

# Information Sharing in Spectrum Auction for Dynamic Spectrum Access

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**Abstract**—Spectrum under-utilization is one of the bottlenecks of the development of wireless communication, and Dynamic Spectrum Access (DSA) is envisioned as a novel mechanism to solve the problem of spectrum scarcity. *Spectrum Auction* has been recognized as an effective way to achieve DSA, wherein the primary spectrum owner (PO) acts as an auctioneer who has free channels and is willing to sell them for additional revenue, and the secondary user (SU) acts as a bidder who is willing to buy a channel from POs for its service. In this paper, we adopt a *progressive spectrum auction* named MAP, which has been proved optimal and incentive compatible in DSA networks with distributed POs and SUs. However, in MAP, the profit of POs is *not* maximized under the equilibrium point due to the scarcity of SUs' *private information* known by POs. We propose an *information sharing* mechanism, in which the POs exchange their local information with each other. We show analytically that, allowing information sharing, each PO is able to *learn* the private information of SUs and increase its profit accordingly. Long term profit acts as the incentive for information sharing that all the POs automatically reveal the true information when they are aware of this. It is notable that information sharing doesn't affect social optimality. Simulation shows the increase of POs' profits in the sense of long term interests.

## I. INTRODUCTION

Nowadays, spectrum underutilization is one of the limitations of wireless systems. On one hand, the spectrum that is permanently allocated to licensed users often suffers from inefficiency of usage. On the other hand, there are more and more starving users whose demands for spectrum can't be met. *Dynamic Spectrum Access* (DSA) aims at solving the above problem. Through DSA, secondary users (SUs) get a chance to transmit by employing free spectrum and primary spectrum owners (POs) gain higher revenue by leasing out spectrum temporarily. A realizable DSA mechanism should be able to provide incentive for POs to share spectrum with others and a scheme to efficiently assign free channels to SUs.

In this paper, we study the problem of spectrum band (channel) assignment in DSA networks with multiple POs and multiple SUs. Each PO has a set of free channels which can be shared by SUs. Each SU has the desire to acquire a channel from PO for service. Optimal channel assignment can be obtained by using centralized algorithm such as a linear-programming-theory-based branch-and-bound algorithm [13] or a graph-theory-based optimal matching algorithm [14]. However, the centralized algorithm has certain limitations due to the fact that DSA networks are essentially distributed and POs (and SUs) are heterogeneous. Moreover, the essential

information needed to carry out the algorithm, e.g., SU's valuation for each channel, is either private or local, which can hardly be obtained by the central node.

We adopt a *progressive spectrum auction*, named as MAP, which works in a totally distributed manner. In MAP, POs act as auctioneers who systematically adjust their respective prices and SUs act as bidders who subsequently decide whether or not to buy the channels and from which PO to buy. It has been proved that MAP converges to an equilibrium, where the channel assignment is optimal compared with the centralized algorithm.

However, in MAP, the profit of POs is *not* maximized at the equilibrium point due to the scarcity of SUs' information in POs. In details, SUs may have surplus in utility that POs can continue to raise prices before those SUs give up the deal and turn to other sellers. The amount of sale price a PO can raise depends on how much utility surplus its clients get. But the utility surplus of SUs are *private* information and SUs have no incentive to share with others. In this paper, we propose an *information sharing* mechanism among POs, from which the POs exchange the *local* information with each other. Allowing information sharing among POs, we show that each PO can gradually learn the private information of SUs', e.g., the preference parameters, and accordingly increases its profit by raising the price with a tolerable value. Long term profit acts as the incentive for information sharing and learning that all the POs automatically reveal the true information when they are aware of this. It is notable that information sharing doesn't affect social optimality. Simulation shows the increase of POs' profit in the sense of long term interests.

