Large Scale Cognitive Cellular Systems: Resource Management Overview

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Abstract

This paper presents recent advancements in resource management for large-scale DSA Systems. Although the problem of spectrum and power allocation is well addressed in the literature, the need for more efficient algorithms still persists due to the exponential growth of the number of wireless devices. Thus, developing efficient distributed approaches became an attractive solution that can follow the systems' rapid growth. Despite the number of economic-driven methods that were presented such as game theoretic solutions, these methods still rely on excessive information exchange, which results in high delays. Inspired from the success of behavioral techniques, mainly learning and filtering approaches, applications of these techniques to spectrum management have attracted more interest due to their distributivity and minimal requirements of information exchange.

I. Introduction

The unprecedented growth witnessed by wireless communication systems over the past decade has brought to light new concerns about the spectrum capability to handle the dramatic increase of the number of wireless devices. This was supported by a common belief that the spectrum has become overcrowded or even running out of space. However, various spectrum measurement studies have shown that the problem is mainly due to lack of efficiency in the spectrum utilization rather than due to scarcity of resources. Therefore, it is anticipated that by enhancing the awareness of wireless terminals about their surrounding environments, the spectrum efficiency could be enhanced remarkably. This is the core idea of Cognitive Radio (CR) which has emerged as a potential candidate for enabling Dynamic Spectrum Access (DSA) [1].

Conventionally, the different portions of the spectrum are allocated using a static manner to specified applications regardless of the activity of users within that system. With the current growth in mobile communication systems, a spectrum shortage is expected. However, in some applications, the spectrum is heavily under-used. The DSA will allow to opportunistically take advantage of the temporary unused portions left in these applications to cover up the shortage of the spectrum resources in other applications (cellular communication systems for example) or even to allow the coexistence of other applications. Hence, within the same portion of the spectrum, two systems with two levels of priority can coexist; a Primary System (PS) with the highest priority to access the spectrum, and a Secondary System (SS) with a lower level of priority to access the spectrum under certain constraints to protect the primary system privileges.

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The main objective with DSA systems is to optimize the performance of the SS while protecting the quality of service of the PS. To achieve that, the key component to enable efficient DSA is the dynamic spectrum management. It is responsible for 1) the awareness of the activity of the PS users, and 2) the efficient spectrum and power allocation with regards to the target Quality of Service (QoS) at the SS users. This requires that the SS be self-aware, self-adaptive, and self-configurable.

The dynamic spectrum management encompasses four tasks which are spectrum sensing, spectrum decision, spectrum sharing, and spectrum mobility. While spectrum sensing and decision are devoted to the identification of the portions of the spectrum that the SS will access with regards to various factors, the spectrum sharing and mobility are dedicated to the access and the seamless communication in the selected portions of the spectrum. Although these tasks have been intensively investigated in the literature [2], the need for efficient algorithms still persists with the growing density of users.

This article provides an overview of DSA systems, the dynamic spectrum management task and the current emerging challenges related to resource allocation in DSA systems. Particularly, we focus on the developed algorithms for the spectrum assignment and power allocation with regards to the growing size of the system. An overview of the DSA system and spectrum management functionality is provided. Then, we present a classification of the proposed distributed resource allocation methods along with the emerging challenges pertaining to scalability as well as spectrum and power efficiency.

II. Dynamic Spectrum Access Overview

DSA is envisioned to be the future of the wireless communication networks. It will enable the coexistence of an intelligent license-exempt systems (the SS) alongside with the already existing licensed system (the PS). The users within the SS are known as Secondary Users (SUs), Cognitive Users (CUs), or DSA agents while the users within the PS are referred to as Primary Users (PUs). The PUs are allowed to access the spectrum whenever they want without being aware of the presence of the SUs. However, the SUs should take into account the activity of the PUs. To do so, an SU should have adequate capabilities of being self-aware and self-adaptive to exploit efficiently the available opportunities in time, frequency, and space.

Based on how the SS will behave in the presence of a PS, three access paradigms, as shown in Fig. 1, have been intensively discussed in the literature [3].

1) **Spectrum Interweave**: In this scenario, the SU avoids harming the PS with interference by only transmitting over a band if it is non-used. No collaboration in this scenario is needed. This access model attracted a lot of interest from the research community as well as regulators and standardization communities and even found its way into practical implementation in different standards (802.22 for WRAN, $802.11af$, etc.).
2) **Spectrum Overlay**: In this scenario, there is a close collaboration between the PS and the SS, where the SS will help the PS transmit its data and at the same time profit from it by transmitting its own data while mitigating the interference that may bother the PS communication. However, security issues may arise with the adoption of this model since a share of the code-books or even the whole messages of the PS is required.
3) **Spectrum Underlay**: This paradigm is known as interference control. The SS uses a transmit power control to keep the resultant interference below a given threshold that guarantees a minimum QoS for the PS. Although in this scenario the SS could access the spectrum at any time using any band anywhere, the challenge is how to accurately estimate the

channel between the PS and the SS to limit the resultant interference.

