Real-Time Incentive Solution for Radio Environment Map Measurements with Crowdsourcing

Huiyang Wang*, Diep N. Nguyen†, Dinh Thai Hoang †, Eryk Dutkiewicz†, Qingqing Cheng†
*Samsung Research Center, System Design Lab, Beijing, China.
†School of Electrical and Data Engineering, University of Technology Sydney, Australia.

***Abstract*—To harvest short-lived whitespaces that account for more than 30% of the cellular bands, it is critical to maintain a radio environment map with the most updated sensing results (i.e., with a fine timescale in minutes/seconds or even real-time). In this work, we develop a novel Real-Time Incentive Solution (RTIS) that rewards mobile users for contributing their spectrum sensing data to a real-time radio environment map. In particular, we first develop a spectrum sensing system including a mobile application for multiple mobile sensors and a cloud database. Then, we develop an incentive mechanism for the system by assessing the sensing results and providing proper incentives to the participants. Specifically, this mechanism will provide pre-prices to the crowdsourcing users to guarantee their minimum payment and encourage them to perform sensing tasks, thereby forming a spatio-temporal model. The coefficients of this model are then learned iteratively and the post-prices are adjusted for the crowdsourcing users according to their contributions to the model. The experiment results show that our proposed solution can achieve better user utility and lower overall system cost than those of some existing works.**

Keywords- Mobile crowdsourcing, incentive mechanism, spectrum sensing, and real-time radio environment map.

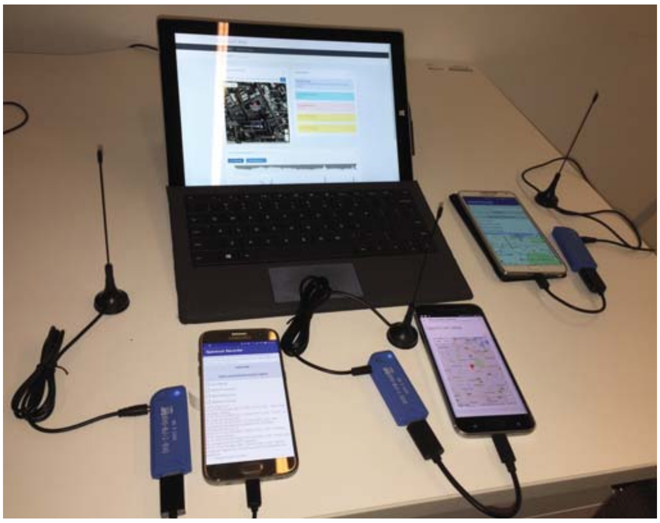


Fig. 1. The implementation system includes (1) the sensors that can be attached to the mobile devices, (2) a web based service and (3) an APP developed to process the sensing results.

I. Introduction

Radio Environment Maps (REMs) have been becoming a promising tool for optimizing radio coverage, interference management and resource allocation in wireless communication networks. REMs provide a comprehensive radio resource usage map for the network providers through utilizing multi-domain information from geolocation databases, characteristics of spectrum use, geographical terrain models, propagation environment, and regulations [1]. REMs are also critical components in the latest spectrum sharing frameworks SAS and LSA proposed by FCC (in the US) and ETSI in the Europe, respectively. However, one of the main challenges for the development of REMs is how to make meaningful predictions about the current and future occupancy of the channels or spectrum usage. Most existing REMs are updated on a coarse time scale (e.g., in days or months like the Google Spectrum Database).

To achieve a good prediction of spectrum usage, the most effective way is to involve explicit calculation of diffractions. However, this method requires prohibitive amounts of data. Alternatively, we also can deploy a sensor network to collect data. However, such an approach may incur an excessive implementation and maintenance cost. Considering the dynamic feature of spectrum usage, the periodic sensing at fixed locations is neither flexible nor efficient. On one hand, continuous and wide spectrum sensing or regularly collecting data is not meaningful, particularly when there is no wireless transmission. Therefore, it is better to hand over the sensing tasks to the crowdsourcing users who are actually the customers and users of the spectrum. Smart phones nowadays are able to act as sensors to provide qualified sensing data for the REMs. However, they are hardware constrained devices with limited battery capacities. Thus, how to encourage mobile users to participate in crowdsourcing tasks is an emerging challenge.

