Game-theoretic Distributed Spectrum Sharing for Wireless Cognitive Networks with Heterogeneous QoS

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***Abstract*— Ubiquitous wireless networking calls for efficient dynamic spectrum allocation (DSA) among heterogeneous users with diverse transmission types and bandwidth demands. To meet user-specific quality-of-service (QoS) requirements, the power and spectrum allocated to each user should lie inside a bounded region in order to be meaningful for the targeted application. Most existing DSA methods aim at enhancing the total system utility. As such, spectrum wastage may arise when the system-wise optimal allocation falls outside the desired region for QoS provisioning. The goal of this paper is to develop QoS-aware distributed DSA schemes using the game-theoretic approach. We derive DSA solutions that respect QoS and avoid naively boosting or sacrificing some users' utilities to maximize the network spectrum utilization. Specifically, we propose two game-theoretic DSA techniques: one resorts to proper scaling of the transmission power according to each user's useful utility range, and the other embeds the QoS factor into the utility function used for dynamic gaming. In addition, we introduce two new metrics to evaluate DSA schemes from a practical QoS perspective, namely "system useful utility" and "fraction of QoS satisfied users." Simulations confirm that the proposed DSA techniques outperform existing game models in terms of spectrum sharing efficiency in heterogeneous networks.**

I. INTRODUCTION

Current wireless networks are characterized by wasteful static spectrum allocation and limited user coordination, resulting in very low efficiency in radio spectrum utilization. The emerging paradigm of dynamic spectrum access (DSA) shows promise in alleviating today's spectrum scarcity problem by ushering in new spectrum agile networks [1], [2]. Equipped with cognitive radios, users in a network can sense and utilize available spectrum opportunistically [1]. In such an open spectrum approach, each user faces intricate tradeoffs between avoiding interference and maximizing spectrum utilization. This challenging DSA issue is further exacerbated in distributed networks where there is little or no central control over the allocation of wireless resources across users.

From an information-theoretic viewpoint, the achievable capacity/utility of a radio is determined by its received signal to interference and noise ratio (SINR) as well as its occupied spectrum bandwidth. In a distributed network, each radio decides on its transmission power and bandwidth based on the sensed radio environment. Its decision not only impacts its own achievable utility, but also affects that of its neighboring radios via negative interference. Hence, radio resource allocation is an interactive decision making process, which can be suitably modeled as a multi-player game. Cognitive radios are game players, each of which takes action on transmission power and spectrum occupancy from the action space consisting of available spectrum and allowable power.

The game theoretic approach has recently attracted increasing attention for the distributed DSA problem [3]-[8]. Some applicable game models are summarized in [3]. For a network of cooperative users, the DSA problem can be modeled as a potential game, whose objective is maximize the total network utility by minimizing the sum of the interference generated by a user and received from its neighbors [4]. A notion of "interference price" is introduced in [6], which reflects interference levels on available channels at different locations. Single-/multi-channel asynchronous distributed pricing (SC-/MC-ADP) algorithms that exchange information on users' interference prices during spectrum sharing are shown to outperform their counterparts ignoring interference prices [5]-[7]. Besides the game theoretic approach, other tools such as the genetic algorithm [8] have also been investigated for the DSA problem.

However, most existing DSA methods aim at enhancing the overall network efficiency, defining the figure of merit to be the total system utility achieved by all users. As such, unbalanced channel allocation is likely to arise, that is, some users gain large portions of the total system utility whereas others get unfairly treated with little spectrum shares. This issue is aggravated in a heterogeneous network consisting of users with diverse application-specific QoS requirements. Based on the existing figure of merit, a naïve DSA scheme might allocate some users with large resources exceeding the needs for their intended low-rate transmissions, while some other users might gain merger capacity below the minimum for successful transmissions. In both cases, the user utility corresponding to its allocated power and spectrum falls outside the acceptable range specified by the user-specific QoS, giving rise to radio resource wastage.