In all the proposed models, the more the SS gets awareness about the PS, the better it achieves its targeted throughput. On the other hand, this results in more complex problems to be solved in addition to the security issues that arise due to this information sharing. In this article, we focus mostly on the spectrum interweave scenario as it is less harming to the PS and needs less collaboration from the PUs as shown in Fig. 1 and Fig. 2. Hence, a DSA will refer to the cognitive system using this model. The mechanism that will allow the SS to identify the spectrum opportunities, the coordination between the different users, and the seamlessness of the communication is the dynamic spectrum management. In what follows, we address the spectrum management functionality and emphasize its importance in DSA.

III. Resource Management for DSA Systems

A. Spectrum Management in DSA

Spectrum management represents the core of DSA. It encompasses all the tasks that will allow DSA users to identify the portions of the spectrum left temporarily by the PS, usually called spectrum holes. Furthermore, it controls the access of these bands by the different users of the DSA system as well as the coordination between them to avoid any collisions between them. Moreover, it takes into account the required QoS at the DSA agents and ensures their seamless communication. It could be performed either by a central unit called a Central Spectrum Manager (CSM) or distributively where each user will play the role of the spectrum manager. There are four vital tasks in spectrum management: spectrum sensing, spectrum decision, spectrum sharing and spectrum mobility.

In the spectrum sensing, the DSA system senses the different portions of the spectrum to detect whether there is an activity of the PS or not. Various methods have been proposed in the literature and classified over various criteria including individual or cooperative, simple or sophisticated, centralized or distributed, single band or multiband [4], [5].

In the spectrum decision, based on the measurements made in spectrum sensing, the DSA system decides on the occupancy of the spectrum. This is the most critical task in spectrum management as it could result in a false alarm or miss-detection scenarios. In fact, if the DSA declares the band as vacant while a primary user is present and active, a mutual interference will harm both systems. In the other case, if there is no primary activity but the SS declares the band as occupied, one can miss the opportunity to take advantage of that available slot which will reduce the system's performance in terms of spectrum efficiency.

In the spectrum sharing, the task consists of controlling the access of the spectrum and the coordination between the different secondary users while accessing the spectrum [6]. The importance of spectrum sharing is the efficient assignment of the spectrum among the users. The objective is to minimize the interference between users and to take into account their requirements in terms of QoS.

The final task is spectrum mobility which aims at supervising the activity of the PS while the SS is accessing the spectrum. In fact, since the PS has the priority to access the spectrum, it is the responsibility of the SS to detect when a PU is back to use the channel. In such a situation, the SS must switch to another band, stop, or reduce the communication in that band in order to give priority to PUs.

In Fig. 2, we present the different spectrum management phases for a DSA system, depending on the used CR paradigm.

B. Spectrum Management Challenges in Large Scale Systems

Conventionally, the spectrum sharing and mobility tasks have attracted less research interest compared to spectrum sensing and decision in DSA systems. This is because it was thought that once the spectrum was declared unused, conventional access techniques could be employed. However, a particular attention has recently been paid to spectrum and resource allocation, driven by the exponential increase of the number of wireless devices. Therefore, large-scale or dense DSA systems are more probable to take place. Such systems will be characterized by a very high number of users but on the other hand a very limited number of available bands. This requires the development of efficient algorithms that account for the system scalability. Hence, sharing the bands is a required solution but controlling the resultant interference represents a real challenge.

The spectrum management process with regards to the large-scale component is anticipated to be different. Conventional spectrum management processes are performed with a centralized manner. However, relying on a CSM makes the resource allocation problem computationally complex and difficult to solve in a relatively acceptable time for practical implementations. The authors in [7] showed that the problem of spectrum and modulation allocation is a non-linear integer programming problem. Hence, the solution is to use a heuristic algorithm that allows to achieve a close-optimal solution with a polynomial complexity. By doing so, the processing delay is minimized but the problem of overhead still persists. This may cause a non-acceptable delay which affects the scalability of the system. Decentralized resource allocation is more attractive from this perspective. The decision would be taken locally by each user by exchanging some information with the DSA system.

Moreover, the heterogeneity of users and services in terms of QoS requirements combined with the scarcity of resources adds one more component in the resource allocation problem [8]. The DSA system should be QoS-aware such that the DSA agents that need higher levels of QoS are prioritized in the allocation of the "best" bands. On the contrary, a DSA agent with low QoS requirements is accommodated bands with weaker channel gains. On the other hand, although the detection of primary user activity is part of the spectrum sensing and decision tasks, it is important to consider that in the process of resource allocation. In fact, if an SU with high QoS requirements is transmitting in a band and the primary user took it back, the SU should be switched to another band that allows it to achieve its required QoS level.

