# Online Incentive Mechanism for Crowdsourced Radio Environment Map Construction

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*Abstract*—**Constructing Radio Environment Map (REM) accurately and cost-efficiently is of great importance to realize dynamic spectrum access. Two kinds of approaches are widely investigated recently, i.e., radio propagation model based approaches and sensor monitoring based approaches. However, these existing approaches are suffering from either inaccurate spectrum availability or high deployment cost. To this end, outsourcing the spectrum sensing task to mobile users that are outfitted with spectrum sensors could greatly reduce the operator's expenditure, and meanwhile, achieve a satisfactory accuracy. The key of crowdsourced REM construction is to attract user participation. In this paper, we propose a novel online incentive mechanism for constructing a fine-grained REM with crowdsourcing in a realistic scenario, where the mobile users arrive and leave in an online manner. The proposed mechanism is proven to satisfy the truthfulness, individual rationality, computational efficiency and consumer sovereignty. Evaluation results demonstrate that the proposed mechanism outperforms the baseline schemes substantially.**

## I. Introduction

Over the past decade, we have witnessed a 4000-fold growth of mobile data traffic due to the tremendous increase of various wireless devices and spectrum-hungry applications. This skyrocketing demand of additional spectrum leads to a surge in a need of paradigm shift from the static and exclusive spectrum usage framework toward a dynamic spectrum sharing framework. To this end, the concept of dynamic spectrum access has been proposed, which allows the secondary users access the spectrum that are underutilized by primary users. To guarantee that there is no harmful interference to primary users, radio environment map (REM) is widely adopted in which the white space information is stored.

Two kinds of approaches for constructing REM have been addressed recently, i.e., propagation model based approach and sensor monitoring based approach. The propagation model based approach predicts the received signal strength (RSS) at any receiver location by taking into consideration transmitter power, location, and antenna pattern, e.g., Spectrum Bridge, Google, Keybridge, etc. This approach is easy to implement, however, it is prone to offer inaccurate and stale spectrum availability in many circumstances, e.g., approximately 40% – 70% of available white space is wasted in urban area [1]. To improve the accuracy of REM, sensor monitoring based approach proposes to deploy a large number of dedicated sensors in regions of interest to collect spatio-temporal spectrum data, and exploit statistical interpolation methods such as Kriging [2] to construct the REM. However the huge cost of such large-scale sensor deployment makes its scalability a major problem.

A practical cost-efficient alternative is to exploit crowdsourcing for the sensing task [3–6], i.e., recruiting mobile users that are outfitted with spectrum sensors. Obviously, these spectrum sensing and reporting operations consume users' own resources in terms of computation, battery, storage and communication. Therefore, a core question is how to attract users to participate. To this end, some forms of reward is expected for the participants, either in the form of money or resource. Incentivizing crowdsourcing for REM construction has attracted considerable attentions recently [7–10]. Ying *et al.* [7] proposed to minimize the interpolation variance for all the spots of interest at a given budget. Gao *et al.* [8] proposed a game-theoretic model based mechanism to incentivize the users with additional spectrum access opportunities. Wang *et al.* [9, 10] proposed incentive mechanisms for fine-grained REM construction by taking into consideration the heterogeneity of spots. These works [7–10] all assume the offline scenario in which all interested users report the required information to the operator at the same time, and the operator selects the winners and determines the reward based on all the collected information. However, in practice the mobile users arrive and leave the network in an online manner, and their availabilities change over time. Several recent studies focus on online incentive mechanism for crowdsourcing [11, 12]. However they cannot applied to the crowdsourced REM construction problem directly, due to the heterogeneity of spots' requirements and properties of Kriging interpolation.