The objective of this paper is to develop distributed DSA solutions that efficiently utilize spectrum with QoS awareness. We introduce QoS information into the game model to avoid spectrum wastage. Specifically, we propose two DSA strategies: the QoS-ps-DSA algorithm performs external power scaling to modify the local decision made by each user in order to meet its QoS, and the QoSe-DSA algorithm embeds the QoS factor into the utility function so as to make QoS-aware decisions during gaming. The interference price concept is also borrowed to construct a secondary local objective for interference management. Simulations confirm that the proposed DSA techniques offer efficient spectrum sharing in heterogeneous networks with QoS constraints.

II. SYSTEM MODEL

We consider a network of spectrum agile users $\mathcal{N}=\{1,\ldots,N\}$ sharing access of K orthogonal channels $\mathcal{K}=\{1,\ldots,K\}$. Each user corresponds to one dedicated pair of transmitting and receiving nodes. Each active transmitter T_i, $1 \le i \le N$, intends to communicate with only one receiver R_i, while its transmission may interfere other receivers tuned to the same channel. The distance between transmitter T_i and receiver R_i is denoted by d_{ij}. The transmission power of each user is constrained within the range $[P_{i\min}, P_{i\max}]$, $0 \le P_{i\min} \le P_{i\max}$, which is determined by the radio design of the transmitter T_i.

Throughout this paper, we consider two DSA problems. The first one targets the single-channel scenario, in which each user can only select and transmit over one channel at a time from the $\mathcal{K}$ available orthogonal channels. The second problem aims at the multi-channel scenario, in which each user can simultaneously transmit over multiple channels.

In our DSA problems, user i allocates power p_i^j for transmission over channel j, while $p_i^j=0$ means that j is not selected. Complying with the total power constraint, we set up a game model by expressing the action space for user i as

$$\mathcal{P}_i = \{\mathbf{p}_i \mid \mathbf{p}_i =< p_i^1, p_i^2, ..., p_i^K >, P_{i\min} \le \sum_{j=1}^{K} p_i^j \le P_{i\max} \wedge p_i^j \ge 0\}, \quad (1)$$

where $\mathbf{p}_i$ is the action vector of user i across all channels. Accordingly, the action vector for all users across all channels is $\mathbf{p}=<\mathbf{p}_1, \mathbf{p}_2, \ldots, \mathbf{p}_N>$. Let $\mathbf{p}^k =< p_1^k, p_2^k, ..., p_N^k >$ denote the power allocations on channel k across all users. The SINR received by user i on channel k is given by

$$\gamma_i^k(\mathbf{p}^k) = \frac{p_i^k \times h_{ii}}{n_0 + \sum_{j \ne i} p_j^k \times h_{ji}}$$

where n_0 is the ambient noise level and h_{ij} is the link gain between T_i and R_j determined by the distance d_{ij} We assume that the background noise level is the same on all channels, and the link gains are static within the transmission period. For each user, we could adopt the total channel capacity gained by this user as its utility function, given by

$$u_{tot-i}(\mathbf{p}) = C_i(\mathbf{p}) = \sum_{k \in \mathcal{K}} \log(1+\gamma_i^k(\mathbf{p}^k)), \ i=1, \ldots, N. \quad (2)$$

Specializing the action space in (1) to the single channel allocation case, we denote $\varphi(i)$ as the channel selection of user i, which takes a single value from channel indices 1 to K. If $\varphi(i) = j$, then $p_i^j \ne 0$, and

$$p_i^l = 0, \forall l \ne j, 1 \le l \le K, \ and \ P_{i\min} \le p_i^j \le P_{i\max}.$$

Accordingly, the utility function in (2) is simplified to

$$u_{tot-i}(\mathbf{p}) = \log(1+\gamma_i^{\varphi(i)}(\mathbf{p}^{\varphi(i)})). \quad (3)$$

From a network perspective, the objective is to determine $\mathbf{p}$ that maximizes the total utility summed over all users, i.e.,

$$\text{P1:} \quad \max_{\{\mathbf{p}\}} u_{tot}(\mathbf{p}) = \sum_{i=1}^{N} u_{tot-i}(\mathbf{p}).$$

This is a centralized non-convex optimization problem subject to scalability issues [5]. We turn to the game theoretic approach to design simple distributed DSA algorithms.