Power consumption is another critical resource in wireless communications which attracts continuous attention since the emergence of the concept of green communications [9]. The power allocation should be optimized for economic and environmental concerns. Hence, the power should be optimized locally such that it allows to reach the target throughput without inducing a non acceptable interference. This helps reducing the effect on the environment as well as the power cost of the global system.

In the following sections, we provide a classification of the already proposed methods that have addressed the problem of resource management in DSA.

IV. EFFICIENT RESOURCE MANAGEMENT

The problem of resource management is the most critical task in wireless communication systems in general and in DSA systems in particular. At this level, we denote by spectrum management only the two tasks of spectrum sharing and spectrum mobility. Broadly speaking, these methods could be classified into centralized and distributed resource spectrum management techniques from a network architecture perspective.

A. *Centralized Approaches*

Based on the primary user behavior, centralized approaches fit the case where the PS activities in the channel do not change constantly. This is the case of accessing the TV white bands, also called spectrum holes, in IEEE 802.22. To do so, after deciding on the available bandwidth, the CSM devotes a part of the spectrum to each DSA agent. For a successful resource allocation scheme, the CSM should perform the following:

(a) The CSM acquires a full knowledge about all the channel gains between the different users and their target throughput as well as their constraints. This could be done using a dedicated control channel.

(b) The CSM coordinates between the different users to avoid harming each other with interference.

(c) The CSM controls the PS activity to keep the secondary users enjoying transmitting without sadden interruption.

(d) The CSM should employ an intelligent and efficient algorithm that succeeds to allocate the resources to the different users within the system in a relatively short time.

(e) There should be a back-up scenario in case of failure or an immediate vacation of the channel.

1) Optimal Approaches for Resource Allocation: In optimal resource allocation, the CSM succeeds to allocate efficiently the spectrum and the power for each user. This could be done for relatively small-networks where the variability of the channels within the system is small compared to the data processing at the CSM. Integer non-linear programming tools are used for solving the joint spectrum and bit allocation with DSA systems [10]. However, if the network population increases, the algorithm suffers from the exponential-increase of the computational time. Hence, sub-optimal approaches become more attractive.

2) Heuristic Approaches for Resource Allocation: Due the inconvenience of optimal approaches for large-scale systems with regards to the computational time, heuristic approaches are more attractive. In [7], the authors considered evolutionary algorithms for an orthogonal frequency-division multiplexing (OFDM) DSA system when trying to minimize the total power consumption. The authors considered a system where the available portions of the spectrum are accessed using OFDM. The CSM jointly allocates the sub-carriers and the bit modulation among the different users. The primary user activity has been also taken into account where at each time episode some bands may be occupied with the PU and leave in the next episode. This will press to consider the re-allocation at each episode. Since the optimal problem is NP-hard, the authors employed evolutionary algorithms to solve the problem sub-optimally. The Genetic algorithm (GA), considered as a heuristic algorithm, was employed by taking advantage of the mutation and crossover to prevent the local optima and thus reach the global optimal in a finite number of iterations. A second method that has been applied to solve the allocation problem is the "ant colony" optimization. It is inspired from the way ants find the optimal path between the food and their nest where the shortest path is identified based on an amount of hormone. When applied to DSA, the vertices model the bands while the edges represent the combination between the users and the modulation levels. Thus, modeling the fact that at each sub-carrier different modulation schemes could be used, at each vertex different edges are issued from. The ant colony optimization was shown to achieve near-optimal performance in terms of power saving compared to the optimal solution and better performance when compared to the genetic algorithm.

B. Decentralized Approaches

Although heuristic approaches could solve the computational complexity in a centralized resource allocation problem, the whole system suffers from scalability issues. In fact, the system is subject to a large amount of signaling overhead to ensure the coordination and the control of the communication between the different users. This results in a high delay which is not inline with the real-time characteristic of DSA (it was envisioned to exploit the instantaneous non-used portions of the spectrum) [11]. Although the use of hierarchical structure (clustering) may improve the scalability issue of the centralized approach, the need for more efficient structure that supports real-time implementation is more pressing. Relying on a distributed DSA structure was seen as the solution to the scalability issue by taking advantage of more cognition.

The employed methods for resource allocation in DSA with a decentralized manner are mainly based on economic or heuristic approaches.