The paper is organized as follows. In Section II, we present related works on spectrum auction and information sharing. In Section III, we introduce the system model and formulate the problem as spectrum auction. In Section IV, we present an progressive spectrum auction named MAP. In Section IV-C, we propose an information sharing mechanism among POs, from which POs achieve higher profit. In Section IV-D, we discuss the iterative learning in details. In Section V, we provide our simulation results on learning and profit increase. Finally, we conclude our work in Section VI.

## II. RELATED WORK

There is a wide range of literature discussing Dynamic Spectrum Access (DSA). The idea of Cognitive Radio (CR)

is first brought up by J. Mitola [2]. The realization of DSA largely depends on the development of cognitive radio. In [3], Zhao *et al.* adopted the term *opportunistic spectrum access* (OSA) and categorized existing work on dynamic spectrum access into three general models: dynamic exclusive use model, open sharing model, hierarchical access model. From the perspective of spectrum owners, DSA is equivalent to dynamically allocating spectrum resources upon requests. This interaction is very much like what happens between buyers and seller in an market. Recent works on dynamic resource allocation include channel allocation for cognitive radio networks [4], design of interference-free spectrum allocation scheme using graph-coloring [5], local bargaining for distributed spectrum assignment [6], and so on.

Auction is an efficient mechanism to allocate resources in market [7], where the auctioneers elicit information from the bidders through bidding. Current works in research focus on short-term, real-time auction for online resource management. Some of the recent works on this type of auction design are as follows: In [8], Gandhi *et al.* formulated a general spectrum auction problem as an optimization problem and emphasized on the choice of market clearing price. Specifically, uniform and discriminatory pricing schemes were compared in terms of efficiency, fairness and so forth. As an important property in auctions, truthfulness (or strategy-proofness) was addressed in [9]. In addition to truthfulness, the author investigated efficiency, complexity as well in the auction design.

Information Sharing is widely used in all kinds of games and supply chain management to improve the performance of various entities involved. In [10], the author categorized information in market as upstream and downstream information. The more informed ones are not willing to give out information unless they get reward from less informed ones. The value of information is characterized by the performance improvement of the supply chain. Incentive for information sharing is also investigated in [10]. Lee *et al.* studied the value of sharing demand information in a supply chain with nonstationary demand process [11]. Lee *et al.* showed that the costs of manufacturers are reduced if retailers share their demand information with manufacturers. In [12], the holding and backlogging cost of warehouse is minimized if it has the real time information about retailers' inventories.

### III. SYSTEM MODEL AND PROBLEM FORMULATION

#### A. System Description

We consider the DSA network consisting of  $M$  POs and  $N$  SUs. Each PO serves a set of primary users (PUs) and the spectrum bands possessed by the PO may be under-utilized, i.e., there may exist some free channels which are not used by PUs at a particular time. Therefore, POs allow SUs to opportunistically access those free spectrum and gain profit from secondary service.

We denote the number of free channels owned by PO  $i$  as  $m_i$ . We assume that  $m_i$  remains a constant in the time period of interest. We further assume that channels owned by the same PO are homogeneous, with the same bandwidth, carrier

frequency and modulating technique etc. But channels owned by different POs may be heterogeneous. Thus we denote the carrier frequency and bandwidth of channels owned by PO  $i$  as  $f_i$  and  $w_i$ , respectively.

We assume that each SU can use only one channel for its service at a particular time since advanced spectrum aggregation techniques are still immature and it is difficult for a radio device to employ multiple channels, whether these channels are possessed by the same PO or different POs. We further assume that each channel can only be allocated to one SU.

#### B. Reservation Price, Sale Price and Valuation

The *Reservation Price* is the minimum price at which a PO is willing to sell a free channel. Reservation price is often defined as the cost of leasing *one* free channel to an SU. We denote the reservation price of PO  $i$  as  $c_i$ , and the reservation price vector of all POs can be written as  $\mathbf{c} = (c_1, c_2, \dots, c_M)$ .

The *sale price* is the actual price that PO charges when leasing a channel. The sale price of PO  $i$  is denoted by  $p_i$ . It is obvious that  $p_i \geq c_i$  or PO will leave the auction. The price vector of all POs is  $\mathbf{p} = (p_1, p_2, \dots, p_M)$ .

