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Maximizing Clearance Rate of Budget-Constrained Auctions in Participatory Mobile CrowdSensing

MAGGIE E. GENDY[1], **(Student Member, IEEE), AHMAD AL-KABBANY**[1,2,3], **(Member, IEEE), AND EHAB F. BADRAN**[1], **(Senior Member, IEEE)**

[1]Department of Electronics and Communications Engineering, Arab Academy for Science, Technology, and Maritime Transport, Alexandria 21937, Egypt
[2]Intelligent Systems Laboratory, Arab Academy for Science, Technology, and Maritime Transport, Alexandria 21937, Egypt
[3]Department of Research and Development, VRapeutic, Cairo 11728, Egypt

Corresponding author: Ahmad Al-Kabbany (alkabbany@ieee.org)

ABSTRACT Mobile devices equipped with diverse sensors have emerged as ubiquitous data collection systems within the rising paradigm of Mobile CrowdSensing (MCS). In MCS, auctions are adopted as effective incentive mechanisms in order to secure an acceptable level of contribution from users in participatory MCS. Recent techniques in the literature have addressed several challenges in auctions-based task assignments in centralized MCS. In this research, towards effective task-participant matching, we focus on maximizing the number of completed tasks, the Clearance Rate (CR), which has not been addressed in the literature to date despite the impact it exercises on the satisfaction of service demanders. We propose new bidding procedures for the task allocation strategy. The proposed procedures generalize well to reputation-aware auctioning while handling practical scenarios experienced during campaigns with budget constraints. Particularly, we show that for campaigns that are held consecutively in time, the adoption of an intuitive *look-back* strategy, for budget transfer from previous campaigns, would remarkably influence the CR. Moreover, observing that tasks with a few bidders should be assigned a higher priority in order to get accomplished, we introduce a new factor for task redundancy. In addition to promoting the accomplishment of *unpopular tasks*, this factor spares the budget to accomplish more tasks by penalizing redundant task assignment. Extensive performance evaluation of the proposed methods is carried out under various system parameters, namely the number of tasks, auctions, and participants. We demonstrate the effectiveness of the suggested procedures through a significant-and-consistent increase, that ranges from $50\% - 500\%$, in the attained CR compared to the most recent techniques in the literature.

INDEX TERMS Auctions, budget, constraints, incentive mechanisms, mobile crowdsensing, participatory crowdsensing, penalization, redundancy.

I. INTRODUCTION

Mobile CrowdSensing (MCS) is a large-scale sensing paradigm based on everyday user-companioned sensor-rich devices. It involves the collaboration of a heterogeneous smart crowd to collect data and was originally inspired by crowdsourcing where a large number of volunteers get involved in order to solve a complex problem [1]–[3], i.e., a distributed problem-solving model.

With the potential of human mobility to offer unprecedented opportunities for both sensing coverage and data transmission [4]–[6], MCS systems have been able to replace single-purpose networks in many applications. This, however, implies that an acceptable volume of human involvement has to be maintained for these systems to succeed. Concerning human engagement, a trade-off is highlighted by [7] who recognized the following two classes of sensing paradigms in centralized MCS applications, which consist of a central platform and a number of smartphones:

- Participatory sensing: This is where the user is required to actively contribute data and make decisions, e.g. taking a photo. To a large part, due to the level of cognition employed in this paradigm, it can support diverse applications; hence, it is widely applied in MCS systems [7].
- Opportunistic sensing: This is where the collection of data is done more autonomously without an action

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required from the user. Particularly, it automatically detects a state of interest and changes the device state accordingly to satisfy an application request, i.e., user involvement is minimal [8].

While opportunistic sensing lowers the user burden, it raises security and privacy problems. On the other hand, even though participatory sensing increases user involvement, and does not suffer from such privacy and phone context challenges, the quality of the gathered data depends heavily on the participants.

The aforementioned trade-off also highlights different concerns that arise from both types of MCS users, namely the service demanders and the participants. The service demander–also be called the leader or the organizer–is the party that sends tasks to the MCS platform to be done. Organizers-related concerns include the budget, the CR, and the quality of gathered information. The participants–alternatively called the followers–is the party that bids for/accomplish the sensing tasks. Their concerns involve privacy, resource-use optimization, and incentive mechanisms [9].