III. SC-ADP AND MC-ADP Algorithms

Our solutions to QoS-aware DSA build upon the single-channel and multi-channel asynchronous distributed pricing algorithms SC-ADP and MC-ADP introduced in [6], [7]. We briefly summarize the results in [6], [7] in this section.

In game-based DSA, each user strives to maximize its own local utility defined by (2) or (3). However, the optimal solution for individual user can deviate from the network-wise optimal solution to problem P1, because individually maximized utility corresponds to increased transmit power, which negatively affects others' utilities by raising interference. To strike a desired tradeoff between individual utility and the negative impact it makes on the system, Huang et al. introduced the notion of "interference price" defined as

$$\pi_i^k = \left| \frac{\partial u_{tot-i}^k(\gamma_i^k(\mathbf{p}_k))}{\partial \sum_{j \ne i} p_j^k \times h_{ji}} \right|, \quad (5)$$

where the derivative operation indicates how much user i's utility $u_{tot-i}^k(\gamma_i^k(\mathbf{p}_k))$ would increase if its received total interference $\sum_{j \ne i} p_j^k h_{ji}$ is decreased by one unit. In the ADP algorithms, users announce their interference prices to all neighboring users. Give the "price rate" information, each user chooses channels and allocates powers to maximize it net benefit, which is defined to the surplus of utility minus interference prices, expressed as a new utility in the form

$$u_{sur-i}(\mathbf{p}_i, \mathbf{p}_{-i}) = \sum_{i=1}^{N} \Big(u_{tot-i}(\mathbf{p}_i, \mathbf{p}_{-i}) - \sum_{k \in \mathcal{K}} (p_i^k \times \sum_{j \ne i} \pi_j^k h_{ij})\Big), \quad (6)$$

where $\mathbf{p}_{-i} =< \mathbf{p}_1, ..., \mathbf{p}_{i-1}, \mathbf{p}_{i+1}, ..., \mathbf{p}_N >$ is $\mathbf{p}$ excluding $\mathbf{p}_i$ of user i.

At each decision making stage of SC-/MC-ADP, user i update its power and channel selections $\mathbf{p}_i$ as follows:

a) selects $\mathbf{p}_i \in \mathcal{P}_i$ to maximize the surplus in (6)
b) updates price information according to (5) and announce to all neighbors

In general, the updates can be asynchronous across users. Users go through a number of decision making stages until reaching steady states, in which case there is no incentive for any user to change its decision. Simulations in [6] show that SC-ADP and MC-ADP outperform other algorithms that do not exchange interference prices, in term of the total system utility achieved by all users. Albeit their high-efficiency in utilizing network spectrum, the ADP algorithms do not take into account of user traffic types and capacity demands, which may lead to performance degradation in heterogeneous networks with critical QoS requirements, as we discuss next.

IV. QoS Supported DSA Solutions

Future wireless networks call for ubiquitous access from heterogeneous users. Users sharing the network resources may have application-specific QoS requirements, which translate into a set of user-specific predefined ranges of the desired rates/utilities $\mathcal{R}_i$: $[R_{i,\min}, R_{i,\max}]$, i=1, …, N. Here $R_{i,\min}$ is the minimum transmission rate required for user i to have a successful transmission, while $R_{i,\max}$ is the maximum rate needed for user i to support its application. For example, multimedia video traffic requires high rates, while voice traffic only needs to acquire relatively low rates from the network. As such, the total system utility used in conventional DSA does not meaningfully describe the practical system utilization efficiency of a heterogeneous network. When QoS is not accounted for, a conventional spectrum allocation solution is subject to the following two degrading issues:

(a) Some user sacrifices its utility to reduce the interference it causes to neighbors. When the utility cannot meet the lower bound $R_{i,\min}$ of its application, a transmission failure arises, and the utility becomes meaningless.

(b) Some user gains more than desired (i.e. maximum $R_{i,\max}$) rate predefined for its QoS. The extra utility gained not only makes no contribution to the user's performance, but also causes unnecessary interference to the network.

Both of the two issues could cause considerable wastage of spectrum resources, from a practical QoS perspective. Indeed, the ADP algorithms are subject to degrading effects caused by these issues, which we elaborate in Section V. Overall, there is a need for new DSA designs that support QoS.