In this paper, we consider a practical scenario that the operator intends to construct a fine-grained REM by outsourcing the sensing tasks to mobile users who arrive in an online manner. Based on the previous research results [13],

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instead of collecting the sensing measurement uniformly, it would be cost-efficient for the operator to only augment the RSS at some particular spots, e.g. the spots that are prone to have large estimation error when using propagation model based prediction. Therefore, those spots could have distinct quality requirements depending on their prediction accuracy. The operator publishes the sensing task periodically, and the mobile users arrive sequentially and show their interests to participate by submitting their profiles to the operator. The operator must decide immediately whether to accept or reject this user for crowdsourcing, and decide the payment if necessary. Once the decision is made, it is irrevocable. The goal is to guarantee the requirements of all spots and meanwhile minimize the total expenditure of the operator. To this end, we propose a novel online incentive mechanism for crowdsourced REM construction by utilizing auction model [14, 15]. The proposed mechanism is proven to be truthful, individual rational, computationally efficient and consumer sovereign. We perform extensive simulations to analyze the properties of the proposed mechanism, and demonstrate that the proposal outperforms the baseline schemes substantially.

The rest of the paper is organized as follows. Section II briefly introduces the used statistical interpolation method. Section III gives the system model and problem formulation. Section IV presents the proposed mechanism. Finally, Section V provides the evaluation results, and Section VI concludes this paper.

## II. Interpolation Method: Kriging

In this section, we briefly introduce a well-known geo-statistical interpolation technique: Kriging [2]. For radio mapping, Kriging uses multiple known location-specific RSS measurements to predict the unknown RSS at a desired location. We consider a 2-D field with the RSS at a point $(x_i, y_i)$ denoted by $z_i$. Given the RSS measurements at a set of locations $\mathcal{N} = \{(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)\}$, Kriging predicts the unknown RSS at a new location $(\hat{z_0})$ from the weighted known RSS as

$$\hat{z_0} = \sum_{i=1}^{n} \lambda_i z_i, \tag{1}$$

where $\lambda_i$ is the normalized weight, i.e., $\sum_{i=1}^{n} \lambda_i = 1$. The optimal weights $\lambda_i$ are determined by minimizing the estimation variance at $(x_0, y_0)$ by using the measurements at set $\mathcal{N}$. By denoting the minimized estimation variance (also called the Kriging variance) as $\phi_{(x_0,y_0)}(\mathcal{N})$, we have

$$\phi_{(x_0,y_0)}(\mathcal{N}) = \min_{\lambda_i} Var\,(\hat{z_0} - z_0). \tag{2}$$

To find $\phi_{(x_0,y_0)}(\mathcal{N})$, a key function, namely *semivariogram* $\gamma_{ij}$, is introduced. $\gamma_{ij}$ models the variance between two points as a function of their distance. The theoretical semivariogram is represented by

$$\gamma_{ij} = \frac{1}{2} E\left[(z_i - z_j)^2\right]. \tag{3}$$

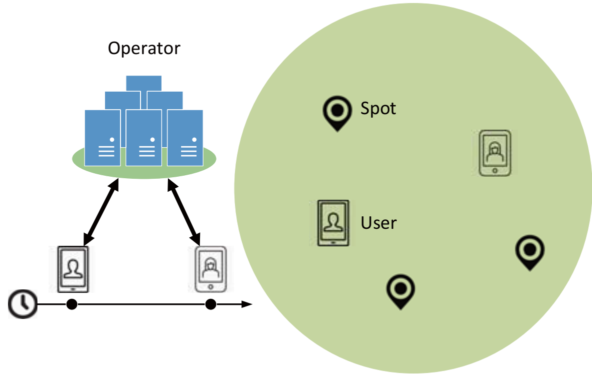


Fig. 1. Illustration of a REM construction system with online user crowdsourcing.

Based on [2], the minimized Kriging variance could be obtained by solving the following matrix.

$$\begin{bmatrix} \gamma_{11} & \gamma_{12} & \cdots & \gamma_{1n} & 1 \\ \gamma_{21} & \gamma_{22} & \cdots & \gamma_{2n} & 1 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \gamma_{n1} & \gamma_{n2} & \cdots & \gamma_{nn} & 1 \\ 1 & 1 & \cdots & 1 & 0 \end{bmatrix} \begin{bmatrix} \lambda_1 \\ \lambda_2 \\ \vdots \\ \lambda_n \\ \mu \end{bmatrix} = \begin{bmatrix} \gamma_{10} \\ \gamma_{20} \\ \vdots \\ \gamma_{n0} \\ 1 \end{bmatrix} \tag{4}$$

where $\mu$ is the Lagrange parameter. Obviously, to obtain the optimal weights $\lambda_i$, the semivariogram $\gamma_{ij}$ is required. For the considered radio mapping scenario, $\gamma_{ij}$ is estimated by fitting a set of RSS measurements to an empirical curve, e.g., exponential or spherical model. $\phi_{(x_0,y_0)}(\mathcal{N})$ represents the RSS estimation uncertainty at an unknown location $(x_0, y_0)$ by using measurements of set $\mathcal{N}$, which is used as a criterion in our online incentive mechanism design.