Considering all aforementioned challenges, in this paper, we propose a **R**eal-**T**ime **I**ncentive **S**olution (RTIS) by applying prediction and aggregation procedures to spectrum data, including hardware and software, as illustrated in Fig. 1. By collecting spectrum sensing data from the crowded mobile users, this model can accommodate complex spatio-temporal models. The model characterizes the temporal trend at each location as a combination of empirically derived temporal basis functions, and embed the spatial domains of coefficients for the basis functions using separate regression models with spatially correlated residuals. The proposed approach allows us to implement a scalable single-stage estimation procedure that may be informative to see snapshots of spatial events in real-time.

The rest of the paper is organized as follows. In Section II, related works and contributions are presented. In Section III, the preliminaries and problem formulation are provided. In Section IV, we describe the details of the proposed RTIS. We then provide simulation results and analysis in Section V. Finally, conclusions are given in Section VI.

II. Related Works and Contributions

A. Related Works

The recent report [2] has pointed out that the database-assisted spectrum sharing is a promising approach to improve the utility of limited spectrum resources. Though significant progress has been made to address various technical issues of spectrum database, very few studies looked at the economic issue of spectrum database [3] [4]. A large-scale spectrum monitoring by the operator can be very costly and may not be necessary all the time. Various auctioning models (e.g., [5] [6]) have been discussed, the pricing setting and spatio-temporal based REM have not been adequately addressed. An economic solution to collect spectrum data is to rely on crowdsourcing (also referred to as crowdsensing) in which the sensing tasks are carried on by the mobile users in exchange for incentives [7] [8] [9].

The authors in [8] consider that the mobile devices tend to behave differently in the crowdsourcing tasks. They characterize the devices heterogeneity in terms of data quality (or hardware noise) and sensing costs. In [10], the users can choose any subset of tasks with pre-defined values and ask for minimum payments. In [9], the authors define an empirical quality indicator for each user as the deviation from the average of its most recent measurements, and focus on minimizing the total payment for users while meeting a certain quality of service. In [11], the authors focus on data quality estimation of uncalibrated devices with an expectation maximization algorithm, and propose a pricing mechanism for general sensing purposes. However, they ignore that the spectrum data is both time-related and space-related. In the space domain, the subregions are generally performed based on the spatial dependence [12] and similarly in [13], the authors produce a land cover map with the maximal spatial dependence. However, there always exists uncertainty in resultant fine-resolution land cover maps, due to the lack of information of the terrestrial spatial pattern.

All the above solutions do not consider the willingness of users to take the sensing tasks and the instant user experience to contribute real-time sensing data. In this work, we develop a pricing mechanism that provides users with real-time incentive and also considers the users' waiting cost.

B. Novelty and Contributions

Crowdsourcing is a prominent method of measuring REM, which achieves reasonable assignment and effective coverage of sensing tasks by taking advantage of the combined knowledge and input of the masses. In comparison with dedicated spectrum measurements, crowdsourcing could be adaptive to dynamic REM. Particularly, in the busy hours, users should be not only the spectrum users, but also the spectrum monitors (e.g., to detect violators of FCC radio spectrum regulations).

The spatio-temporal models are useful tools for the spectrum usage prediction. However, as spatio-temporal kriging based on the complete database is computationally expensive [8], it poses a question of how to select the best subset from the spatio-temporal space. This implies that the crowdsourcing users have to wait until the decision is made, and thus they may fail to take the sensing tasks.

Moreover, most existing works aim to optimize the system's cost in the perspective of the system instead of the user's utility. In this paper, we provide a flexible two-step pricing, i.e., fixed pricing and variable pricing. The fixed pricing is pre-pricing, which aims to guarantee the user's minimum payment, while the variable pricing is post-pricing, which helps the system to measure the user's contribution to the system.

Our proposed solution focuses on an incentive mechanism based on the real-time spatio-temporal model. The main contributions of this paper are as follows.

- **Dynamic model**: we further develop the spatio-temporal model which periodically updates the prediction model to adapt to the spectrum's dynamics.
- **Instant payment**: rather than selecting the best set of crowdsourcing users, we provide a real-time incentive solution for every user with different payment. This reduces the risk/cost of users' waiting and then further improves the user utility.
- **Fixed and variable pricing**: we design a two-part pricing mechanism for the crowdsourcing users, i.e., pre-price/fixed price and post-price/variable price. The fixed pricing guarantees the users' minimum payment, while the variable pricing helps the system measure the users' contributions to the prediction model to provide the right incentive.

III. Problem Formulation

A. User Model

The incentive architecture and the interactions between the users and the system are shown in Fig. 2. In the sequel, we adopt the basic spatio-temporal model [14].