Next, we propose QoS-aware DSA schemes based on the distributed game approach. Our goal is to maximize the meaningful network utility under QoS constraints, taking advantage of the interference suppression capacity of ADP.

A. QoS Provisioning via External Power Scaling

The first DSA scheme we propose resorts to proper scaling of the transmit power level in accordance to the QoS requirements $\mathcal{R}_i$: $[R_{i,\min}, R_{i,\max}]$. At every decision-making stage of the game for user i, we first employ the game approach to make a tentative decision on the action space $\mathbf{p}_i$ defined by power allocation. Depending on whether the resulting utility falls within or outside the desired range $\mathcal{R}_i$, the user decides to retain or adjust the tentative decision. Adjustment is performed by scaling up or down the transmit power level to the closest point within the predefined QoS requirement. Details of the QoS-aware game with power scaling, which we term as *the QoS-ps-DSA algorithm*, are described next for the single-channel and multi-channel cases.

A.1 Single Channel Spectrum Allocation

In single channel spectrum allocation, for user i who selects channel $\varphi(i)$, the resulting utility (3) is an increasing function of power $p_i^{\varphi(i)}$. Thus, in order to scale the utility, we simply need to scale $p_i^{\varphi(i)}$ in the same direction. The following two cases of QoS violation may arise after the local utility optimization step at each decision making stage.

[Case 1] $u_{tot-i}(\gamma_i^{\varphi(i)}(p_i^{\varphi(i)}, \mathbf{p}_{-i})) < R_{i,\min}$

In this case, user i needs to increase its power level to a new level $p_i^{\varphi(i)}{'}$ in order to scale utility up to $R_{i,\min}$, which is the minimum requirement for a success transmission. However, if channel $\varphi(i)$ is of bad quality for user i, it is possible that user i cannot provide QoS at the current stage, even at the maximum transmit power $P_{i,\max}$, i.e., $u_{tot-i}(\gamma_i^{\varphi(i)}(P_{i\max}, \mathbf{p}_{-i})) < R_{i,\min}$. When this situation occurs, user i should avoid transmission by setting $p_i^{\varphi(i)}{'} = P_{i\min}$. Summing up, power scaling is performed as follows:

$$\begin{array}{l} \text{if } u_{tot-i}(\gamma_i^{\varphi(i)}(P_{i\max}, \mathbf{p}_{-i})) < R_{i,\min} \\ \qquad p_i^{\varphi(i)}{'} = P_{i\min} \\ \text{else} \\ \qquad \text{user } i \text{ selects } p_i^{\varphi(i)}{'} \in [\, p_i^{\varphi(i)}, P_{i\max}\,], \\ \qquad\qquad \text{s.t. } u_{tot-i}(\gamma_i^{\varphi(i)}(p_i^{\varphi(i)}{'}, \mathbf{p}_{-i})) = R_{i,\min} \end{array}$$

[Case 2] $u_{tot-i}(\gamma_i^{\varphi(i)}(p_i^{\varphi(i)}, \mathbf{p}_{-i})) > R_{i,\max}$

In this case, user i needs to decrease its power level to scale utility down to $R_{i,\max}$, which is the desired rate for a best transmission, so that it could eliminate the extra power.

$$\begin{array}{l} \text{user } i \text{ selects } p_i^{\varphi(i)}{'} \in [\, P_{i\min}, p_i^{\varphi(i)}\,], \\ \qquad \text{s.t. } u_{tot-i}(\gamma_i^{\varphi(i)}(p_i^{\varphi(i)}{'}, \mathbf{p}_{-i})) = R_{i,\max} \end{array}$$

In both Cases 1 and 2, once the game output $p_i^{\varphi(i)}$ is externally adjusted to the new level $p_i^{\varphi(i)}{'}$ according to QoS, the next stage of game-based decision making starts, until all users reach the steady-state actions/allocations.