## III. System Model and Problem Formulation

### A. System Model

Fig. 1 illustrates the REM construction system with online user crowdsoucing. The system consists of a centralized operator (e.g., cloud server) and multiple mobile users with devices that are outfitted with spectrum sensors. The mobile users are connected to the operator by cellular networks or wi-fi connections. Instead of completely replacing the propagation model-based REM by collecting large-scale sensing results uniformly, we consider that the help of sensor measurements are only needed for augmenting partial particular spots. Therefore, this architecture is capable of improving the REM accuracy with only a modest sensing effort. The spots need to be augmented could be selected based on the machine learning based prediction [13], which is out of the scope of this paper. The selected spots could have distinct augmenting requirements which are quantified by Kriging variances, e.g., higher requirements (i.e., lower Kriging variance) for spots with poorer prediction results. Specifically, the set of spots that needs to be augmented is denoted by $\mathcal{M}$ with spot index $j$. Each spot $j$ has an individual augmenting requirement $r_j$, i.e., spot $j$'s RSS needs to be interpolated with a maximum Kriging variance $r_j$.

We consider a set of mobile users with index $i$, and each user $i$ knows its location $(x_i, y_i)$. The mobile users arrive online in a random manner, and each user $i$ has an arrival time $a_i$. In this work, we assume an impatient user model, in which the arrival time of each user equals his departure time. We leave the discussions on unequal arrival-departure time model to future work. While participating in crowdsourcing, there is a *cost* $c_i$ occurring to user $i$, since the sensing and reporting activities consume resources. The location, cost and arrival information constitute the *profile* of user $i$ as $f_i = (x_i, y_i, c_i, a_i)$. Notice that the profile is a private information and thus is only known by the user himself.

We use online auction framework to model the interactions between the operator and mobile users. The operator is a buyer who wants to buy sensing measurements, and the mobile users are sellers. We consider that the operator publishes the sensing task periodically, and the spots that need to be augmented may change in each round. Notice that the sensing task only contains the central frequency information, the location information of the spots are not included in the sensing task. When a user $i$ arrives, it competes for the sensing task by submitting a *bidding profile* $f_i' = (x_i', y_i', b_i, a_i')$, where $x_i', y_i'$ and $a_i'$ are reported location and reported arrival time respectively, and $b_i$ is a bid which is a price he expects. Notice that the bidding profile $(x_i', y_i', b_i, a_i')$ may or may not be his real profile $(x_i, y_i, c_i, a_i)$. Upon receiving the bidding profile from mobile user $i$, the operator needs to decide whether to buy this measurement immediately, and at what price if so. The operator tells user $i$ his decision, and the accepted mobile user reports its sensing measurement and gets paid.

### B. Problem Formulation

We assume that the users are game-theoretic and intend to maximize their utilities. For instance, they may report an untruthful location, cost or arrival time to the operator, if he believes this could improve his utility. The utility of user $i$ is defined as

$$u_i = \begin{cases} p_i - c_i, & i \in \mathcal{W} \\ 0, & \text{otherwise}, \end{cases} \tag{5}$$

where $p_i$ is the payment that the user $i$ received from the operator, and $\mathcal{W}$ is the accepted user set. The operator expects to accept a set of users for minimizing the total expenditure under the augmenting requirements of all spots. Therefore, we have

$$\begin{aligned} &\min_{i \in \mathcal{W}} c_i \\ \text{subject to} \quad &\phi_j(\mathcal{W}) \le r_j, \forall j \in \mathcal{M}. \end{aligned} \tag{6}$$

In Eqn. (6), the constraint ensures that the augmenting requirement for each spot is met, i.e., the Kriging variance at spot $j$ by the interpolation of the selected user set is no larger than $j$'s requirement. Moreover, the designed online incentive mechanism should satisfy the following desirable properties, which are not imposed explicitly in the constraints in Eqn. (6).