1) Economic-Based Approaches: Although economic approaches could be considered as centralized approaches [12], they attracted more attention in solving distributed resource management problems. The authors in [11] presented game theory as a powerful tool to analytically deal with decentralized spectrum allocation. It is a class of optimization techniques useful for solving optimization problems with conflicting resources. The basic concept is to find the best strategy for each player in order to maximize a given payoff. When considering DSA systems, it could be employed at different levels of the network where at each time the players could model a particular entity of the network [12]. Game theory could model the negotiation or the cooperation between the decision makers to solve the problem of resource management at the highest level between the SS and the PS. In the context of a large DSA system, the players could represent the DSA agents (the pair of a transmitter and its corresponding receiver) in their competition between each other for the available resource or even the competition when accessing the spectrum using the underlay approach with the primary users. The strategy represents the set of bands that will be selected while the payoff may differ according to the context but could be taken as the achieved throughput or the energy efficiency in some contexts.

The major limitation of game theoretic approaches is that an exchange of information between users is still needed, even if it is minimal. For instance, each user should know the cost function (payoff) of the other players which is, from a practical perspective, very difficult to acquire unless if a control channel is dedicated for this information exchange. Hence, we focus next on approaches that need limited feedback from the network.

2) Heuristic-Based Approaches: Learning- and filtering-based approaches have great potential for enabling efficient resource management in large-scale DSA systems.

a) Reinforcement learning: Reinforcement Learning could be formulated as a class of Markov Decision Problems where a given number of agents try to learn from their environment based on their taken actions. The agent, based on the set of actions that could be taken, visits a given number of states and computes the associated reward. The objective at the end is to select the appropriate action that maximizes the accumulated reward. This accumulated value of reward is the combination of the past accumulated rewards (exploitation) and the future received reward (exploration). When applied in the context of spectrum management in large-scale DSA, each DSA agent selects the best channel bands that allows it to receive the highest accumulated reward. For instance, Q-leaning has been applied to promote efficient spectrum allocation targeting the maximization of the per-agent reward [13]. Specifically, in these works, efficient objective functions have been designed, depending on the traffic model, and shown to achieve high performance in terms of scalability and learnability in addition to guaranteeing a distributed implementation. In Fig. 3, we detail the main steps of the Q-learning method when employed for resource allocation in DSA systems.

Although this method is very simple to apply with limited complexity, it may suffer from some inconvenience with fast time-varying channels. In fact, for a given channel state, the performance of the learning could be efficient if all the states have been explored. However, if the channels vary rapidly with time, this will deteriorate the learnability of the approach as the perceived reward for a given state will change with time. Hence, this method is very effective with quasi-static or slow varying channels only.

b) Filtering: Filtering-based algorithms could be very useful for addressing the limitations pertaining to the varying nature of the channels thanks to their tracking capabilities. In [14], Extended Kalman Filtering (EKF), which is a derivative of the Kalman filtering adapted to non-linear scenarios, have been applied for the tracking of the transmission power and the channel variations distributively. However, in general, Kalman filtering and its derivatives fail to reach acceptable performance especially with non-Gaussian noise. The estimation may suffer from large biases, convergence, or lack of robustness. Particle Filtering (PF) emerges as a key candidate to overcome these deficiencies.

The PF algorithm includes three main steps as shown in Fig. 4: i) generating the particles according to a given importance density, ii) weighing the particles using current observations and the previous weights, and iii) re-sampling to avoid particles degeneracy: making the particles with large weights more dominant than the ones with small weights. Like Kalman-based filters, two model equations are needed for PF: (i) A state evolution equation to characterize the time evolution of the state. This could be the prediction equation of the channel allocation given the previous allocation from the channel fading temporal correlation. (ii) An observation equation that relates the observation to the state and will be useful in the weighing and re-sampling phases of the filtering algorithm.

PF was applied for distributed resources management for DSA in [15] where each particle represents a possible channel allocation among the users. Hence, each user generates a given number of particles according to a given importance density. The prediction equation of the channel allocation could be derived using the previous allocation and by exploiting the channel fading temporal correlation. For the observation equation, it could model the objective function that each user wants to maximize. For a general setup, joint multiband selection and power allocation could be employed along with the consideration of the primary user's activity.

C. Summary and Comparison

We summarize in Table I the main performance characteristics of the different algorithms.

In Fig. 5, we investigate the achieved reward compared to the case when Q-learning is employed. This figure shows the efficiency of the filter-based approach to follow channel variations and better allocate channels to optimize the performance in a changing environment.