For SUs, the *valuation* of a channel is defined as the income of using this channel. The valuation is often related to the channel capacity (e.g., for data service) and channel quality (e.g., for voice service). Without loss of generality, we consider the scenario of data service in this paper. The valuation of SU  $j$  is defined as a linear function of the preference parameter  $k_j$  and the capacity of the used channel.  $k_j$  is a SU-specified parameter which reflects the preference of SU  $j$  for channels. Since the channels in the same PO are homogeneous, we denote the valuation of SU  $j$  on the channels from PO  $i$  as  $v_{ji}$ , and we can write  $v_{ji}$  as follows:

$$v_{ji} = k_j C_{ji} = k_j \cdot w_i \log(1 + \Gamma_{ji}) \quad (1)$$

where  $C_{ji}$  is the channel capacity given by Shannon-Hartley theorem and  $\Gamma_{ji}$  is the signal-to-noise ratio (SNR) between SU  $j$  and PO  $i$ . The valuation vector of SU  $j$  can be written as  $\mathbf{v}_j = (v_{j1}, v_{j2}, \dots, v_{jM})$ , and the valuation matrix is composed of all SUs' valuation vectors, i.e.,  $\mathbb{V} = (\mathbf{v}_1; \dots; \mathbf{v}_N)$ .<sup>1</sup>

It is notable that the valuation of SU is private information, which can hardly be obtained by others. In detail, the preference of SU  $j$  (i.e.,  $k_j$ ) is completely *private information* which can not be observed by others. The SNR is *local information* which can only be observed by the related SU and PO, that is, only PO  $i$  and SU  $j$  have knowledge of  $\Gamma_{ji}$ .

#### C. Problem Formulation

From (1), it is easy to see that valuation depends on channel quality and SU's preference parameter. Thus it is an essential problem for DSA that how to assign the free channels among the SUs with highest spectrum utilization.

We denote a channel assignment as an  $N \times M$  matrix  $\mathbb{R} = \{r_{ji}\}_{N \times M}$ , where  $r_{ji} \in \{0, 1\}$ ,  $\forall i, j$ , and  $r_{ji} = 1$  denotes an assignment from PO  $i$  to SU  $j$  and  $r_{ji} = 0$  otherwise. A *legal*

<sup>1</sup>Note that  $(\mathbf{v}_1; \dots; \mathbf{v}_N)$  is the pileup of vector  $\mathbf{v}_i$  in row sequence.

channel assignment must satisfy: (i)  $\sum_{i \in M} r_{ji} \leq 1$ , since each SU can only use one channel, and (ii)  $\sum_{j \in N} r_{ji} \leq m_i$ , since each channel can only be used by one SU.

From social perspective, we define the *net profit* of an assignment from PO  $i$  to SU  $j$  as  $v_{ji} - c_i$ . We further define the *social income* as the aggregate net profits of all assignments in  $\mathbb{R}$ . The social income is also regarded as the spectrum utilization of the whole network. An *optimal channel assignment* refers to a legal channel assignment which maximizes the social income and can be formally written as:

$$\mathbb{R}^* = \arg \max_{\mathbb{R}} \sum_{j \in N} \sum_{i \in M} r_{ji} \cdot (v_{ji} - c_i) \quad (2)$$

subject to the above constraints (i) and (ii).

Although the centralized algorithm (e.g., branch-and-bound algorithm [13] or kuhn-munkres algorithm [14]) can solve the above problem efficiently, it is not practical to use in a distributed DSA network.

#### IV. AUCTION-BASED CHANNEL ASSIGNMENT

We formulate the above problem as a *progressive spectrum auction*, named as MAP, which works in a totally distributed manner. In essence, MAP is an *open-bid* auction wherein each PO systematically adjusts its sale price for increased profit and each SU subsequently chooses the channel which brings it maximum profit. We show that MAP achieves optimal channel assignment meaning that it is equivalent to the centralized algorithm. We then show how information sharing can be used for POs to learn the private information of SUs and increase their own profit as a result. A novel MAP algorithm with information sharing and iterative learning is also proposed.

