Distributed Fair Spectrum Assignment for Large-Scale Wireless DSA Networks

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Abstract. This paper proposes a distributed and fair resource allocation scheme for large-scale wireless dynamic spectrum access networks based on particle filtering theory. We introduce a proportionally fair global objective function to maximize the total network throughput while ensuring fairness among users. We rely on particle filtering theory to enable distributed access and allocation of spectrum resources without compromising the overall achievable throughput. Through intensive simulation, we show that our proposed approach performs well by achieving high overall throughput while also improving fairness between users.

Key words: Particle filtering, dynamic spectrum access, distributed spectrum assignment, user fairness.

1 Introduction

The increasingly growing number of wireless devices, along with the continually rising demand for wireless bandwidth, has created a serious shortage problem in the wireless spectrum supply. This foreseen spectrum shortage is shown to be due to the lack of efficient spectrum allocation and regulation methods rather than due to the scarcity of spectrum resources [1]. As a result, Dynamic Spectrum Access (DSA) has been promoted as a potential candidate for addressing this shortage problem, which essentially allows spectrum users to locate spectrum opportunities and use them efficiently without harming legacy users [2]. Many research attempts have been conducted to enable effective DSA. While many of them have focused on spectrum sensing related challenges, others have focused on developing resource allocation techniques that help access and utilize spectrum resources efficiently [3].

Enabling DSA while maximizing the total throughput has been one of the key challenges for resource allocation in DSA systems [3]. Many researchers have proposed centralized approaches aiming to maximize the total throughput [4]. Although these methods achieve optimal or near-optimal performances, they have limitations when it comes to scalability and computational complexity, especially when applied to large-scale systems. Therefore, distributed approaches are more attractive, and can be more effective when applied to DSA. This is because the decision will be taken locally by each user instead of being taken centrally, making each user send its information to the central agent so as to allow it to make such a decision.

There have been many resource allocation approaches proposed in the literature for enabling distributed DSA [3, 5, 6]. For example, the authors in [6] proposed Q-learning for distributed multiband spectrum access and power allocation. The authors in [7] proposed objective functions that rely on Q-learning to allocate spectrum resources in a distributed manner, where the focus was on the throughput maximization. In [8], particle filtering theory was used also for promoting distributed resource allocation in DSA systems, where it was shown that it can achieve higher throughput than what the technique proposed in [7] achieves when using the same objective functions.

One common concern with most of these distributed approaches is that they aim to increase throughput but without taking into account any fairness consideration. Even though throughput maximization-based approaches maximize the overall network throughput, they may lead to starvation of some Secondary Users (SU)s, resulting thus, in not treating all users equally fairly. This means that some users may get very limited amounts of throughput when compared to others. It is therefore important that fairness should be taken into account when designing these distributed allocation techniques. In the literature, fairness has been proposed with centralized approaches [8–10]. The authors in [8] considered the maximization of the minimum objective function to address user fairness. Although, the proposed objective function achieves better fairness, proportionally fair methods [11] are anticipated to achieve higher fairness. They target to balance between two conflicting behaviors: the cooperative behavior using the sum maximization and the minimum maximization which penalizes the users with high throughput.

With all of this in mind, this paper proposes a distributed allocation technique that jointly combines proportional fairness with particle filtering to assign spectrum in large-scale DSA networks. Since the global spectrum assignment optimization problem suffers from a high computational complexity and does not scale well, our technique aims to achieve suboptimal allocation while ensuring fairness among the different users. Using simulation, we compare the throughput performance of the proposed technique with that of the minimum fairness technique, proposed in [8].

The remainder of this article is organized as follows. In Section 2, we describe our system and channel model. In Section 3, we formulate the resource allocation problem for large-scale DSA systems, and discuss the issues related to the derivation of the optimal solution with respect to the used objective function. We apply particle filtering for distributed spectrum allocation in Section 4. Evaluations are provided in Section 5. Finally, we conclude the paper in Section 6.

2 Large-Scale DSA System Model

We consider a DSA system composed of n DSA agents competing to communicate over m non-overlapping bands, where a DSA agent represents a transmitter-receiver pair of SUs. The n agents are uniformly distributed within a cell where a primary system is communicating as illustrated in Fig. 1. We assume that the m bands have been perfectly sensed and declared as available using spectrum sensing technique (we will not discuss this technique as it is beyond the scope of this paper). As we are considering a large-scale system, the number of users is assumed to be very high compared to the number of the available bands ($n >> m$).