A.2. Multiple Channel Spectrum Allocation

In multi-channel spectrum allocation, each user distributes its transmit power over multiple or even all channels. It is quite complex to find an optimal power scaling approach across multiple channels. To simplify the problem, we select only one candidate channel according to some judicious criteria, and perform power scaling on this channel only. Given that the candidate channel has been decided, the same power scaling operation used in the single channel case can be applied, viewing the candidate channel as $\varphi(i)$. The only remaining issue is how to select the candidate channel, which we present in the following two cases.

[Case 3] $\sum_{k\in\mathcal{K}} u_{tot-i}^k(\gamma_i^k(p_i^k, \mathbf{p}_{-i})) < R_{\min}$

When the locally optimized utility is below the lower threshold, user i needs to increase the transmit power on one channel to increase the utility collected from that channel, which in turn raises the interference level to neighbors sharing the same channel. To balance between QoS provisioning and interference alleviation, our objective is select a candidate channel that causes the minimum extra interference due to power up-scaling. To this end, we define the channel selection criterion as follow:

$$\arg\min_{k\in\boldsymbol{\varphi}(i)} \sum_{j\neq i} \pi_j^k h_{ij} \ ,$$

where $\sum_{j\neq i} \pi_j^k h_{ij}$ represents the sum of interference pricing rates that user i would be charged by all other users. Thus, selecting the channel with the lowest sum price can minimize the increased negative influence due to power up-scaling.

[Case 4] $\sum_{k\in\mathcal{K}} u_{tot-i}^k(\gamma_i^k(p_i^k, \mathbf{p}_{-i})) > R_{\max}$

In this case, user i decreases its power on certain channel to get rid of the extra utility that gives rise to unnecessary interference to other users. Following the rationale in Case 3, in this case power down-scaling on the channel with the highest interference pricing rate can maximally reduce the unwarranted interference caused by the extra utility. Thus, we define the channel selection criterion as follow:

$$\arg\max_{k\in\boldsymbol{\varphi}(i)} \sum_{j\neq i} \pi_j^k h_{ij}$$

Both Cases 3 and 4 adopt the power scaling scheme used in the single-channel case to reduce system utility wastage according to user-specific QoS, while the candidate channel is selected optimally by minimizing the negative impact of the interference profile changes incurred by power scaling.

B. QoS Provisioning via QoS-embedded Dynamic Gaming

Besides power scaling, QoS provisioning can be factored into the distributed dynamic gaming process by redefining the utility function of each user. In this section, we propose an alternative QoS-aware DSA scheme that embeds the QoS information $\mathcal{R}_i$: $[R_{i,\min}, R_{i,\max}]$ in the local utility function.

First, we introduce a new figure of merit for evaluating the performance of DSA solutions in heterogeneous networks. Replacing the conventional utility, we define a new metric *useful utility*, which refers to the portion of acquired utility considered to be useful based on QoS criteria. Specifically, if the utility is lower than $R_{i,\min}$, then transmission fails and the useful utility is in fact zero; on the other hand, if the acquired utility exceeds $R_{i,\max}$, then the extra utility does not result in meaningful improvement to user's performance, and the useful utility should be bounded at $R_{i,\max}$. It is only when the utility falls within the QoS range $\mathcal{R}_i$ that it can be fully appreciated by the user, and thus coincides with the useful utility. Summing up, given action $\mathbf{p}$, the *useful utility* $g_{tot-i}(\mathbf{p})$ of user i is related to its total achievable utility in (2) and (3) by

$$g_{tot-i}(\mathbf{p}) = \begin{cases} u_{tot-i}(\mathbf{p}) & R_{i,\min} \le u_{tot-i}(\mathbf{p}) \le R_{i,\max} \\ R_{i,\max} & u_{tot-i}(\mathbf{p}) > R_{i,\max} \\ 0 & u_{tot-i}(\mathbf{p}) < R_{i,\min} \end{cases} \qquad (7)$$