##### A. Spectrum Auction Basic

In spectrum auction, once an PO  $i$  sells a free channel to SU  $j$  at price  $p_i$ , the profit of PO  $i$  is  $p_i - c_i$ , and the profit of SU  $j$  is  $v_{ji} - p_i$ . Additionally, if a free channel of PO  $i$  is not purchased by any SU, the profit of this channel is 0 for PO  $i$ . Similarly, if an SU does not buy any channel from POs, its profit is 0.

In an open-bid auction, the auctioneers specify the sale prices of items and the bidders decide whether to buy an item. Thus we can write the *strategies* of PO  $i$  and SU  $j$  as  $\mathbf{y}_i = p_i$  and  $\mathbf{x}_j = (x_{j1}, x_{j2}, \dots, x_{jM})$ , respectively, where  $x_{ji} \in \{0, 1\}$ ,  $\forall i \in M$  and  $x_{ji} = 1$  denotes that SU  $j$  is willing to buy the channel from PO  $i$ .

It is easy to see that the *strategy space* of PO  $i$  is  $[c_i, \infty)$ , and the strategy space of any SU is  $\Theta = \{\mathbf{e}_M^0, \mathbf{e}_M^1, \dots, \mathbf{e}_M^M\}$  where  $\mathbf{e}_M^0 = \mathbf{0}_M$  and  $\mathbf{e}_M^i$ ,  $i \neq 0$ , is the  $M$ -dimensional unit vector with the  $i$ <sup>th</sup> element equal to 1 and all other elements equal to 0. The *strategy profile* of all SUs is:

$$\mathbb{X} = (\mathbf{x}_1; \mathbf{x}_2; \dots; \mathbf{x}_N) \quad (3)$$

where  $\mathbf{x}_i \in \Theta$ ,  $\forall i \in N$ .

##### B. MAP Mechanism and the Equilibrium

The trading behavior between POs and SUs is comparable to a multi-auctioneer progressive auction with products (channels) of the same kind but of differentiated qualities.

Due to the progressive nature, MAP is defined as a *round-based* distributed process. In each round, the POs dynamically adjust the sale prices according to the market demand and an equilibrium will be reached at last. These adjustments drive the outcome of the auction to social optimality. Formally, we present the detailed mechanism of MAP as follows:

- 1) Initialization
  - (For POs)  $p_i = c_i$ ,  $d_i = 0$ ,  $\forall i \in M$ ;
  - (For SUs)  $\mathbf{x}_j = \mathbf{e}_M^0$ ,  $\forall j \in N$ ;
- 2) Asking
  - if  $\sum_{j \in N} x_{ji} > m_i$ , then  $p_i = p_i + \varepsilon$ ,  $\forall i \in M$ ;
- 3) Bidding
  - if  $v_{jk^*} - p_{k^*} \geq 0$ , then  $\mathbf{x}_j = \mathbf{e}_M^{k^*}$ , else  $\mathbf{x}_j = \mathbf{e}_M^0$ , where  $k^* = \arg \max_{k \in M} (v_{jk} - p_k)$ ,  $\forall j \in N$ ;
  - if  $\mathbf{p} = \mathbf{p}'$ , then auction ends, else go back to 2);

where  $\mathbf{p}'$  is the price vector of POs at the penultimate round and  $\varepsilon$  is an arbitrarily small positive number which determines the converging speed of the auction.

The above process ends with an equilibrium and the final assignment is equivalent to the one derived from centralized algorithms. We present this result in Lemma 1 and 2, and we don't go through proofs of the lemmas due to the space limitation.