The spectrum sensing data are contributed by a countable set of crowdsourcing users, defined by $\mathcal{N} = \{(s_i, t_i) : i = 1, 2, ...\}$, in which $s_i \in \mathbf{R}^2$ is the location and $t_i \in T$ is the time. Denoting the sensing result (e.g., received signal strength) within a band modeled by $z(s, t)$, the spatio-temporal field can be expressed as follows:

$$z(s, t) = \mu(s, t) + \delta(s, t), \tag{1}$$

where $\mu(s, t)$ is the mean and $\delta(s, t)$ is the essentially random space-time residual.

The crowdsourcing users' payment is not a constant [3] [8] [5], but a variable, depending on their *contributions* to

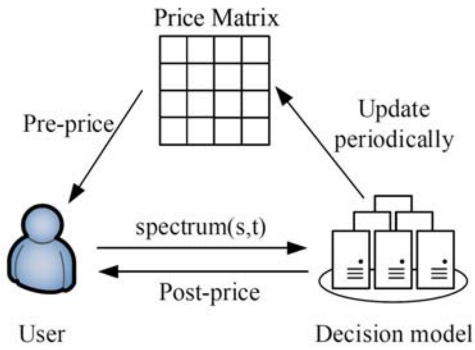


Fig. 2. System model: the price matrix is updated based on the decision model and released to the crowdsourcing users.

the system's prediction. For example, if the spectrum sensing data is very different from the system's prediction, then the spectrum sensing data will contribute to modify the system prediction model. Note that if the spectrum sensing data is the same as the system's prediction, this sensing data has no contribution to the prediction model. Although the spectrum sensing data has no contribution to the prediction model, the crowdsourcing user still had spent *some energy* for this task. For this reason, the crowdsourcing user should be paid. Therefore, we define the pricing by two parts, i.e., the pre-price $\underline{p}(s,t)$ and the post-price $\overline{p}(s,t)$. The pre-price $\underline{p}(s,t)$ is a fixed reward for the user's energy, and it is paid to the user before the task, while the post-price $\overline{p}(s,t)$ is variable aiming to help the system to measure the user's contribution and happens after the sensing task. Thus, the user's expected payment is defined by:

$$p_i(s,t) = \underline{p_i}(s,t) + \overline{p}_i(s,t). \tag{2}$$

The existing inventive mechanism [8] focuses on selecting the best subset users and to have an optimal REM with a lower system cost, which actually ignores the time factor due to not considering user's waiting time. For example, in the existing approaches, the crowdsourcing users have to wait and have some risk to be rejected until the system's decision. Furthermore, they may not be selected in the best subset, which can cause bad user experiences or reduce the user's utility. Hence, we define the user's utility with the waiting factor as follows:

$$u_i(t) = p_i(s,t)e^{-at}, a \geq 0. \tag{3}$$

where a is non-negative and reflects the tolerance of the waiting. For example, a small a means that the user still wants to take the task even though he/she has to wait for a long time. In our proposed RTIS, we have $a = 0$, which means that the crowdsourcing user will have an instant payment.

Then, we further define the cost of the system as the summation of all the users' payment as follows:

$$\mathcal{C} = \sum_{i \in \mathcal{N}} p_i(s,t). \tag{4}$$

For a system, it has a budget B to reward all the crowdsourcing users, and the summation of payment should meet $B \geq \mathcal{C}$.

Note that the user can immediately execute the sensing tasks rather than wait for the other participants and compete against them. This is a significant difference from the existing work [8] and the auction model [5], which process multiple users at a certain time and determine the winners and losers. Because the mobile devices have limited battery capacities, the users should be the ones to trigger a spectrum transaction rather than the system.

B. Estimation Model

The system collects the sensing results $z(s,t)$ and updates them to the spectrum database $\mathcal{Z}^-(s,t)$, then forms the latest spectrum database as $\mathcal{Z}(s,t) = \mathcal{Z}^-(s,t) \cup z(s,t)$. Since all the spectrum data is stored, the decision component can estimate the future spectrum usage pattern by

$$\begin{aligned} z^+(s',t') &= \mathcal{Z}^+(s',t') - Z(s,t), \text{for } t' > t. \\ &= \mathcal{E}_{\Delta t}(\mathcal{Z}(s,t), s', t'), \text{for } t' > t. \end{aligned} \tag{5}$$

where $\mathcal{E}$ denotes the estimation algorithm, $z^+(s',t')$ denotes the estimated future result at time of $t'(t' > t)$ and location s', $\mathcal{Z}^+(s',t')$ denotes the estimated spectrum database at the time of $t'(t' > t)$ and location s'. Δt is the learning interval (how often the estimation model is updated). Moreover, if the prediction model is updated at a short period Δt, there may not be sufficient training data and the model may be inaccurate. Therefore, a proper Δt should be investigated to achieve a good trade-off.