Next, we present a QoS-embedded dynamic gaming scheme for DSA in heterogeneous networks, which we terms as *the QoSe-DSA algorithm*. Following the game-theoretic approach, each user adopts the useful utility in (7) as its local objective, which yields the best action $\mathbf{p}_i$ at each decision-making stage. Respecting the power constraint $[P_{i\min}, P_{i\max}]$, user i's best response to the utility function is

$$\mathcal{B}_i(\mathbf{p}_{-i}) = \begin{cases} \arg\max_{\{\mathbf{p}_i\}} g_{tot-i}(\mathbf{p}_i, \mathbf{p}_{-i}) & \max_{\{\mathbf{p}_i\}} g_{tot-i}(\mathbf{p}_i, \mathbf{p}_{-i}) > 0 \\ P_{i\min} & \max_{\{\mathbf{p}_i\}} g_{tot-i}(\mathbf{p}_i, \mathbf{p}_{-i}) = 0 \end{cases} \qquad (8)$$

The above response reflects two situations that user i could encounter, given fixed actions $\mathbf{p}_{-i}$ from other users. In the first situation, the power range $[P_{i\min}, P_{i\max}]$ covers at least one optimal allocation $\mathbf{p}_i$ that maximizes the useful utility. In the second situation, there does not exist a valid $\mathbf{p}_i$ that satisfies user i's QoS lower bound, in which case user i should transmit at its minimum power $P_{i\min}$. Coming back to the first situation, $\mathcal{B}_i(\mathbf{p}_{-i})$ might consist of multiple alternatives, each of which yields the same best possible useful utility. In this case, we further screen the action space based on the negative impact that each action makes, namely interference. Restating, we select among the multiple alternatives the action that is charged with lowest interference price, refining $\mathcal{B}_i(\mathbf{p}_{-i})$ to

$$\arg\min_{\mathbf{p}_i\in\mathcal{B}_i(\mathbf{p}_{-i})} \sum_{k\in\mathcal{K}} p_{ik} \times \sum_{j\neq i} \pi_{jk} \times h_{ij} \qquad (9)$$

The above QoSe-DSA algorithm applies to both the single- and multi-channel cases. The steps are summarized below.

a)	selects $\mathbf{p}_i \in \mathcal{P}_i$ to maximize the utility function (7) according to (8);
b)	if multiple actions are selected in a) further screen the action set obtained from a) according to (9)
c)	announce updated interference price according to (5)

Comparing ADP with the proposed QoS-ps-DSA and QoSe-DSA algorithms, several remarks are in order.

- The proposed algorithms are QoS-aware by adopting the useful utility rather the conventional utility to reflect each user's local objective. In contrast, ADP's are QoS-blind; as such, the proposed algorithms are more suitable for heterogamous networks with user-specific QoS.
- All algorithms conduct interference management, but in a different manner. The ADP algorithms subtract the interference prices in the utility functions and make decisions based on surplus; in contrast, the proposed QoS-aware algorithms directly use the (useful) utility as its local objective, and resort to interference prices as a

secondary objective only when multiple actions yielding the same utility need to be screened, such as in Case 4 of QoS-ps-DSA and Step 2 of QoSe-DSA.

Intuitively, the network interest in resource utilization efficiency (i.e., maximizing total utility) is directly reflected in the local objectives of our QoS-aware algorithms, and is only indirectly reflected in the surplus used in ADP. As such, we expect our proposed algorithms to outperform ADP under QoS constraints, which we will testify via simulations next.

V. NUMERICAL RESULTS

This section presents numerical results that illustrate the performance of QoS-aware DSA solutions, with reference to ADP algorithms that are QoS-blind. In all tests, we set $n_0 = 10^{-2}$, $h_{ij} = d_{ij}^{-4}$, and the feasible power range for each user is $[P_{i\min}, P_{i\max}]$ = [0, 200] for any i. A number of K channels are available, each having the same bandwidth of 1 unit. A number of N transmitters are uniformly distributed within a 10m $\times$ 10m square area. The N corresponding receivers are randomly distributed within 2m$\times$2m square area centered at their dedicated transmitters. The minimum distance between each transmitter-receiver pair is set to be 1m to avoid trivial solutions. Based on the network setup in our simulations and with reference to (4), we define the numerical QoS bounds $\mathcal{R}$ for three types of network applications:

web browsing	$\mathcal{R}$: [2,3]
stream audio	$\mathcal{R}$: [3,5]
stream video	$\mathcal{R}$: [5,10]