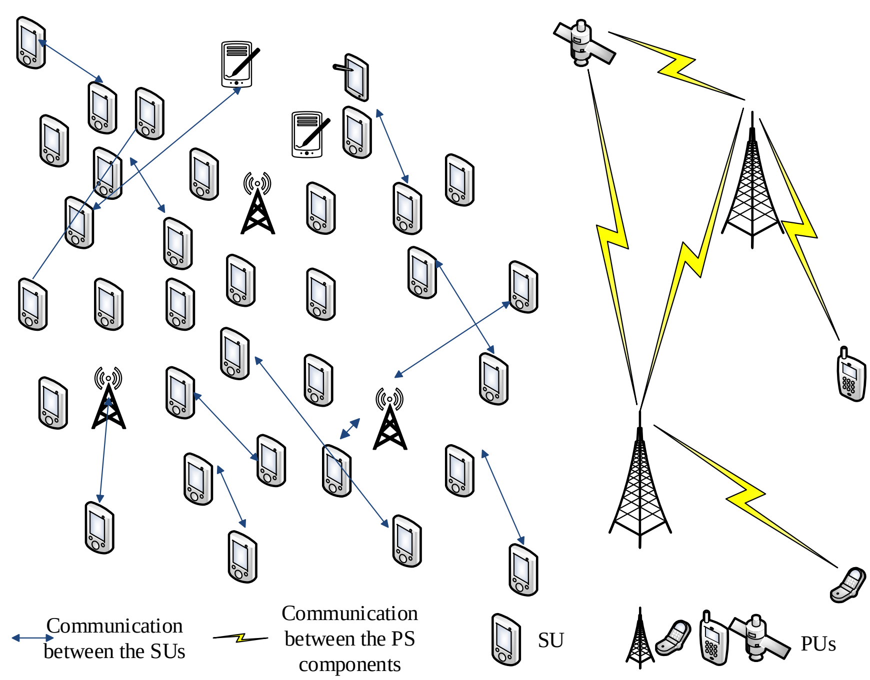

Fig. 1. Large scale DSA system.

At each time slot t, user (agent) i tries to communicate with its correspondent receiver by selecting one band from the pool of the available bands. Each user aims to achieve the maximum possible throughput R_i with respect to its allowed power budget P_i. If we assume that user i selects band j, then the achieved throughput can be expressed as

$$R_i(t) = B^{(j)} \log_2(1 + \gamma_i^{(j)}(t)), \tag{1}$$

where $B^{(j)}$ is the j^{th} channel bandwidth and $\gamma_i^{(j)}(t)$ is the received Signal to Interference plus Noise Ratio (SINR), expressed as

$$\gamma_i^{(j)}(t) = \frac{P_i^{(j)} |h_{ii}^{(j)}(t)|^2}{\sum_{\substack{k=1 \\ k \neq i}}^{n} a_k^{(j)} P_k^{(j)} |h_{ik}^{(j)}(t)|^2 + N_0 B^{(j)}}. \tag{2}$$

Here $h_{ik}^{(j)}(t)$ is the j^{th} channel impulse response from the k^{th} transmitter to the i^{th} receiver, N_0 is the power spectral density of the noise which is assumed to be constant and the same for all spectrum bands, and $a_k^{(j)}$ is the band's selection mapping index. If band j was selected by user k, then $a_k^{(j)} = 1$, otherwise $a_k^{(j)} = 0$.

The channel is modeled as a first order Auto-Regressive (AR(1)) process [12]. Hence, at time slot t, the channel impulse response $h_{ik}^{(j)}(t)$ is given by

$$h_{ik}^{(j)}(t) = \alpha_0 h_{ik}^{(j)}(t - l) + (1 - \alpha_0) w_i^{(j)}(t), \tag{3}$$

where α_0 is the AR parameter expressed as $\alpha_0 = J_0(2\pi f_d T_b)$ with J_0 is the 0^{th} order Bessel function of the first kind, f_d is the maximum Doppler frequency, T_b is the channel coherence time, and $w_i^{(j)}$ is a complex Gaussian noise with zero mean and unit variance.