IV. Proposed Pricing Mechanism

A. Learning Interval Δt

RTIS is an adaptive model that will be updated at the period of Δt, called the learning interval. This is due to keeping pace with the dynamic changes in REM. On the one hand, merging the new coming data into the training data set contributes to modifying the existing prediction model. On the other hand, frequently updating the prediction model is not always necessary because this may cause more energy cost or when training a large scale of data, this even can not be completed within time of Δt. Therefore, the minimum Δt must be longer than the training time. Note that considering the practice and our data scale, we only set the learning interval Δt as 1, 2, 5, 10, 15, 20, 30 and 60 minutes.

B. Prediction Model

The spatio-temporal models are often used to represent and manage the dynamically changing geographic data, such as weather data and air pollution [14]. Because data is collected in the manner of discrete sampling in terms of time and location, interpolation methods are used to rebuild the whole map at any time and location. However, spectrum data is more dynamic and it is very difficult to achieve a good prediction of REM. Therefore, we adopt the feature-based models and further estimate the model parameters using machine learning techniques.

Based on the basic spatio-temple model (1) in [14] and the spectrum feature duration the period of Δt, we rewrite:

$$\mu(s,t) = \sum_m \beta_m T_m(s,t) + \sum_n \gamma_n(s) g_n(t) \tag{6}$$

where the $T_m(s,t)$ is time interval effect, and m and n are the indices of the time and locations' functions, β_m is the coefficient for the interval effects, $\gamma_n(s)$ are spatially varying coefficients for the temporal functions, and $g_n(t)$ are smooth temporal basis functions.

To learn a good prediction model, one needs to adjust involved parameters. Following the basic idea of machine learning, we treat all the input data with different features. Then, following (5), we rewrite (1) and (6) as follows:

$$\begin{aligned} \mathcal{Z}^+_{\Delta t}(s,t) &= \{z^+(s',t') | t < t' \le t + \Delta t\} \\ &= \{\mathcal{E}_{\Delta t}(\mathcal{Z}(s,t), s', t') | t < t' \le t + \Delta t\} \\ &= \{\mathcal{E}_{\Delta t}(x,y,m,n,\beta,\gamma,\delta) | t < t' \le t + \Delta t\} \\ &= \{\sum w_i f_i(x,y,m,n,\beta,\gamma,\delta) | t < t' \le t + \Delta t\} \\ &= \{Fw | t < t' \le t + \Delta t\}, \end{aligned} \tag{7}$$

where $Z^+_{\Delta t}$ is the estimated spectrum data set for the next duration Δt, f_i indicates the features, and w_i is the feature's weight. Note that (x,y) is a transformation of location s and represents the geographic coordinates. However, it is not enough to capture the people's activities. We add more information or covariates to the spectrum data, like the distance to the nearest main road and the apartment region.

We use the Mean Squared Prediction Error (MSPE) to evaluate the prediction model.

$$\text{MSPE}(Z, \mathcal{Z}^+_{\Delta t}) = \sum (Z - \mathcal{Z}^+_{\Delta t})^2. \tag{8}$$

C. Pre-pricing Rule

The payment consists of pre-price $\underline{p}(s,t)$ and post-price $\overline{p}(s,t)$. Accordingly, to ensure the budget balanced $B \ge \mathcal{C}$, we also separate the budget in two parts as

$$B_{\Delta t} = \underline{B} + \overline{B}, \tag{9}$$

where $B_{\Delta t}$ is the total budget for all crowdsourcing users in the duration Δt; and $\underline{B}$ and $\overline{B}$ are total pre-budget and post-budget respectively. Furthermore, we also use

$$\eta = \frac{\underline{B}}{B_{\Delta t}}, \tag{10}$$

to investigate how they affect the final system cost and user utility, and this is illustrated in Section V. Assume that the expected number of participating users within time Δt is

$$k = E(\mathcal{Z}(s,t)|\Delta t) = \sum_{\Delta t} |\mathcal{Z}(s,t)| \phi(s,t), \tag{11}$$

where $\phi(s,t)$ is the probability that a user takes the sensing task. So for each user, we have

$$\underline{p}(s,t) \le \frac{\underline{B}}{k} = \frac{\underline{B}}{\sum_{\Delta t} |\mathcal{Z}(s,t)| \phi(s,t)}, \tag{12}$$

which means that all the crowdsourcing users would equally share the guaranteed pre-budget.