**Lemma 1:** *MAP converges to a strong equilibrium, if  $\varepsilon$  is small enough.<sup>2</sup>*

**Lemma 2:** *The channel assignment of MAP is optimal, if  $\varepsilon$  is small enough.*

Actually, the essence of auction is resource assignment and profit transfer. The social utility doesn't depend on sale price but the optimal matching. We show here that MAP is efficient enough that the final assignment is social optimal.

##### C. Information Sharing

In this section, we discuss the possibility for information sharing and its impact on POs' profit. Actually, the sale prices in equilibrium is not the best POs can do. Some SUs may still have utility surplus and a certain PO can further raise the sale price before any of its clients turns to other POs. Figure 1 shows this situation where  $\delta$  is an arbitrarily small positive number. The price in (b) is already the equilibrium price of MAP but PO  $a_1$  can further increase its sale price to  $3 - \delta$ , which is shown in (c), and guarantee that SU  $s_2$  still stays with it. But the premise is that PO  $a_1$  have to know the amount of utility surplus its client gets from it and PO  $a_2$ .

POs and SUs can be seen as upstream and downstream entities in a *supply chain* of channels that POs are suppliers and SUs are customers. In supply chain theory, information can be categorized as public information, local information and private information [10]. Public information is known by all

<sup>2</sup>We say  $\varepsilon$  is *small enough*, as long as  $\varepsilon \leq \min_{i,j,k,l} |v_{ij} - v_{kl}|$ .

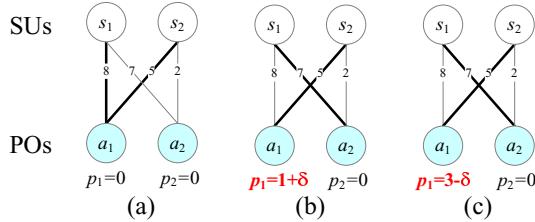


Fig. 1. Utility Surplus of SUs in Equilibrium of MAP.

the entities in the supply chain. In MAP, the sale prices of POs and the pattern of SUs' utility function are public information. Local information refers to the things known by a certain entity and its direct downstream entity. SNR information  $\Gamma_{ji}$  is an example of local information that it is only known by PO  $i$  and SU  $j$ . Private information is represented by POs' reservation prices  $\mathbf{c}$  and the preference parameters of SUs.

We will show that POs can earn more profit if they share the local information SNR with each other. Figure 2 shows the information sharing among POs. The remaining question is how can POs infer SUs' utility surplus from shared local information. Then they have a chance to further increase the price beyond equilibrium price. We propose a novel iterative algorithm in the next section that solves the above problem.

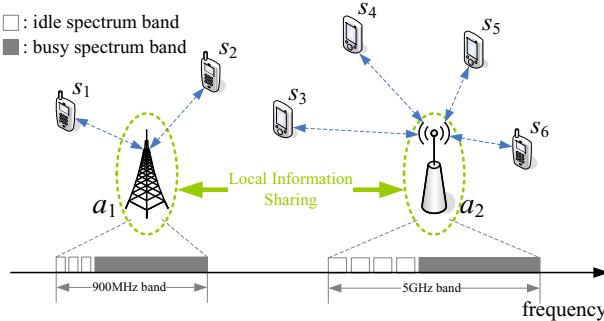


Fig. 2. The Sharing of Local Information among POs.

#### D. Iterative Learning and Profit Increase

We assume that local information  $\Gamma_{ji}$  is shared among POs and  $k_j$  is bounded by  $[k_{min}, k_{max}]$  for  $\forall j \in N$ . POs get to learn the private information of SUs (i.e.,  $k_j$ ) iteratively during the asking and bidding rounds. Consider the scenario that SU  $j$  bids for PO  $i$  in round  $t$ , the following inequalities hold:

$$k_j \cdot w_i \log(1 + \Gamma_{ji}) - p_i \geq k_j \cdot w_k \log(1 + \Gamma_{jk}) - p_k, \quad \forall k \neq i \quad (4)$$