In our simulations, 40% users run web browsing applications, another 40% users run stream audio, and the rest run stream video. In view of the QoS requirements, we adopt two new performance metrics to evaluate DSA algorithms, namely, "*system useful capacity*" and "*fraction of QoS satisfied users*". The former metric is the sum of useful utilities of all users in the network, which represent the overall network spectrum utilization with QoS provisioning. The latter metric refers to the fraction of users in the entire network whose utilities meet their QoS lower bounds $R_{i,\min}$. This is a conservative measure of how well the DSA solution contributes to individual users' applications, and is a good indicator of QoS outage. The game approach in both ADP and our QoS-aware algorithms involve repeated games, in which users announce the new price information at the end of each decision-making stage, and proceed to the next stage until the decisions converge, or after a maximum of 50 iterations have been executed. Each simulate data point is averaged over 20 random topologies.

We first compare DSA algorithms with respect to the number of users N in the network, for K=3 channels. Fig. 1 shows the results for the single-channel allocation problem. As N increases, the system useful utility increases until saturating to flat levels when N >25. The saturation is due to the limited channel bandwidth resources, which constrained the total utility that can support the QoS. Both the single-channel power scaling scheme SC-QoS-ps-DSA and the QoS-embedded scheme SC-QoSe-DSA outperform the SC-ADP solution that does not account for QoS during decision making. The performance gap increases as the network becomes dense, until reaching saturation. Meanwhile, the fraction of QoS satisfied users decreases as N becomes larger. This indicates that improving the system total utility in a dense network leads to a larger percentage of users sacrificing their utilities, and thus most spectrum resources are consumed by a smaller percentage of users. Similar observations can be made for the multi-channel resource allocation case, as shown in Fig. 2. Overall, QoS awareness is more critical for spectrum sharing in denser heterogeneous dense networks.

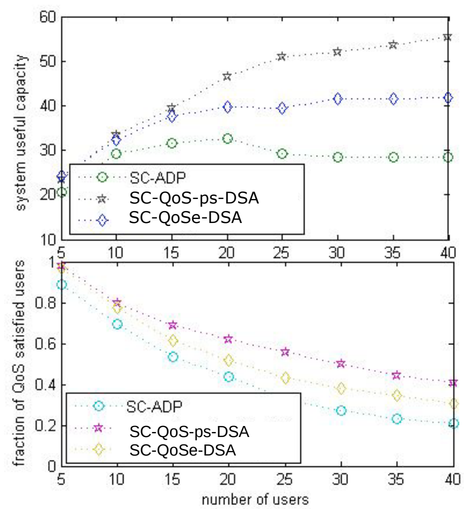

Fig. 1. System useful utility and fraction of QoS satisfied users versus number of users for single-channel DSA solutions

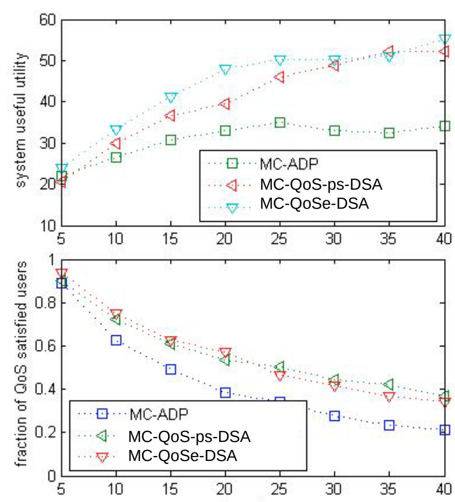

Fig. 2. System useful utility and fraction of QoS satisfied users versus number of users for multi-channel DSA solutions

Next, we turn focus on the existing ADP algorithms to shed light on how QoS-blind DSA algorithms behave in a heterogamous network. For SC-ADP and MC-ADP in a network with 10 users and 3 channels, Fig. 3 shows the acquired utility of each user after convergence or 50 iterations are reached. The individual utilities are calculated using (2). It can be observed that MC-ADP has higher deviation of utility values across all users than SC-ADP does. This phenomenon implies that MC-ADP is more likely to cause QoS outage than SC-ADP. As a result, single-channel DSA solutions generally outperform multi-channel DSA ones when the number of users N is small. As N increases, multi-channel networks are more advantageous, since they can afford more flexibility in spectrum sharing, and thus overweight the drawback of imbalanced allocation among users at the convergence state. This assessment is confirmed by Fig. 4.