V. Future Research Directions

Even though spectrum management in large-scale DSA systems is a well investigated subject, efficient spectrum assignment and power allocation are still needed. It is very important to consider a holistic framework where all the components of the DSA system are taken into consideration which, despite the ever growing literature discussing DSA, is still missing. In the following, we present some of the directions that need further research investigation in order to enhance the performance of resource management of DSA systems:

- *Traffic prediction models:* The system should use traffic prediction models to anticipate the network traffic. In particular, predicting the primary users' activity is an important information for the resource management to have an advance knowledge of the channels' occupancy.
- *Users' interactions in a distributed model:* Even though a distributed model is adopted, a resource allocation system may require the presence of a permanent channel to ensure communication success and prevent other users from interfering with the PS. Some issues about the identification of the opportunities in the spectrum have already been addressed using cooperative communication (trade-off between sensing complexity and sensing time reporting should be carefully addressed).
- *Channels variability:* Channels variability represents a real challenge. Re-doing the allocation at each channel variation may not be efficient especially in fast changing environments. Tracking techniques offer a faster adaptation capability but modeling the channels' variations is a persistent problem. Developing efficient prediction models for the channels' variations will allow to enhance resource allocation through better prediction of suitable resource allocations. It can be employed either in learning or filtering techniques.
- *QoS awareness:* Spectrum resource assignment should not account only for the user's absolute satisfaction. If a user gets resources that exceed its requirements in terms of QoS, switching to another band or reducing allocated power may leave some resources to other users with higher requirements. The challenge resides in designing efficient utility functions that allow obtaining optimal performance with regards to requirements.
- *Scalability:* Not only do scalable protocols allow to handle large systems in an acceptable time, but also to efficiently use resources according to the system size. For instance, reducing the exchange data and the processing delays and increasing the re-usability of the bands will allow maximizing the optimization criteria.

VI. Conclusion

This paper presented an overview of the main methods for resource management for large scale DSA systems. Centralized approaches are not adapted for large DSA systems due to their high computational complexity. In distributed approaches, heuristic methods based on behavioral evolution of resource allocation reward represent a promising solution due to their ease of implementation and low requirements in terms of information exchange and ability to track environment changes.

In particular, we compared the learning and particle filtering based DSA algorithms and showed that particle filtering could achieve a better performance in terms of throughput especially in fast changing environments. Research is still open in this direction to propose efficient approaches to predict environment changes based on previous observations notably the primary users' occupancy, the channels' conditions, and other users' behaviors.

VII. Acknowledgment

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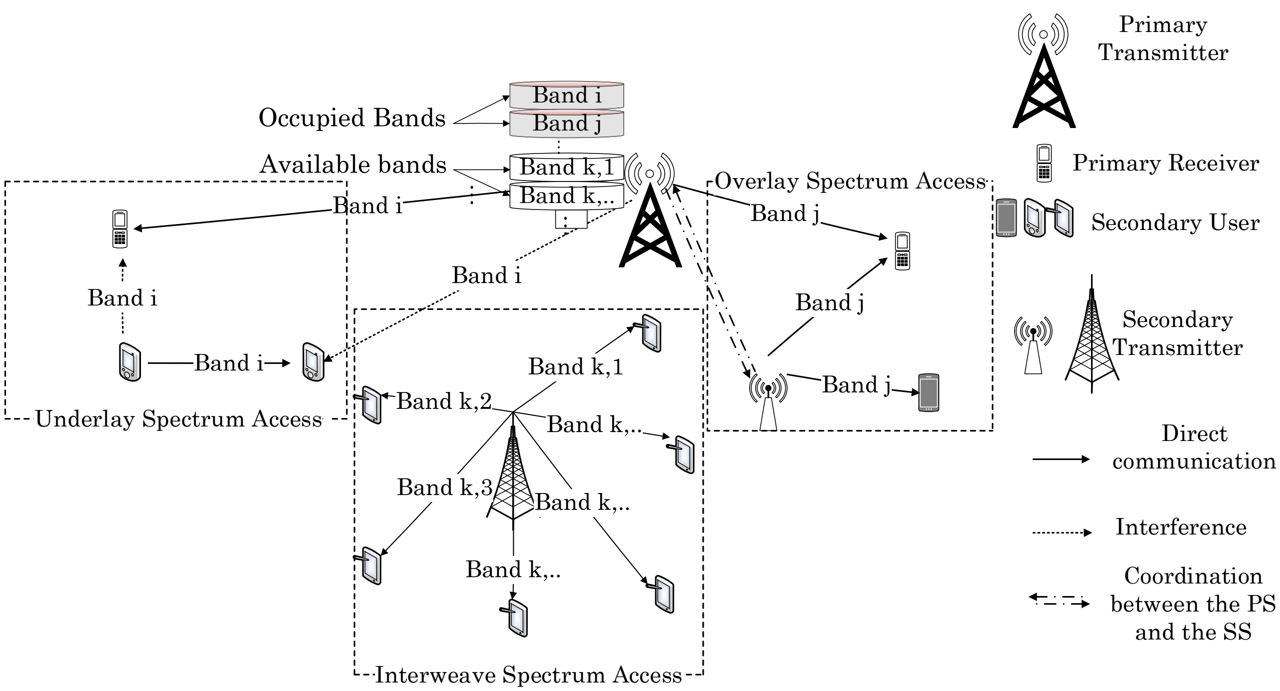

Fig. 1. Large scale DSA system coexisting of a primary system with different spectrum sharing paradigms.