In MCS, participants need a compensation in order to maintain their willingness to provide computational and power resources required by the sensing devices. Consequently, a growing body of research has focused on developing effective monetary and non-monetary incentive mechanisms [10]. We focus our discussion, though, on monetary mechanisms due to the scope of the proposed research. Monetary approaches involve the following two models for payments, as defined by [11], which involve a budget controlled by the coordinating platform:

1) A platform-centric model, where static payments for winners are determined by the platform.
2) A user-centric model, which takes the form of a reverse auction. In that sense, the platform has no control over payments to winners.

The latter model has been shown to be vulnerable to untruthful bidding, which inspired the proposal of the MSensing auction [11], [12]. The vulnerability of MSensing to malicious data contributions, then, inspired reputation-aware incentive mechanisms [13]. Moreover, other features were proposed to increase the robustness of monetary approaches such dynamic pricing [14] which addresses cost explosion, and dynamic incentives [15] in which the platform empowers the service demanders by not just coordinating the auctions, but also estimating the best budget for a particular campaign of tasks and the best set of winners, given the number of winners the demander can afford using that budget.

In addition to effective incentive mechanisms, efficient and effective task-participant matching (or similarly, the task allocation) is another challenge towards building robust MCS systems. One possible approach to classify task allocation techniques depends on the number tasks that are required to get accomplished by the crowd, i.e. single-task [16], [17] and multi-task [18] approaches. The former family of methods usually necessitates the preservation of one or more constraint, e.g., budget constraints [19] and spatial coverage requirement [20]. The authors of [21] recognized another approach for classifying task allocation methods which depends on participant traits. This *participant model* characterizes the attributes and the requirements of the crowd. In this context, a reputation-aware (RA) algorithm for task allocation was proposed by [13]. Also, user-dictated constraints such as privacy and energy efficiency were the scope of [22] and [23] respectively.

This research aims at enhancing the Quality of Service (QoS) in MCS systems. Particularly, we focus on a characteristic of sensing campaigns that has recently started to be addressed in the literature, namely the clearance rate (CR) of auctions–the number of accomplished tasks in auction-based campaigns. Given a fixed budget and auction constraints, it is obvious that a service demander would require to accomplish as many tasks as possible. Hence, maximizing the CR has a significant impact on the QoS, and is directly proportional with a high platform's utility and efficiency. However, it has been given much less attention compared to other components of MCS applications, e.g., incentive mechanisms and task allocation. To the best of our knowledge, our proposed research in [24] and [25] were two of the earliest methods to address CR-maximized auctions. In the rest of this paper, we use the terms *clearance rate*, *task completion ratio*, and *task coverage ratio* interchangeably.

This research presents key improvements over previous CR-maximized bidding methods. The proposed bidding formulations handle real-life scenarios, experienced during budget-constrained sensing such that the inherent characteristics of campaigns are employed to maximize their clearance rate. Particularly, we show that we can make use of our prior knowledge about specific contexts for sensing campaigns to increase the CR significantly. In this research, we adopt a *look-back* strategy to realize a budget transfer among campaigns, given that they are held consecutively in time. Furthermore, we introduce a new factor for task redundancy in the objective function of participant-task matching. We show that this factor promotes the accomplishment of tasks with a few bidders, and also penalizes redundant task assignment, which spares the budget to accomplish more tasks. It is worth mentioning that the proposed procedures lend themselves well to the existing reputation-aware auctioning. Actually, a reputation score can seamlessly be embedded in the governing objective functions for the proposed procedures, resulting in a reputation-aware (RA) version of that procedure, as will be shown in the following sections of this document.

The key contributions of this article can be summarized as follows:

1) We introduce a new bidding procedure that is inspired by the maximum contribution algorithms in [13], [26], and that combines the merits of descriptive and hybrid bidding of [24]. Since the decision on adopting descriptive or hybrid bidding is not done *proactively*, and that user utility computations have to be done first, we name this procedure **Reactive Bidding** in the rest

of this document. We show that it increases the CR by an average of 1.5% compared to the most recent techniques in the literature.