- **Truthfulness**. For every user, reporting its true location, cost and arrival time is its dominant strategy regardless of other users' strategies.
- **Individual Rationality**. The utility for any user is non-negative.
- **Computational Efficiency**. The outcome of the mechanism can be computed in polynomial time.
- **Consumer sovereignty**. For every user, there is a chance to win the sensing task.

## IV. Proposed Online Incentive Mechanism

### A. Mechanism Design

The proposed online incentive mechanism is virtually a dynamic threshold updating process. We use a *threshold* $\theta$ to judge whether or not to accept the arrived user, and dynamically update $\theta$ based on the previous accepted user set. We consider that the value of a user depends on two factors, i.e., its contribution to Kriging variance and its bidding price. To this end, we define a *marginal efficient contribution* of the arrived user $i$ as

$$\alpha_i(\mathcal{W}) = \frac{m_i(\mathcal{W})}{b_i}, \tag{7}$$

where $b_i$ is $i$'s bid, and $m_i(\mathcal{W})$ is $i$'s *marginal contribution* based on the current accepted user set $\mathcal{W}$. $m_i(\mathcal{W})$ is calculated by

$$m_i(\mathcal{W}) = \sum_{j \in \mathcal{M}} \frac{\max\left(\phi_j(\mathcal{W}), r_j\right) - \max\left(\phi_j(\mathcal{W} \cup \{i\}), r_j\right)}{r_j}, \tag{8}$$

where $\phi_j(\mathcal{W})$ and $\phi_j(\mathcal{W} \cup \{i\})$ are the Kriging variance achieved by the accepted user set $\mathcal{W}$ without and with $i$, respectively. Here, the Kriging variance improvements to all the spots $\mathcal{M}$ are considered, and we allocate weight $1/r_j$ to different spots, i.e., the spot with small variance requirement has large weight.

The proposed online mechanism is illustrated in Algorithm 1. The whole process ends if the requirements of all spots are satisfied (line 2). When a user $i$ arrives, for each member $k$ in the current accepted user set $\mathcal{W}$, we construct a temporary user set $\mathcal{W}'_k$, in which $k$ is removed from $\mathcal{W}$. For all $\mathcal{W}'_k$, we calculate user $i$'s marginal contribution $\alpha_i(\mathcal{W}'_k)$ based on Eqn. (7). And the minimum of them, $\alpha_i'$, is used to represent $i$'s marginal contribution (lines 5 – 8). The operator accepts user $i$ as long as his $\alpha_i'$ is no less than the current threshold $\theta$. Meanwhile, the accepted user receives a payment $\frac{\alpha_i' \cdot b_i}{\theta}$ from the operator and is added to the accepted user set $\mathcal{W}$ (lines 9 – 11). Notice that this payment is the maximum bid user $i$ could submit that allows it to win. To guarantee the user sovereignty, the threshold is set to a sufficiently small value initially, and start to update after $t'$ users arrived (lines 14–15). After the user acceptance and payment determination, the spot set $\mathcal{M}$ is updated. Specifically, the spots whose requirements are satisfied by the current $\mathcal{W}$ are removed from $\mathcal{M}$ (lines 16 – 18).

The threshold update function is illustrated in Algorithm 2. After $t'$ users arrived, the threshold is updated as long as accepted user set $\mathcal{W}$ changes. The rationale is to set the threshold as the $\delta$-quantiles of marginal contribution for all members $k$ in $\mathcal{W}$, which is calculated based on user set

$\mathcal{W}'_k = \mathcal{W} \setminus \{k\}$. For instance, we could use the median marginal contribution for all members in accepted user set by setting $\delta = 0.5$, or use a slight underestimated threshold $\delta < 0.5$ to guarantee that enough users could be accepted.

