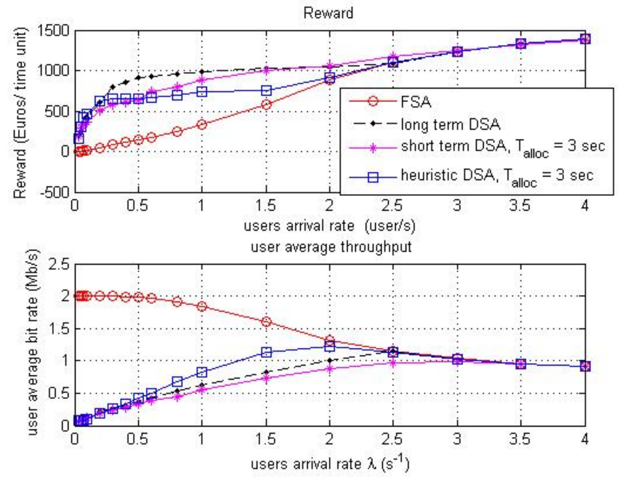

Fig. 8. Total reward and average user throughput using *long term DSA*, *short term DSA*, heuristic DSA and FSA. T_{alloc} = 3 sec. P_{thrs} is set to 20%.

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