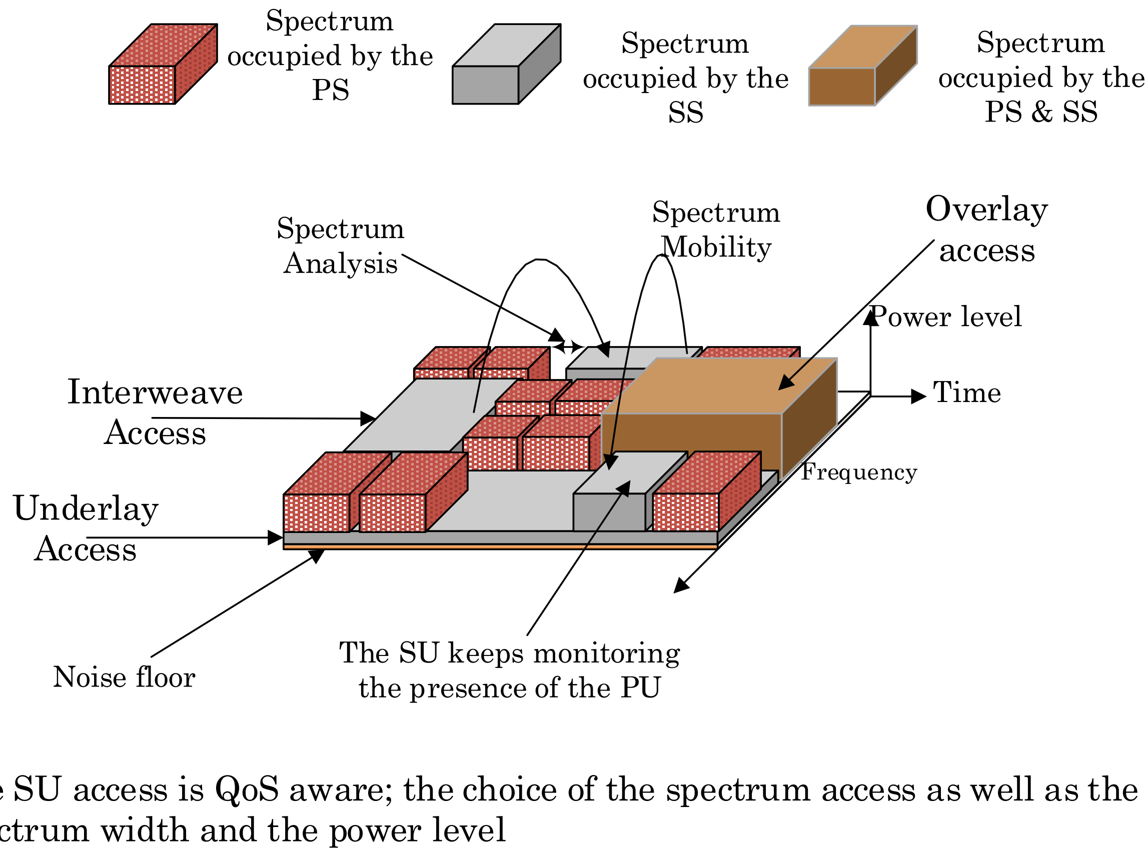

Fig. 2. Spectrum management protocols for DSA systems.