2) We propose a new strategy for auctioning that incorporates prior knowledge about sensing campaigns. Rather than dealing with auctions as individual and separate events, we deal with temporally successive auctions. In this context, remaining budgets from previous auctions can be **looked back** at, resulting in the augmentation of the current budget as well as the maximization of the overall CR. We show that this strategy further enhances the CR performance attained by *Reactive Bidding*. We name this procedure **Look-back Auctioning**. We believe that temporally consecutive sensing, as a concept, has been considered before with different manifestations in the literature [27], [28]. Nevertheless, to the best of our knowledge, we are the first to employ it for increasing the CR by transferring remaining budgets to future auctions.
3) Other than the earlier version of this work that appeared in [25], to the best of our knowledge, this research is the first to use redundant task assignment in formulating a new bidding procedure for CR maximization in participatory reputation-aware MCS systems. Basically, we propose a new objective function for user utility that involves a redundancy score. This score results in prioritizing *unpopular tasks* and sparing the budget by penalizing redundant task assignment. We report remarkable improvements in CR using this new procedure.
4) We simulate, examine, analyze, and discuss the impact of each proposed method individually, as well as their combined impact, in the presence of varying system parameters, e.g., the geographic area, the number of tasks, auctions, and participants. We demonstrate the effectiveness of the suggested procedures through a significant-and-consistent increase in the attained CR compared to the most recent techniques in the literature.
5) Use-cases and strength points of each proposed algorithm are presented, aiming to help the cloud platform in choosing the right algorithm depending on the given scenario.

The rest of this document is organized as follows: In Section II, we describe the problem and highlight the system model in the light of the most pertinent research literature of MCS. Section III discusses the previous CR-maximized auctioning methods in the literature. Afterwards, the proposed methods will be presented in Section IV. Section V features the performance analysis for the suggested algorithms, before we draw conclusions in Section VI.

II. PROBLEM DESCRIPTION AND SYSTEM MODEL

Auction theory has been used as a theoretical tool for modeling incentive mechanisms design and tasks allocation for MCS. In a typical auction, buyers compete to obtain goods by offering increasingly higher prices. In MCS auctions, however, sellers compete to underbid each other. Because the roles of buyers and sellers are reversed in the latter type of auctions, it is typically called a "reverse auction". In the rest of this work, we are going to use the term "reverse auction" and the word "auction" interchangeably.

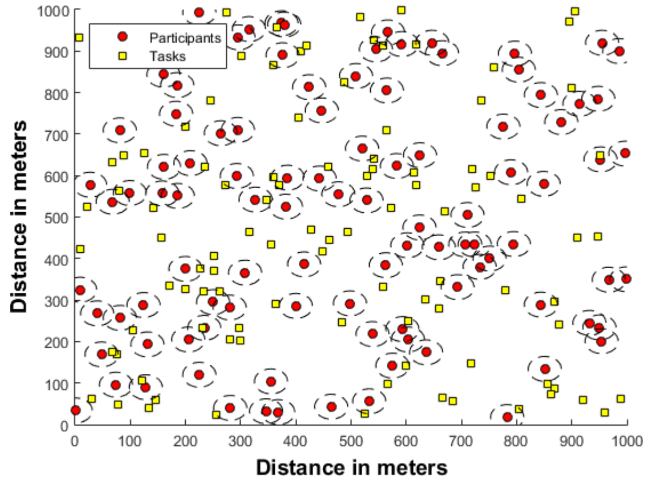

FIGURE 1. A depiction inspired by [11] in which tasks are shown as yellow squares, participants are shown as red dots, whose areas of interest are depicted as dashed circles.