There are altogether  $M - 1$  inequalities in (4), each indicating the possible lower or upper bound of  $k_j$ . In details, if  $\phi_{ik}^j > 0$ , then  $k_j \geq \frac{p_i - p_k}{\phi_{ik}^j}$  where  $\phi_{ik}^j \triangleq w_i \log(1 + \Gamma_{ji}) - w_k \log(1 + \Gamma_{jk})$ . Similarly, if  $\phi_{ik}^j < 0$ , then  $k_j \leq \frac{p_i - p_k}{\phi_{ik}^j}$ . Finding the intersection of the current  $M - 1$  bounds and the learning result in previous round, we have an

estimated range of  $k_j$ , i.e.,

$$\begin{aligned} k_{j\_min}^{(t)} &= \max k_{j\_min}^{(t-1)}, \max_{k \in M, k \neq i, \phi_{ik}^j > 0} \frac{p_i - p_k}{\phi_{ik}^j} \\ k_{j\_max}^{(t)} &= \min k_{j\_max}^{(t-1)}, \min_{k \in M, k \neq i, \phi_{ik}^j < 0} \frac{p_i - p_k}{\phi_{ik}^j} \end{aligned} \quad (5)$$

for all  $j \in N$ .

POs can utilize the private information they learnt to continue the price raising after the equilibrium and guarantee no SU is scared away. For simplicity, we first denote the set of SUs who are willing to buy the channels from PO  $i$  as  $N_i$ . The additional price raising scheme goes like this. In each round  $t$ , for each SU  $j \in N_i$ , PO  $i$  finds the bounds of  $k_j$  with which SU  $j$  may turn to other POs if PO  $i$  raises the sale price by  $\varepsilon'$ .<sup>3</sup> Formally, we can write this bound as follows:

$$S_i^j = \{s \mid s \cdot \phi_{ik}^j < p_i + \varepsilon' - p_k \quad k \neq i, k \in M\} \quad (6)$$

Further, for each SU  $j \in N_i$ , PO  $i$  finds the bounds of  $k_j$  in which SU  $j$  may drop out the auction if PO  $i$  raises the sale price by  $\varepsilon'$ . Formally, we can write this bounds as follows:

$$D_i^j = \{d \mid d \cdot w_i \log(1 + \Gamma_{ji}) - (p_i + \varepsilon') < 0\} \quad (7)$$

PO  $i$  can raise the price only if all of its clients (i.e.,  $N_i$ ) still get the highest and positive utilities from it, which is equivalent to the following condition:

$$\bigcup_{j \in N_i} S_i^j \cap D_i^j \cap [k_{j\_min}^{(t)}, k_{j\_max}^{(t)}] = \emptyset \quad (8)$$

We say PO  $i$  is in *utility surplus* if equation (8) is satisfied, which means that PO  $i$  can raise the price by  $\varepsilon'$  without driving any SU in  $N_i$  away. This process continues until all the POs fail equation (8). We present the MAP algorithm with information sharing and iterative learning in the following list. Due to space limitation, we only present the related processes.

- 1) Initialization
- 2) Asking
  - update the estimated range of  $k_j, \forall j \in N$ ;
  - if  $\sum_{j \in N} x_{ji} > m_i$ , then  $p_i = p_i + \varepsilon$ , else if (8) satisfies, then  $p_i = p_i + \varepsilon', \forall i \in M$ ;
- 3) Bidding

#### E. Incentive for Information Sharing and Learning

There is a remaining question that why POs want to share their local information with each other. We show in previous section that information sharing makes the learning of SUs' private information possible. The final outcome of information sharing is the increase in POs' profits. If POs are aware of this, they should be willing to share information with others. Long term profit increase acts as the incentive here for POs to share and learn.

<sup>3</sup>Note that  $\varepsilon'$  is the step of price adjusting in learning stage and it is often a positive number smaller than step  $\varepsilon$ .