**Algorithm 1:** Proposed Online Mechanism

**Input**: Spot set $\mathcal{M}$
**Output**: Winner set $\mathcal{W}$, payment vector $P$
1 $\left(\mathcal{W}, \mathcal{W}'_k, \alpha'_i, t', \theta\right) \leftarrow (\emptyset, \emptyset, 0, 5, 1)$;
2 **while** $\mathcal{M} \neq \emptyset$ **do**
3     **if** *a user i arrives at time slot t* **then**
4         $\mathcal{W}'_k \leftarrow \emptyset$;
5         **forall the** $k \in \mathcal{W}$ **do**
6             $\mathcal{W}'_k \leftarrow \mathcal{W} \setminus \{k\}$;
7             $\alpha_i(\mathcal{W}'_k) \leftarrow \frac{m_i(\mathcal{W}'_k)}{b_i}$;
8         $\alpha'_i = \min_{k \in \mathcal{W}} \alpha_i(\mathcal{W}'_k)$;
9         **if** $\alpha'_i \geq \theta$ **then**
10             $\mathcal{W} \leftarrow \mathcal{W} \cup \{i\}$;
11             $p_i \leftarrow \frac{\alpha'_i \cdot b_i}{\theta}$;
12         **else**
13             $p_i \leftarrow 0$;
14         **if** $t \geq t'$ **then**
15             $\theta \leftarrow$ *UpdateThreshold*$(\mathcal{W})$;
16         **forall the** $j \in \mathcal{M}$ **do**
17             **if** $\phi_j(\mathcal{W}) \leq r_j$ **then**
18                 $\mathcal{M} \leftarrow \mathcal{M} \setminus \{j\}$;
19     $t \leftarrow t + 1$;
20 return $\mathcal{W}, P$;

**Algorithm 2:** Update Threshold

**Input**: Winner set $\mathcal{W}$
**Output**: Threshold $\theta$
$\mathcal{W}'_k \leftarrow \emptyset$;
**forall the** $k \in \mathcal{W}$ **do**
    $\mathcal{W}'_k \leftarrow \mathcal{W} \setminus \{k\}$;
    $\alpha_k(\mathcal{W}'_k) \leftarrow \frac{m_k(\mathcal{W}'_k)}{b_k}$;
return $\theta =$ *quantile* $(\alpha_k(\mathcal{W}'_k), \delta)$;

### B. Proof of Properties

In this subsection, we prove that the proposed incentive mechanism is truthful, individual rational, computationally efficient and consumer sovereign.

***Theorem 1:*** The proposed incentive mechanism is truthful.

*Proof:* We show that the proposed incentive mechanism is truthful in terms of arrival time, location and cost. For arrival time, based on the impatient user model, no user has incentive to report an earlier or a later arrival/departure time, since the user cannot perform sensing task and obtain a payment in those cases. Achieving location-truthfulness is also trivial. The user simply cannot report a false location that is close to the augment spots, since spots' information is not included in the sensing task. Finally, the proposed incentive mechanism is cost-truthful since the online algorithm is bid-independent, i.e., the threshold is determined by historical data and thus changing the bid could not improve user's utility. This completes the proof. ■

***Theorem 2:*** The proposed incentive mechanism is individually rational.

*Proof:* Based on lines 9 – 11 in Algorithm 1, the user receives payment $p_i \geq b_i$ if he is accepted, otherwise $p_i = 0$ (line 13). Therefore, the utility of user is nonnegative. ■

***Theorem 3:*** The proposed incentive mechanism is computationally efficient.

*Proof:* Computing the marginal efficient contribution (lines 5 – 7 in Algorithm 1) and updating the threshold (Algorithm 2) have the same complexity, which is $O(NM)$. Therefore, the online mechanism's computation complexity at each time step is bounded by $O(NM)$. ■

***Theorem 4:*** The proposed incentive mechanism is consumer sovereign.

*Proof:* The proposed algorithm does not have a sampling process which automatically rejects all the users arrive in this period. On the contrary, the users arrive before $t'$ would be accepted with quite high probability since the initial threshold is set to a substantially small value. And the users arrive after $t'$ have the chance to be accepted as long as its marginal efficient contribution is not less than the current threshold. ■

## V. Evaluation Results

In this section, we evaluate the performance of the proposed online mechanism, and compare it with online fix-price scheme, offline scheme [9] and bid-based offline scheme. The online fix-price scheme sets a static price and accepts the arrived user as long as its bid is lower than this price. We tried different prices and the following results show the optimal one (impossible in practice). The offline scheme [9] is proposed in our previous work, it minimizes the operator's expenditure by using all users' information in an offline fashion. And the bid-based offline scheme selects the users with the highest bid repeatedly among the remaining bidders until the requirements of all spots are satisfied. Notice that except the online fix-price scheme, the proposed online scheme, offline scheme [9] and bid-based offline scheme all could guarantee the truthfulness.