3 Spectrum Assignment Problem Formulation

The main challenge that we address in this paper is how to assign the available bands among the n users efficiently so as to maximize the per-user achievable throughput while ensuring fairness. Achieving this requires, ideally, collaboration among the different users to gather information at a central unit. It exploits this collected information to make centralized spectrum assignment decisions. Alternatively, and in order to avoid the need for collaboration between users, which often results in an excessive communication overhead, one can rely on users themselves to use local information to make their decisions in a distributed manner. As mentioned earlier, examples of such distributed approaches are learning based approaches, in which users rely on an objective function to maximize their achieved throughput. Authors in [7] showed that while the use of intrinsic objective functions results in fluctuating behaviors, the use of global objective functions, which take into account other users' decisions, though improve the overall system performance, are slow in doing so. The sum objective function is then defined as

$$\mathcal{O}_i^{\text{sum}}(t) = \sum_{k=1}^{n} R_k(t). \tag{4}$$

A common problem with the above functions is that they do not ensure fairness among users. In an attempt to address fairness, using a common global objective function known as bottleneck optimality, *max-min* approach has been proposed in [13] and is expressed as

$$\mathcal{O}_i^{\min}(t) = \min_{1 \le k \le n} \; R_k(t). \tag{5}$$

This objective function is more suitable for users having the same requirements, which is generally not the case in wireless communications. Although max-min solves the problem of starvation, users with high requirements will be penalized while users with low requirements will get more service than what they need. For a more efficient fair allocation, proportional fair [11], is shown to strike a good balance between two conflicting objectives: the maximization of the total throughput and the max-min fairness which may penalize users with high requirements. It is defined as

$$\mathcal{O}_i^{\mathrm{PF}}(t) = \sum_{k=1}^{n} \log_2(R_k(t)). \tag{6}$$

Using the proportional fair global objective function, we formulate our optimization for each user i as follows

$$\max \quad \mathcal{O}_i^{\mathrm{PF}}(t) \qquad \forall\, t \tag{7a}$$

$$\text{s.t.} \quad \sum_{j=1}^{m} a_i^{(j)}(t) = 1 \qquad \forall\, t. \tag{7b}$$

This is a non-linear integer programming problem of the allocation index $\mathbf{a}_i^{(j)}(t) = [a_i^{(1)}(t), a_i^{(1)}(t), ..., a_i^{(m)}(t)]$. The constraint (7b) is used to control the number of the bands that each user could select at each time. This is behind the combinatorial nature of the problem where each user is allowed to select one single band.

Optimally allocating the m bands among the n users requires relaying all the network information such as the channels' fading and the users' power budgets to a central processing unit. By doing so, not only the system suffers from a huge network overhead, but it also incurs high computational processing time. The computational complexity is m^n and thus, it increases exponentially with the network scale. Hence, the allocation problem is NP-hard. Therefore, applying a distributed approach is more appealing to reduce the exchange overhead. In this case, each user has to take its own decision, $\mathbf{a}_i(t)$, and exchange its measured throughput and allocated channel to other users such that the global system evolves towards an optimum spectrum allocation $\mathbf{a}(t)$.

One of our main contribution in this paper is to consider fair distributed resource allocation. To the best of our knowledge, fairness has been addressed with centralized spectrum allocation so far and without any focus on the system scalability [3].

4 Fair Distributed Spectrum Assignment for Large-scale DSA

One key merit that distributed resource allocation schemes possess is low signaling overhead. Local decisions are made following the exchange of some information (e.g. the achieved throughput and the selected band) among users and tracking the system evolution over time. In this context, particle filter based approaches are known to have strong tracking capabilities and can be adapted to non-linear and non-Gaussian estimation problems [14]. However, since the problem of spectrum assignment comes down to an estimation problem, we propose distributed particle filtering to estimate at each time slot the best spectrum allocation that achieves the fairness goal.

The concept of distributed particle filtering is derived from the sequential estimation and importance sampling techniques. Each user needs to interact with some or all other users in order to get the best estimation of the unknown. We model the evolution of the estimation of the best spectrum allocation as a discrete-time state-space model given by

$$\mathbf{a}(t) = \mathcal{X}(\mathbf{a}(t-1)) + \mathbf{u}(t), \tag{8a}$$

$$R_i(t) = \Psi_i(\mathbf{a}(t)) + v_i(t), \tag{8b}$$

where $\mathcal{X}(.)$ is a known function that describes the state's change. $\Psi_i(.)$ is the function that links the global state $\mathbf{a}(t)$ to the local observation $R_i(t)$. It is a non-linear function of the state $\mathbf{a}(t)$. $\mathbf{u}$ and $v_i(t)$ are two stochastic noises of the state and the observation models, respectively. The noises are assumed to be white and independent of the past and the present states. Equation (8a) describes the relation between the state at instants t and $t-1$. Note that $R_i(t)$ is seen as the measurement to be observed locally by user i.