D. Post-pricing Rule

On the one hand, the post-pricing is designed to reward the users by measuring how much contribution they made to the REM prediction model. Let $\overline{b}(s,t)$ denote the user's post-budget and similar to (12), we have

$$\overline{p}(s,t) \le \overline{b}(s,t) = \frac{\overline{B}}{k} = \frac{\overline{B}}{\sum_{\Delta t} |\mathcal{Z}(s,t)| \phi(s,t)}. \tag{13}$$

So $\overline{b}(s,t)$ is also the maximum payment for the user's post-price $\overline{p}(s,t)$. Specifically, aiming at relating it to how many contributions the user makes to the prediction model, we further define the post-price $\overline{p}(s,t)$ as

$$\overline{p}(s,t) = \overline{b}(s,t)(1 - e^{-\alpha}), \tag{14}$$

where

$$\alpha = \mathcal{K} || z(s,t) - \mathcal{Z}^+_{\Delta t}(s,t) ||, \tag{15}$$

is the contribution factor. Here, the coefficient α is calculated by the distance function $\mathcal{K}$ to measure the goodness of the estimated value. For example, if the distance is big, which means the prediction is not accurate, then we treat this sensing task as a big contribution (i.e., $\alpha \to \infty$) and the user deserves full post-budget as $\overline{p}(s,t) = \overline{b}(s,t)$. Otherwise, if the distance is close to zero (i.e., $\alpha \to 0$), the user will be paid by $\overline{p}(s,t) \to 0$.

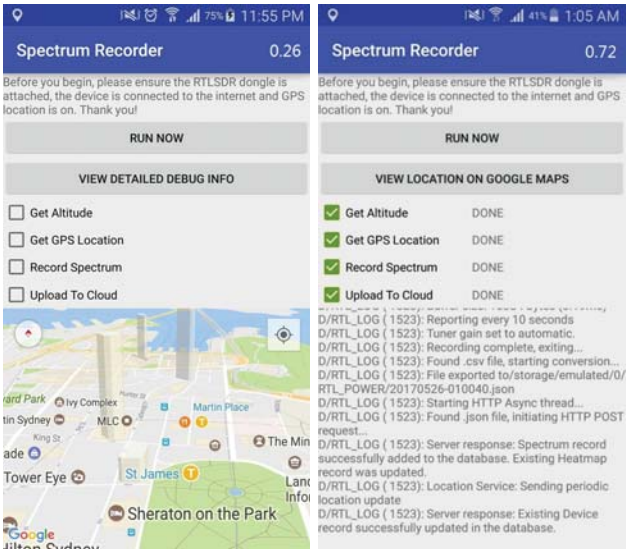
The distance can be calculated as the straightforward difference as $\alpha = \sum Z(s,t) - \mathcal{Z}^+(s,t)$. However, this may be incorrect to measure the difference between them, so we use another method to measure the increment of the information (or mutual information) that the sensing result brings to the prediction model, i.e.,

$$\begin{aligned} \alpha &= I(Z; \mathcal{Z}^+) \\ &= H(Z) - H(Z|\mathcal{Z}^+) \\ &= H(Z) + H(\mathcal{Z}^+) - H(Z, \mathcal{Z}^+) \\ &= \sum_s \phi(s) \log \frac{1}{\phi(s)} + \sum_t \phi(t) \log \frac{1}{\phi(t)} - \\ & \sum_{s,t} \phi(s,t) \log \frac{1}{\phi(s,t)} \\ &= \sum_{s,t} \phi(s,t) \log \frac{\phi(s,t)}{\phi(s), \phi(t)}. \end{aligned} \tag{16}$$

where $\phi(s,t)$ is the probability at the spatio-temporal space. This is because the coming sensing result will bring some certainty to the existing model and help to enhance the accuracy. Note that the probability ϕ of the crowdsourcing users can be derived by the statistical history data $\mathcal{Z}^-(s,t)$.

E. Overall RTIS Procedure

The overall pricing algorithm is shown in Algorithm 1 where $|\mathcal{N}|$ denotes the number of training data, and the prediction model $\mathcal{E}_{\Delta t}$ is updated at the learning interval of Δt. First, the probability $\phi(s_i)$ a user takes the task at this



(a) APP screenshot 1: before taking the task; (b) APP screenshot 2: after taking the task.

Fig. 3. A mobile user can monitor the real-time pre-price (0.26) and also obtain the post-price (0.46) after completing the sensing task.

location of s_i, probability $\phi(t_i)$ a user take the task at this time of t_i, and the probability $\phi(s_i, t_i)$ can be calculated by the history database. Second, the pre-price is given to the user, and the user can choose to accept the task or not. Third, if the task is accepted and submitted, the post-price will be calculated by the system and given to the user. Otherwise, the spectrum database is not updated and the user is paid as zero.