We consider a region with size 2000m by 2000m. The number of spots that we try to augment varies from 5 to 30 with step 5. The augment requirements are set uniformly distributed in $[0.5, 5]$ above the optimal value. The number of mobile users varies from 100 to 300 with step 50, and their costs are uniformly distributed in range $(0, 1)$. We use the exponential model $\gamma_{ij} = c(1 - e^{-d(i,j)/r})$ as the empirical semi-variogram $\gamma_{ij}$ in Kriging, with optimal parameter $c = 21.15$ and $r = 24.99$ (obtained by `variogramfit` function in Matlab). The evaluation results are averaged by 50 trials with randomly generated spots, users, requirements and costs.

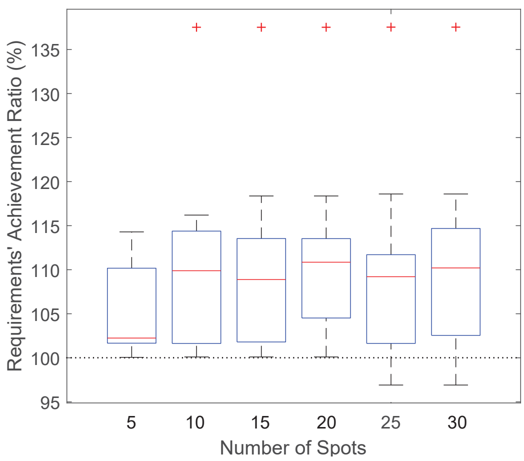


Fig. 2. Requirements' Achievement Ratio varies with number of spots. (300 users.)

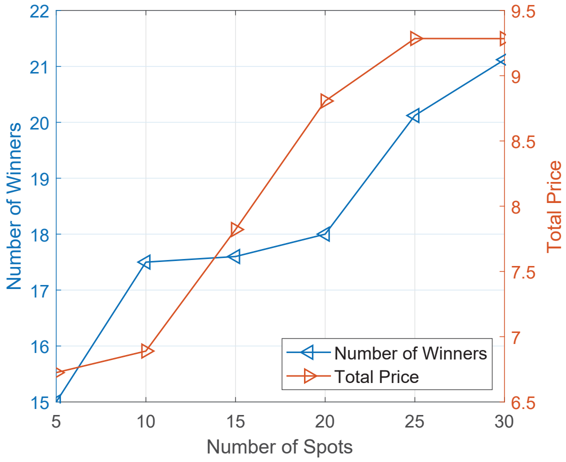


Fig. 3. Number of winners and Total payment vary with number of spots. (300 users.)

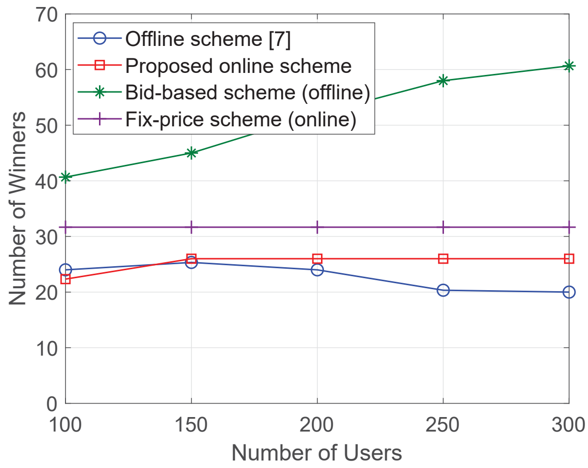


Fig. 5. The performance comparison in terms of number of winners. (20 spots.)