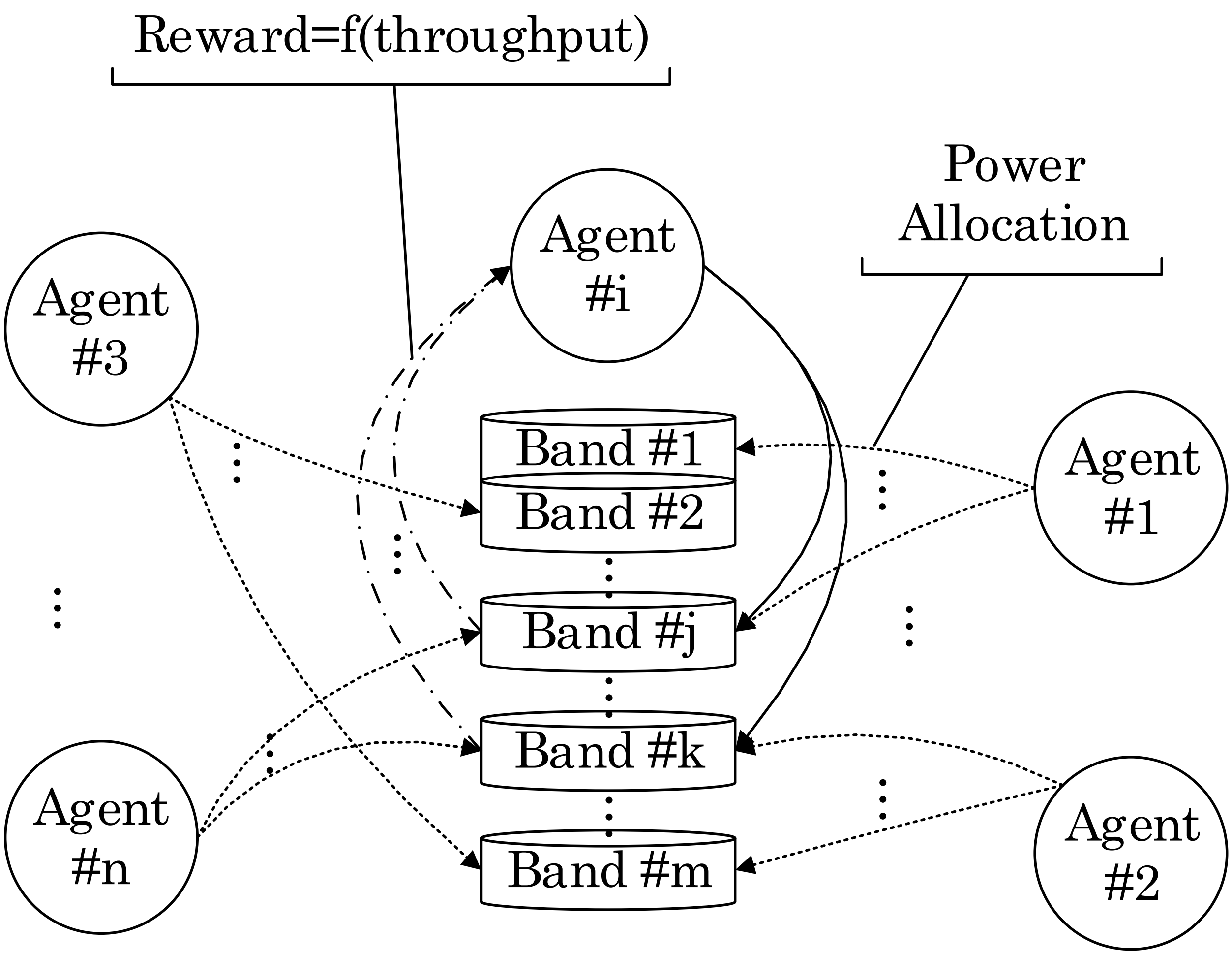

Fig. 3. Q-learning for Large scale DSA.