The two equations (8a) and (8b) provide a probabilistic model of our problem formulation. The goal of distributed particle filtering is to get the channel assignment matrix $\mathbf{a}(t)$ sequentially using all the local measurements $R_i(t)$ of all the users i up until the current time t.

Since the channels' fading changes over time for the whole system, this affects the spectrum selection for each user at each time slot. Fortunately, with the presence of an inherent correlation between the channel realizations, the channel state at time t could be estimated from the previous spectrum assignment; i.e., at time $t-1$. We assume that each user relays its band selection, denoted as $\mathbf{a}_i(t) = (a_i^1, ..., a_i^m)$, along with its measured observation, $R_i(t)$, to the other users. This information allows the other users to estimate their best selections during the next time slot. Denoting the other users' band selections by $\mathbf{a}_{-i}(t-1)$, the global function that governs the state change and executed by each user could be expressed as

$$\mathcal{X}(t) = \arg\max_{\mathbf{a}_i(t)} \mathcal{O}_i^{\mathrm{PF}}(t) | \{\mathbf{a}_{-i}(t) = \mathbf{a}_{-i}(t-1), \tilde{h}(t)\}, \tag{9}$$

where $\tilde{h}$ is the estimate of the channel according to (3).

With conventional Bayesian approaches, to estimate $\mathbf{a}(t)$, we should compute the posterior $f(\mathbf{a}(t)|R_{1:n}(0:t))$, where f denotes a probability density function and $R_{1:n}(0:t)$ is the vector that contains the observed throughput from $t'=0$ until $t'=t$. The state can be sequentially estimated in two steps: a prediction phase given by Equation (10a) and an update phase using Equation (10b) [14].

$$f(\mathbf{a}(t)|R_{1:n}(0:t-1)) = \int f(\mathbf{a}(t)|\mathbf{a}(t-1))f(\mathbf{a}(t-1)|R_{1:n}(0:t-1)), \quad (10a)$$

$$f(\mathbf{a}(t)|R_{1:n}(0:t)) = \frac{f(R_{1:n}(t)|\mathbf{a}(t))f(\mathbf{a}(t)|R_{1:n}(0:t-1))}{f(R_{1:n}(t))|R_{1:n}(0:t-1))}. \quad (10b)$$

Although the recursion can simplify the derivation of $f(\mathbf{a}(t)|R_{1:n}(0:t))$, it could not be straightforwardly computed due to the non-linearity and the involvement of an integral quantity.

Particle filtering theory provides an interesting tool to overcome this issue. Instead of computing the posterior $f(\mathbf{a}(t)|R_{1:n}(0:t))$, it is sufficient to consider a large number of samples from this distribution. These samples should be carefully drawn to reflect the original probability density function. Hence, it could be approximated by

$$f(\mathbf{a}(t)|R_{1:n}(0:t)) = \sum_{k=1}^{N_s} w^k(t)\delta(\mathbf{a}(t) - \mathbf{a}^k(t)), \quad (11)$$

where N_s is the number of samples, $\mathbf{a}^k(t)$ is the k^{th} sample and $w^k(t)$ is the correspondent weight. But, since we will apply the particle filter distributively, instead of estimating $\mathbf{a}(t)$, user i estimates only its channel selection $\mathbf{a}_i(t)$ by considering a local density function known as importance density $f(\mathbf{a}_i(t)|R_i(0:t), \mathbf{a}_i(t-1), \mathbf{a}_{-i}(t))$. In this case, the particles, $\mathbf{a}_i^k(t)$, are composed by the other users' selections, $\mathbf{a}_{-i}(t)$, and a possible selection of user i. User i forwards its optimal selection $\mathbf{a}_i(t)$ to the other users to be considered in their particles. Although this importance density is optimal [15], its implementation is challenging, and hence, we instead consider the following

$$\pi(\mathbf{a}_i(t)|\mathbf{a}(t-1)) = f(\mathbf{a}_i(t)|\mathbf{a}^k(t-1), \mathbf{a}_{-i}(t)). \quad (12)$$

The weight at each sample is deduced from the previous weight and by taking into consideration the new observation. From the importance function in (12), it follows that

$$w_i^k(t) = w_i^k(t-1)f(R_i(t)|\mathbf{a}^k). \quad (13)$$

These weights are then normalized.