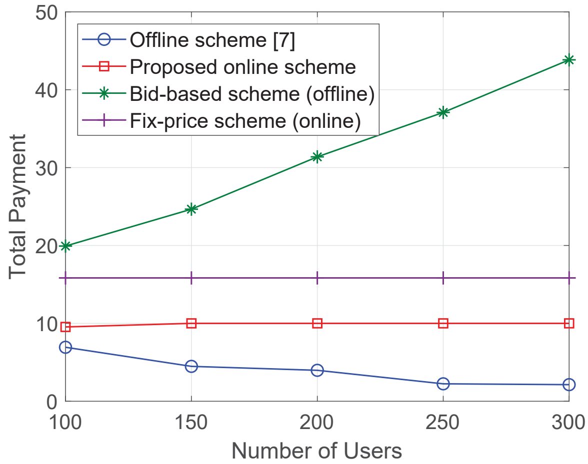


Fig. 6. The performance comparison in terms of total payment. (20 spots.)

Firstly, Figs. 2 and 3 show the performance variance of the proposed mechanism as the number of augment spots increase. Fig. 2 shows the distribution of requirements' achievement ratio. Here 100% ratio indicates the Kriging variance achieved by winning user set is exactly same as the requirement, which is the ideal result. We could observe that when the number of spots is larger than 20, some spots' requirements cannot satisfied by the given user set. And there exist some outliers beyond 135%, which can be considered as a waste of operator's expenditure. The reason is that every selected user contribute to all spots based on Kriging interpolation (instead of a particular spot), and the achieved spots' requirement ratio depends on both their location and requirement value. Fig. 3 demonstrates the variance of number of winners (left y-axis) and total payment (right y-axis). As expected, both of them rise as the increase of number of spots.

Next, in Fig. 4, we compare the requirements' achievement ratio of the offline scheme [9], proposed online scheme, bid-based offline scheme and fix-price online scheme (denoted as off, on, bid and fix in the figure respectively). We notice that besides the proposed scheme in 100 users case, all the schemes achieve the augment requirements of the spots, i.e., higher than 100%. And as expected, the offline scheme [9] has the most effective augment results whose achievement ratio is closest to 100%. For the proposed online scheme, it outperforms the bid-based offline scheme and fix-price online scheme (except that in the 100 users case in which the number of users is not enough for the proposed scheme). Finally, Figs. 5 and 6 illustrate the number of winners and total payment changing with number of users, respectively. The proposed online scheme outperforms the bid-based offline scheme and fix-price online scheme (untruthful and the optimal fix price is impossible to obtain in reality), and the offline scheme [9] (truthful but needs all information in advance) achieves the optimal results as expected.

## VI. Conclusions

In this paper, we have proposed an online incentive mechanism for REM construction by taking into consideration the

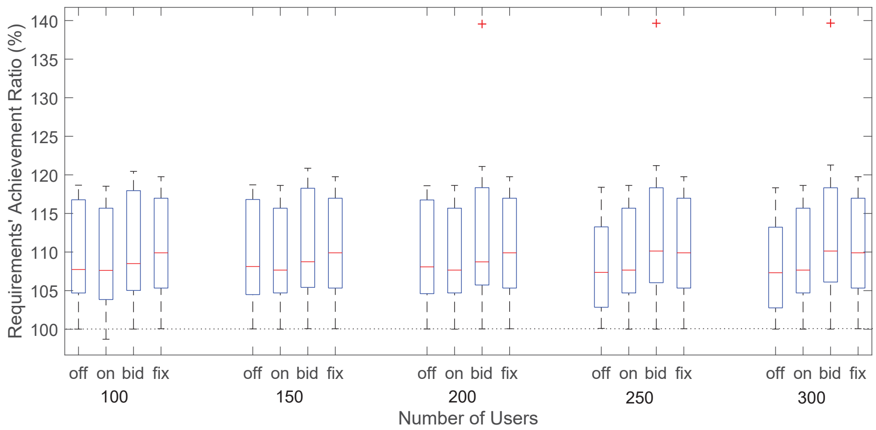


Fig. 4. The performance comparison in terms of requirements' achievement ratio. (20 spots.)

dynamically arrived users. The proposed mechanism aims at minimizing the operator's total expenditure while guaranteeing distinct quality requirements of spots. The simulation results show that the proposed mechanism achieves better performance over two baseline schemes and keeps an acceptable gap from related offline scheme.

## ACKNOWLEDGMENTS

This research was supported by JSPS Grant-in-Aid for Young Scientists (B) (17K12670).

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