Algorithm 1: Real-time Incentive Procedure

Input: $z(s,t)$ and history $\mathcal{Z}^-(s,t)$
Output: payment $p(s,t)$ and $\mathcal{Z}(s,t)$
calculate the probabilities:
$\phi(s_i) \leftarrow |\mathcal{Z}^-(s_i)|/|\mathcal{N}|$
$\phi(t_i) \leftarrow |\mathcal{Z}^-(t_i)|/|\mathcal{N}|$
$\phi(s_i, t_i) \leftarrow |\mathcal{Z}^-(s_i, t_i)|/|\mathcal{N}|$
present the pre-price $\underline{p}(s,t)$, following (12)
if *accepted* **then**
    update the current sensing result to the history
    following (14)(16), calculate the post-price $\overline{p}(s,t)$
    $\mathcal{Z}(s,t) = z(s,t) \cup \mathcal{Z}^-(s,t)$
    $p(s,t) = \underline{p}(s,t) + \overline{p}(s,t)$
else
    no update to the history $\mathcal{Z}(s,t) = \mathcal{Z}^-(s,t)$
    $p(s,t) = 0$
end

V. Performance Evaluation

In this section, we evaluate the performance of the proposed RTIS. We first present the screenshots of APP and web service, which are shown in Fig. 3 and Fig. 4, and then give the analysis of the prediction model. Here, a in (3) is set at 1.

A. Software and Data Discretization

We feed the collected sensing data which is in the scale of thousands into the model. One collected data is displayed in the web service, as shown in Fig. 4. The continuous data may not be convenient, so we discretize all the submitted sensing results into 10MHz-channels as

$$z(s,t) = \left\{ Q(c_i) | i = \left\lfloor \frac{bandwith}{10} \right\rfloor \right\}, \tag{17}$$

where i is the index of the channel, the $bandwidth$ is the bandwidth that the sensor can monitor, e.g., $bandwidth = 700$ MHz, and $Q(c_i)$ indicates channel c's quality, defined as

$$Q(c_i) = \frac{\int_{c_i} z(s,t)}{10}. \tag{18}$$

B. Gradient Descent Model

Considering the spatio-temporal model is a multi-variable function, we choose gradient descent as our machine learning model [15]. Following (7), we treat $\mathcal{Z}^+_{\Delta t}$ as the estimated set and Z as the test set, to minimize the loss function, which is defined as

$$L = \frac{1}{2}(Z - \mathcal{Z}^+_{\Delta t})^T (Z - \mathcal{Z}^+_{\Delta t}), \tag{19}$$

and we have

$$\frac{\partial L}{\partial w} = F^T(Fw - Z). \tag{20}$$

The model will keep learning iteratively until it reaches the minimum of (20). We compare two methods of gradient descent, i.e., fixed learning rate and adaptive learning rate, known as Adagrad [15]. We compare their efficiency and MSPE as shown in Fig. 5. The Adagrad method takes less time and has lower MSPE, so we select it as our machine learning model in this paper. Note that RTIS can adopt any learning model to learn the parameters of the spatio-temporal model.

C. System Cost and User Utility

In Fig. 7 and Fig. 6, the main performance of average user utility and system cost are shown, and the proposed RTIS and *Ying*'s approach [8] are compared. In Fig. 6, the user utility is always better than that of *Ying*'s approach. Especially, when the learning interval Δt becomes longer, RTIS's advantage is more significant. This is because reducing the user's waiting time leads to a higher utility because waiting users may not take the tasks.

Furthermore, in Fig. 7, although the system's cost increases when the learning interval becomes larger, the slope of the curves decreases. This is because when the learning interval is longer, the training model has more data and higher accuracy so the post-price is given less to the users, i.e., the users are provided fewer rewards. When the learning interval is longer than about 15 ($\Delta t \geq 15$), RTIS's performance is always better than *Ying*'s. This is because a too short learning interval causes a bad prediction model but a proper learning interval can improve the performance.