Over time, the weights of the different particles at each user become negligible, i.e., $w_i^k(t) \approx 0 \ \forall\ k$ except for a few particles whose weights become very large. This problem is often known as the *samples degeneracy*. This implies that huge computations will be dedicated to update particles with very minor contributions. The idea of re-sampling is to make the particles with large weights more dominant while rejecting the particles with small weights [16]. This results in Algorithm 1.

Algorithm 1 Distributed particle filtering for fair spectrum assignment in large-scale DSA systems.

INPUT: The available bands: m.
OUTPUT: The assigned spectrum for each user: $\{\mathbf{a}_i\}_{1\leq i\leq n}$

Initialization At the first time slot $t = 0$
for all DSA user i **do**
– Generate random samples of the possible channel assignment $\{\mathbf{a}_i^k(0)\}_{k=1}^{N_s}$;
– Set the weights to be equal $\{w_i^k\}_{k=1}^{N_s} = \frac{1}{N_s}$;
– Select the best band;
– Exchange the received throughput and the selected band with other users;
end for
for all time slot t **do**
for all DSA user i **do**
1. **Prediction:** Compute possible particles using (12);
2. **Decision:** Select the band of the particle giving the highest reward;
3. Start the transmission on the selected bands;
4. Update the channels estimation;
5. **Weighting:** Compute possible particles using (13);
6. **Normalizing the weight:**
7. **Re-sampling:** Apply re-sampling to avoid degeneracy;
8. Exchange the received throughput and the selected band;

end for
end for

5 Simulation results

We consider a DSA system with $n = 100$ agents communicating over $m = 10$ bands. We assume that at the beginning of each time episode, the sensing process is performed and the available bands are determined. The channels between the transmitter and its correspondent receiver as well as the other receivers are assumed to be Rayleigh fading channels with an average channel gain $\left[\frac{d}{d_{ki}}\right]^{\eta}$ where $d = 1Km$ is a reference distance, d_{ki} is the distance between the i^{th} transmitter and the k^{th} receiver and η is the path-loss exponent that is set to 3. We set the average gain of the direct channel link to be 3 dB stronger than the average gains of the interference channels. The number of particles at each user is set to $N_s = 20$ particles. We assume that each user uses an elastic traffic model [6]. In this model, each user i has its own throughput requirement threshold, $R_i^{\text{th}}(t)$, which is uniformly distributed in the interval $[0, 10kbit/s]$. The power budget for all the users is set to $4dBm$. We rely on this model to allow each user to specify its own QoS requirements, which can be different across different users. Hence, instead of considering $R_i(t)$ in the observation, we consider the reward $r_i(R_i(t))$ that follows the elastic model.

To study the performance of our scheme, we investigate the per-agent achieved throughput at each time slot. Fig. 2 shows that the distributed particle filtering approach achieves better per-agent throughput, on the average, when compared to the minimum throughput approach. This could be explained by the fact that the minimum scheme tends to penalize the users with good channels at the expense of favoring those users with poor channels to achieve the same level of throughput. On the other hand, the sum objective approach achieves, as expected, the highest throughput among the other approaches.

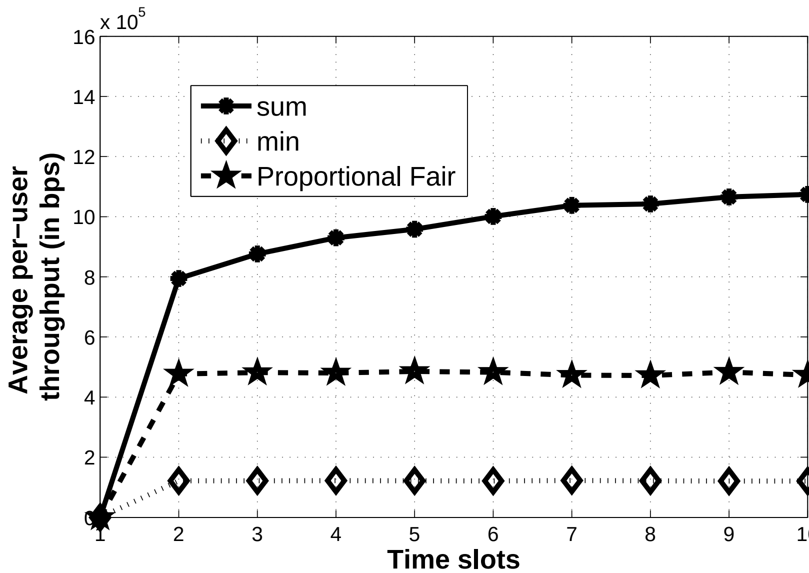

Fig. 2. Achievable throughput under the studied schemes: sum throughput, minimum throughput, and the proportional fairness.