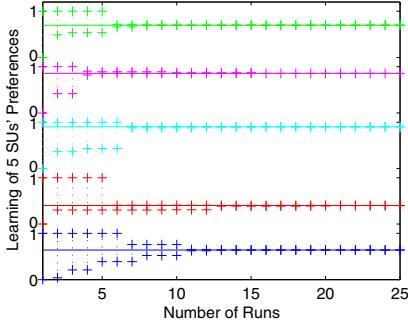


Fig. 3. The convergence of learning.

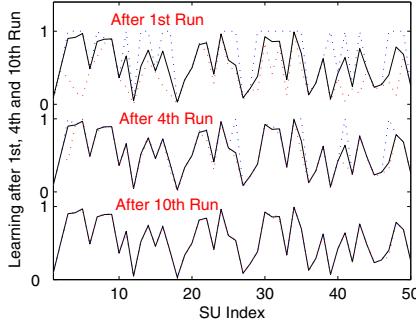


Fig. 4. The increasing accuracy of learning.

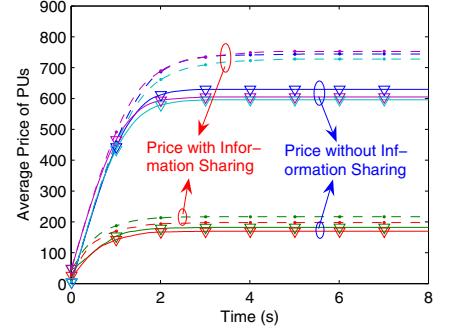


Fig. 5. The average increase of price of POs.

## V. SIMULATION RESULTS

We implement the MAP algorithm with information sharing and iterative learning in MATLAB. In the simulation, we assume that the network contains 5 POs and 50 SUs in a square area of  $1000 \times 1000$ m. The bandwidth of channels can be 2MHz or 0.2MHz. The carrier frequency is 900MHz when the bandwidth is 0.2MHz or 2400MHz otherwise. The  $\varepsilon$  is 5 before equilibrium is reached, while  $\varepsilon' = \varepsilon/2$  in the additional price raising process.

In this paper, we adopt a simple path loss model written as  $L_{ji} = 1/(f_i^2 d_{ji}^2)$  where  $d_{ji}$  is the distance between PO  $i$  and SU  $j$  in meters [1]. Without loss of generality, the antenna gains and system loss factor is normalized to 1. Additionally,  $k_{min}$  and  $k_{max}$  is assumed to be 0 and 1 before the iteration.

### A. The Learning of SU's Preference Parameters

Figure 3 shows the learning of 5 SUs' preference parameters after 25 times of run. The cross denotes the upper or lower bound of  $k_j$ . We can see from the figure that the learning converges to tight bounds very quickly. In Figure 4, the blue dotted line indicates the learnt upper bounds of  $k_j$  and red line as lower bounds. The figure shows the learning error after the 1<sup>th</sup>, 4<sup>th</sup> and 10<sup>th</sup> run. We can see that the error for all  $k_j$  is less than  $10^{-2}$  after the 10<sup>th</sup> run.

### B. PO's Profit Increase with Information Sharing

We run the algorithm 100 times. Figure 5 shows the average price of POs with or without information sharing. Different POs are denoted by different colors. The dotted lines indicate POs average prices with information sharing and solid lines otherwise. As seen in the figure, the average price increase is around 20%. POs with higher demand at the beginning of the auction have higher increase in price in the end. So they are more willing to participate in information sharing than others.

## VI. CONCLUSION

In this paper, we study the problem of how POs can utilize information sharing and iterative learning to increase their long term profit in MAP. In conventional MAP, POs systematically raise the prices until the auction reaches an equilibrium. We show that POs can do better with sharing of local information and learning of SUs private information. We propose a novel

iterative algorithm that POs gradually learn the bounds of SUs' preference parameters. They then utilize the information to raise prices after the equilibrium is reached. We also study POs' incentive for information sharing and learning. In the end, we made simulations to show the learning process and the long term profit increase of POs.

## ACKNOWLEDGMENT

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