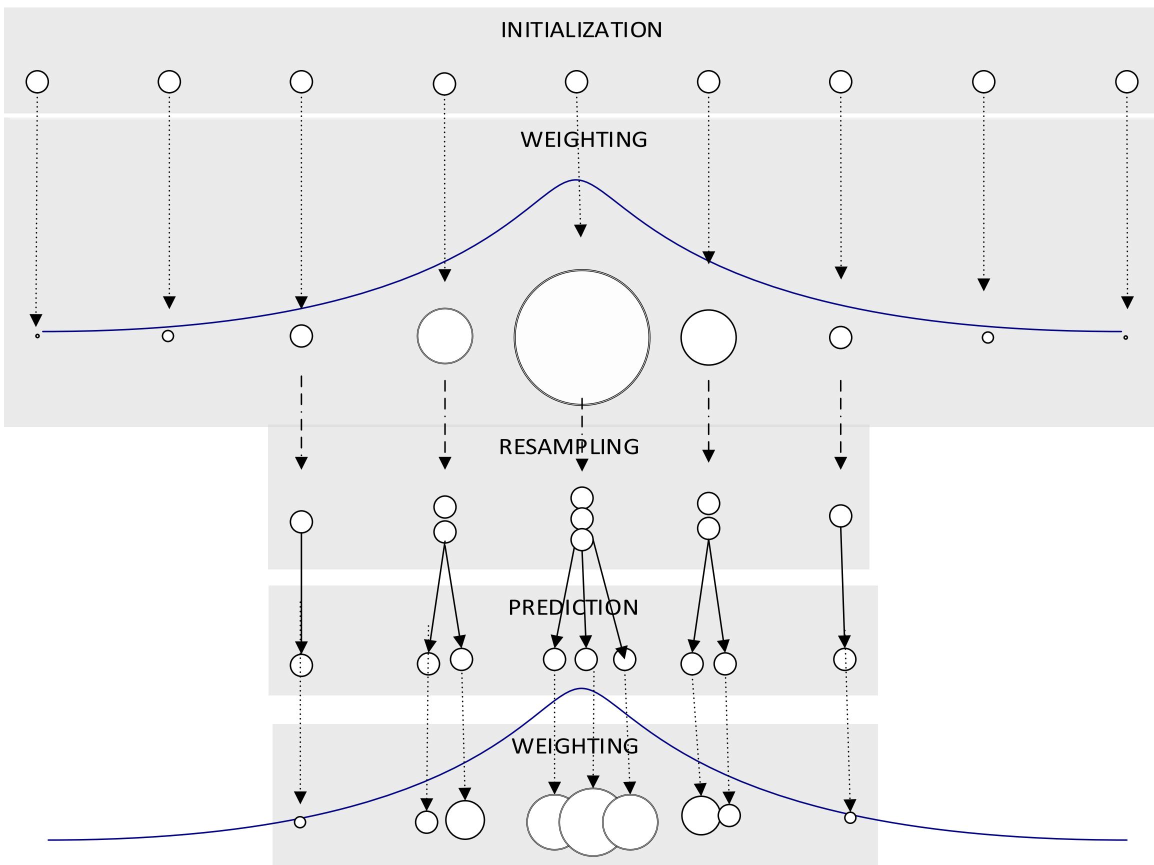

Fig. 4. Particle filter approach for large scale DSA.

TABLE I
CHARACTERISTICS OF SPECTRUM MANAGEMENT APPROACHES FOR DSA SYSTEMS.

Algorithm	Distributive	Optimal	Complexity	Comments
Integer linear programming [10]	No	optimal	exponential	discrete power allocation
Evolutionary algorithms [7]	No	sub-optimal	linear	
Extended-Kalman Filtering [14]	No	close-optimal	linear	valid for Gaussian noise
Game-theoretic methods [11]	Yes	optimal	linear	cooperation needed
Q-learning [13]	Yes	close-optimal	linear	performance's degradation with rapid changing environments
Particle filtering [15]	Yes	close-optimal	linear	complexity proportional to number of particles

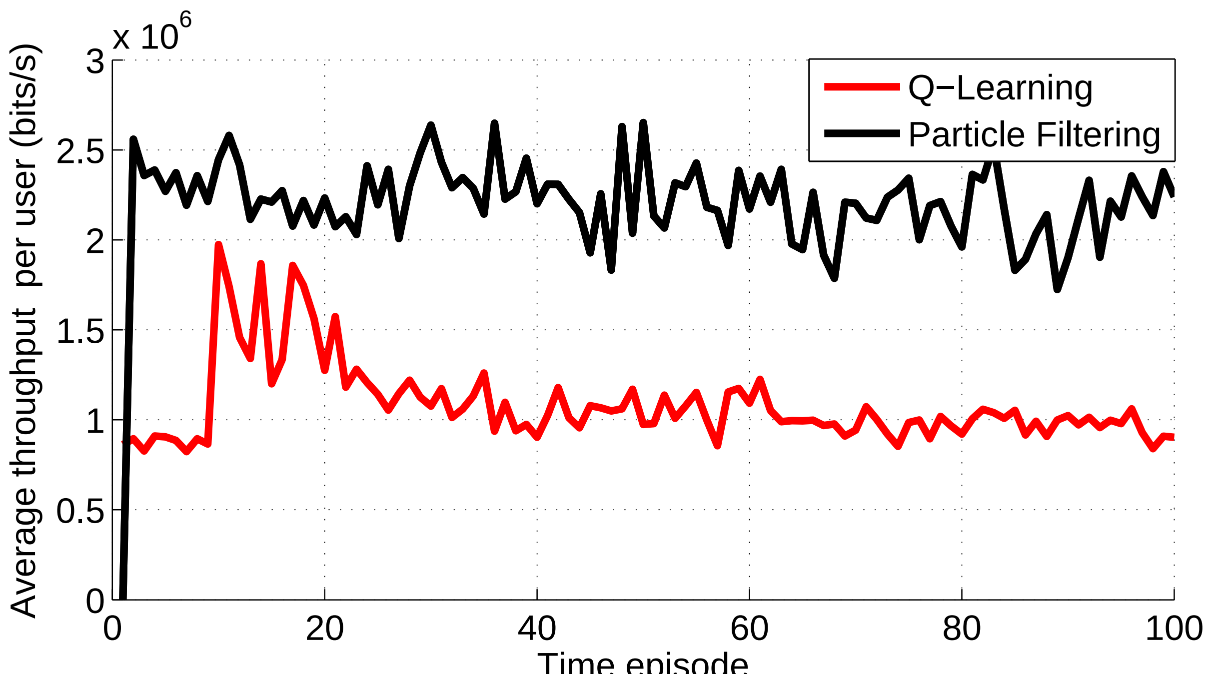

Fig. 5. The achieved per-agent throughput reward with multiband selection, power allocation, and primary user activity: Particle Filtering vs. Q-Learning. The system parameters are: $n = 100$, $m = 11$, $N = 20$ particles, bandwidth 6 MHz, PU's activity in 10% of the bands. Each user could select up to 2 bands.