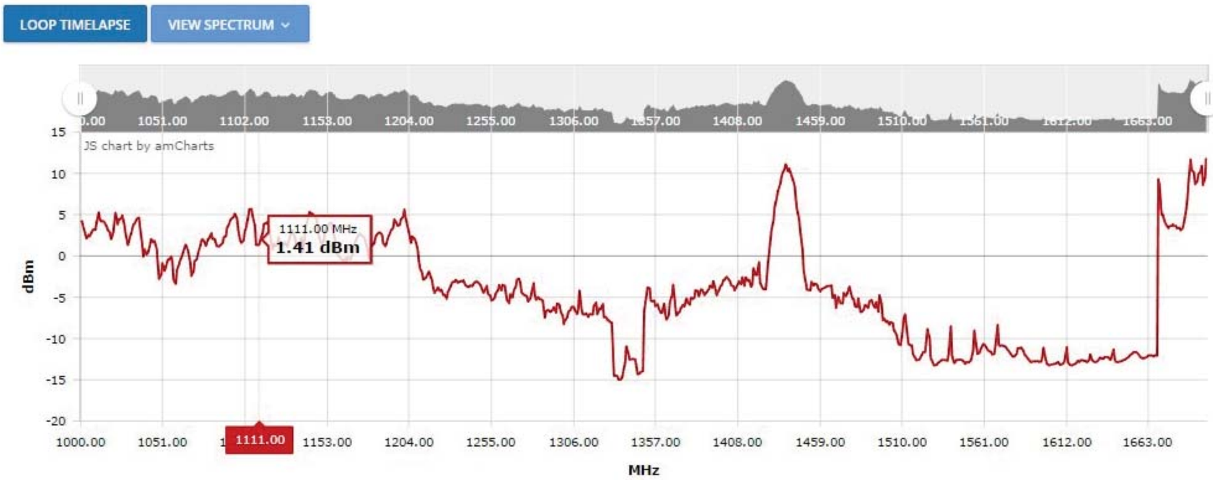


Fig. 4. Screenshot: the sensing result over band 1000-1700 MHz shown in the web service.

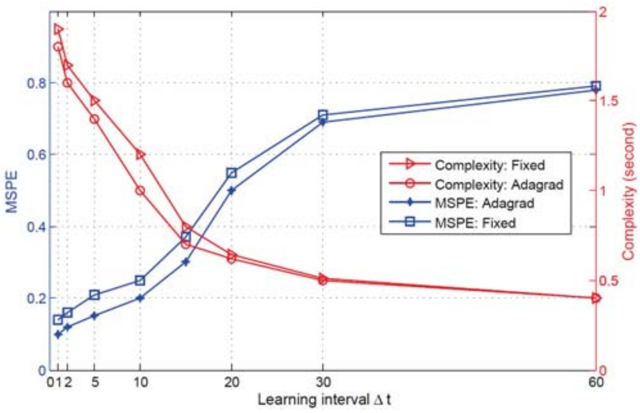


Fig. 5. Comparison of the fixed and Adaptive gradient decent models in terms of MSPE and complexity.

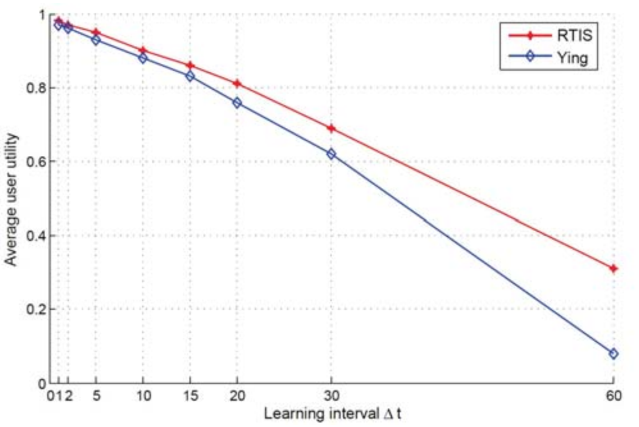


Fig. 6. Providing an instant payment can improve the user's utility, and the advantage is more obvious when the learning interval is larger.

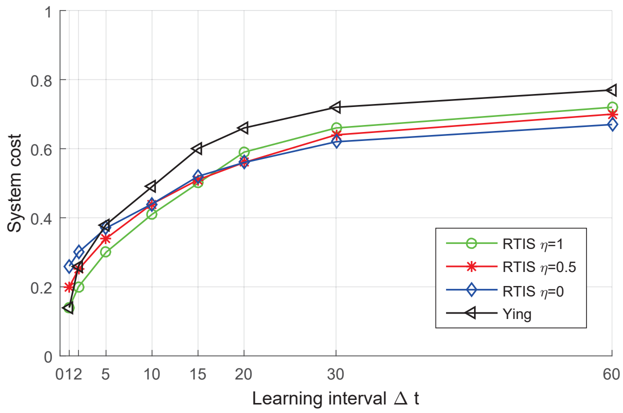


Fig. 7. The effect of budget ratio on the cost: a higher percent of pre-budget is better when the learning interval is shorter. This is because short interval leads to lower accuracy, and more post-budget is paid. Thus, setting the pre-budget in short interval higher is attractive for more users to take the task.