Now, in order to evaluate the fairness of the proposed distributed approach, we use and measure the Jain's fairness index [17], defined in Eq. (14), under each of the studied approaches, and compare that achieved under our scheme with those achieved under the other ones.

$$J(t) = \frac{\left(\sum_{i=1}^{n} R_i(t)\right)^2}{n\sum_{i=1}^{n} R_i^2(t)}. \tag{14}$$

In Fig. 3, we plot the Jain's index $J(t)$. We first notice that our proposed fair distributed approach achieves better fairness than the two other approaches. The total sum throughput has the lowest fairness index since the objective is to select the best channels that allow to reach the highest total throughput rather than accounting for every user's satisfaction. Recalling Fig. 2, we conclude that ensuring fairness comes at the expense of lowering the total throughput that the network as a whole can achieve. The figure also illustrates that our approach outperforms the minimum fairness when different users have different QoS requirements. Although the latter achieves better fairness performance when users have the same requirements, for non-homogeneous environment, our approach is more suitable.

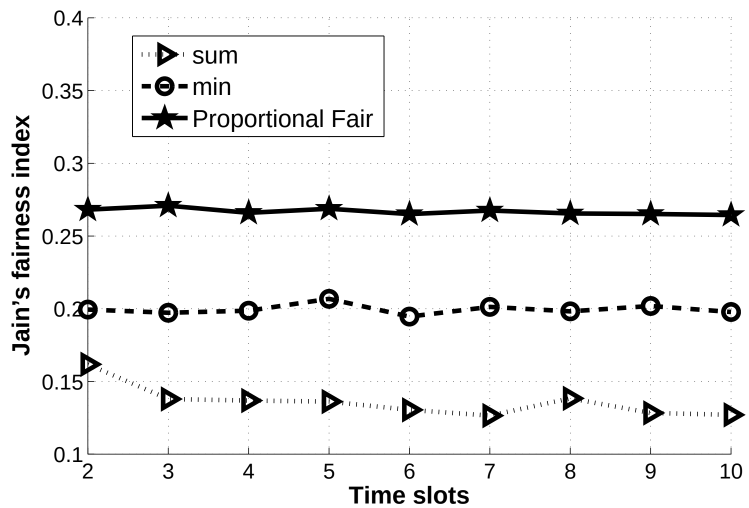

Fig. 3. Achievable Jain's fairness index under the studied schemes: sum throughput, minimum throughput, and the proportional fairness.

For completeness, we also show in Fig. 4 the achievable Jain's fairness indexes under different numbers of available bands.

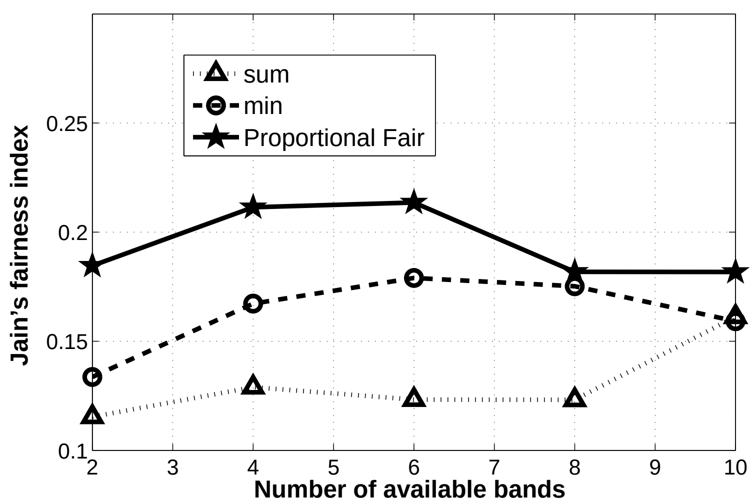

Fig. 4. Achievable Jain's fairness index when varying the number of bands.

6 Conclusions

This paper proposes a particle filtering-based technique for fair and distributed spectrum allocation in large-scale DSA systems. When compared with other approaches, the technique is shown to ensure the best fairness among users while still achieving a reasonably high network throughput.

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