Fig. 5 depicts the average processing time needed for each DSA algorithm to converge. In general, it takes longer time to converge in a denser network, and the QoS-aware schemes have slower convergence rates than QoS-blind algorithms.

VI. SUMMARY

Taking on a game approach, we have proposed two QoS-aware distributed DSA schemes for heterogeneous wireless networks with user-specific QoS. The proposed schemes either resort to external power scaling or embed the QoS information in the utility function, both using the useful utility as local objectives. Interference pricing is incorporated into our schemes as a secondary objective to diffentiating multiple actions yielding the same utility. When both objectives are optimized, the proposed schemes yield good performance in terms of both total network useful utility and interference suppression. We have also introduced two new metrics, “system useful utility” and “fraction of QoS satisfied users”, which are suitable for quantifying the performance of DSA solutions from the QoS perspective. Simulations confirm the effectiveness of our proposed schemes in efficiently sharing spectrum along with QoS provisioning.

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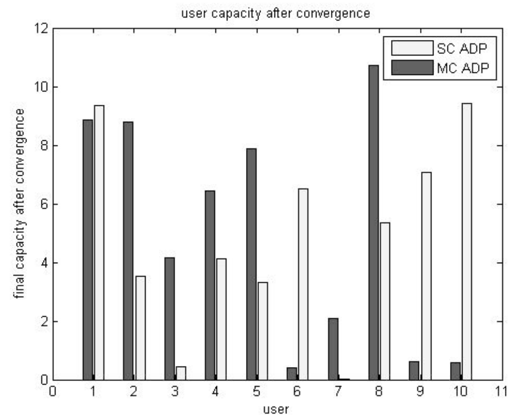

Fig. 3. Steady-state capacity for each user in the network with 10 users and 3 channels

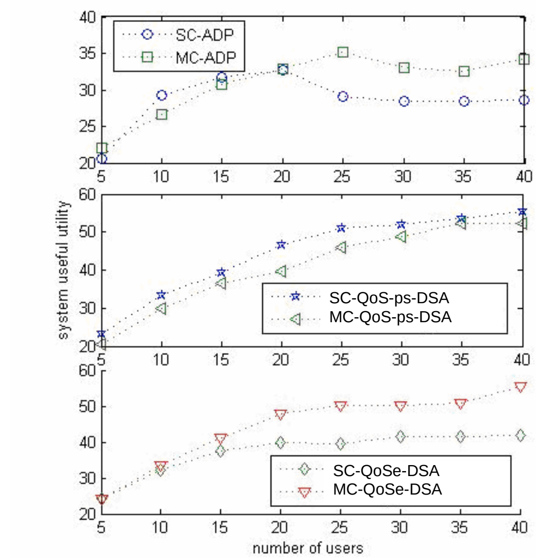

Fig. 4. Comparison of system useful utility between SC and MC networks

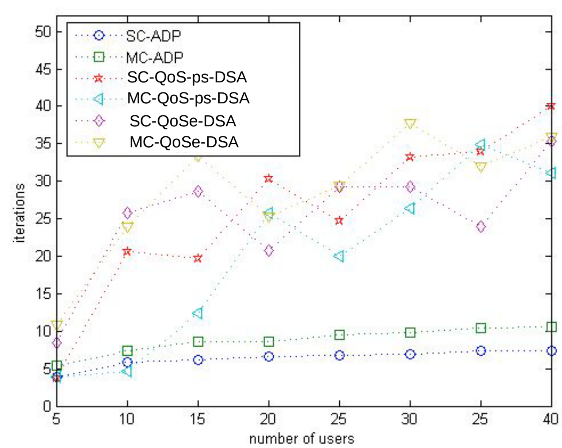

Fig. 5. Comparisons of the average convergence time between the ADP algorithms and the QoS-aware DSA solutions