VI. Conclusion

In this paper, we propose a novel Real-Time Incentive Solution (RTIS) that encourages mobile users to participate in sensing tasks and evaluates their contributions to the radio environment map in a real-time manner. We also present a demonstration about how to outsource the spectrum sensing tasks to the mobile users and compare the proposed solution with some current works in terms of the system cost and the user utility. The contribution of this paper is a formalization of the real-time pricing mechanism based on spatio-temporal prediction and aggregation with respect to spectrum sensing. From the hardware to the software and the algorithm, it can be clearly seen the feasibility and flexibility of the crowdsourcing spectrum sensing tasks achieved by the proposed RTIS. In the future work, we will focus on how to improve the prediction accuracy and scale the existing spectrum sensing using RTIS with massive data.

References

[1] H. B. Yilmaz, T. Tugcu, F. Alagz, and S. Bayhan, "Radio environment map as enabler for practical cognitive radio networks," *IEEE Communications Magazine*, vol. 51, no. 12, pp. 162–169, December 2013.

[2] Federal Communications Commission, "Order on reconsideration and second report and order," vol. FCC-16-55, April 2016.

[3] Q. Z. X. Feng and J. Zhang, "A hybrid pricing framework for tv white space database," *IEEE Transactions on Wireless Communications*, vol. 13, no. 5, pp. 2626–2635, 2014.

[4] L. G. Y. Luo and J. Huang, "Price and inventory competition in oligopoly tv white space markets," *IEEE Journal on Selected Areas in Communications*, vol. 33, no. 5, pp. 1002–1013, 2015.

[5] J. Barrera, A. Garcia, and M. Hong, "Auction design for spectrum allocation under interference constraints," in *2013 IEEE Global Communications Conference (GLOBECOM)*, Dec 2013, pp. 3035–3041.

[6] W. Dong, S. Rallapalli, L. Qiu, K. K. Ramakrishnan, and Y. Zhang, "Double auctions for dynamic spectrum allocation," *IEEE/ACM Transactions on Networking*, vol. 24, no. 4, pp. 2485–2497, Aug 2016.

[7] Y. Zhang, Y. Fang, and S. Zhong, "Incentive mechanism design for smartphone crowdsensing," in *2015 IEEE Fifth International Conference on Big Data and Cloud Computing*, Aug 2015, pp. 287–292.

[8] X. Ying, S. Roy, and R. Poovendran, "Incentivizing crowdsourcing for radio environment mapping with statistical interpolation," in *2015 IEEE International Symposium on Dynamic Spectrum Access Networks (DySPAN)*, Sept 2015, pp. 365–374.

[9] I. Koutsopoulos, "Optimal incentive-driven design of participatory sensing systems," in *2013 Proceedings IEEE INFOCOM*, April 2013, pp. 1402–1410.

[10] *Crowdsourcing to smartphones: Incentive mechanism design for mobile phone sensing*, New York, NY, USA, 08 2012.

[11] D. Peng, F. Wu, and G. Chen, "Pay as how well you do: A quality based incentive mechanism for crowdsensing," in *Proceedings of the 16th ACM International Symposium on Mobile Ad Hoc Networking and Computing*, ser. MobiHoc '15. New York, NY, USA: ACM, 2015, pp. 177–186. [Online]. Available: http://doi.acm.org/10.1145/2746285.2746306

[12] S. C. Park, M. K. Park, and M. G. Kang, "Super-resolution image reconstruction: a technical overview," *IEEE Signal Processing Magazine*, vol. 20, no. 3, pp. 21–36, May 2003.

[13] Y. D. Feng Ling, Xiaodong Li and F. Xiao, "Super-resolution land cover mapping with spatialtemporal dependence by integrating a former fine resolution map," *IEEE JOURNAL OF SELECTED TOPICS IN APPLIED EARTH OBSERVATIONS AND REMOTE SENSING*, vol. 7, no. 5, May 2014.

[14] L. S. T. L. S. D. A. Adam A. Szpiro, Paul D. Sampson and J. Kaufman, "Predicting intra-urban variation in air pollution concentrations with complex spatio-temporal dependencies," *Environmetrics*, vol. 21, pp. 606–631, 2010.

[15] P. Dangeti, *Statistics for Machine Learning*. Packt Publishing, July 2017.