In an auction-based crowdsensing campaign, participants submit their bids which represent a compensation that covers the costs incurred due to sensing, i.e., their sensing costs. Afterwards, the platform that coordinates the auction matches the tasks to the suitable participants–the winners. Following winners selection, the stage of payment determination is carried out. Several payment determination approaches with varying objectives have been proposed to date. Without the loss of generality, the objective in an auction is to maximize the demand (in this case, the sensing tasks) given the following: 1) the supply/the resources (in this case, the platform budget) and 2) the users' bids. For every sensing campaign [29]:

- Each smartphone $i \in 1, \cdots, N$ represents a participant in the auction.
- The platform sends the details of the M campaign tasks, where tasks are indexed by $j \in 1, \cdots, M$.
- All of the participants should take part in the bidding process for the tasks they are interested in, and each bidder should at least bid on one task.
- Participants are assumed to be interested only in tasks that exist geographically nearby to them, e.g., an area of interest of 30m radius. Figure 1 depicts a geographical area in which participants and tasks are uniformly distributed, and each participant is surrounded by an area of interest out of which that participant does not bid on any tasks.
- The set of winners S and their payments $\{P\}$ are then identified. Greedy algorithms are proposed as an approximation of the NP-hard problems of task allocation and winner selection.

For a campaign with a set of tasks T, with cardinality $|T| = M$, every potential participant, who is interested in a subset of tasks $T_i \subset T$, is supposed to send a bid to compete in the auction. In the literature of MCS, a participant typically sends a collective bid for the whole set of tasks he/she is interested in. To the best of our knowledge, this research is one of the earliest [24], [25] to adopt and benefit from another approach of bidding, namely the descriptive bidding.

Collective bidding, the commonly used approach in the literature, resembles a wholesale or bidding in bulk. For descriptive bidding, however, a participant sends a list of tasks and a separate bid for each of them. We refer to this list as *the list of per-task user bids* throughout this document. Descriptive bidding is more flexible in assigning tasks to participants. Different from collective bidding, it can assign the user to only a subset of tasks contained in the set of tasks he/she is interested in. This helps the platform in addressing the specific tasks that are in high demand while preserving the *user's individual rationality*.[1] It is worth mentioning that, unless the bidder is interested in only one task, the sum of the descriptive bids is usually more than the collective bid [30]. Hence, descriptive bidding is budget demanding.

In the remainder of this manuscript, we either adopt descriptive bidding, or a hybrid of collective and descriptive bidding, with the goal of maximizing the CR while allocating tasks to participants. Unlike previous techniques that do not take budget constraints and/or the CR into consideration [13], and/or assume a constant-yet-arbitrary budget [31], we propose bidding procedures that link the number of campaign tasks to the platform budget, and simultaneously maximize the task completion ratio. Moreover, unlike previous techniques, for the sake of budget management, these algorithms do not assign the same task to more than one user in case of descriptive bidding. Furthermore, similar to the work of [13], the presented research addresses the problem of malicious information in auctions. Particularly, for every proposed bidding procedure, we present a Reputation-Aware (RA) version of it. This version takes the users' reputation into consideration while selecting winners in auctions.

While their scope is considerably different, we are aware of other research in the literature that considered redundant task assignment, such as [32] and [33]. The authors of [32] were concerned with energy consumption and proposed to send the sensing data during phone calls. This is done while guaranteeing the following: 1) a minimum number of contributors within a time frame, and 2) a minimum number of redundant task assignments to maintain an energy efficient scheme. The authors of [33] addressed vehicle-based public sensing. While they avoided redundant coverage (for reputation assessment) to maintain a cost-effective recruitment, their proposed system allowed the service demander to determine an acceptable redundancy level, if redundancy is required for data reliability.

[1]This means that the user takes a payment equal to or more than his bidding

TABLE 1. Frequently used notations and symbols.

$\mathcal{B}$	Platform budget
Γ_j	Set of participants handling task j
$\mathcal{P}$	Sum of all payments to primary winners
$\mathcal{P}_i$	Payment to winner i
$\mathcal{V}$	Sum of campaign tasks values
b_i^c	Collective bid for user i
b_i	Total Descriptive bidding for user i
b_{ij}	descriptive bid of user i for task j
B^{HMCDB}	remainder budget from the current auction using HMCDB algorithm
B^{MCDB}	remainder budget from the current auction using MCDB algorithm
B^r	remainder budget from last auction
CR^{HMCDB}	Clearance Rate acheived by the HMCDB algorithm
CR^{MCDB}	Clearance Rate acheived by the MCDB algorithm
M	Number of tasks
M_i	The number of tasks done by user i
N	Number of participants
P	Set of participants
P^t	Set of participants bidding on task t
R	Participants reputation set
r_i	Reputation of user i
R_d	Participants' Redundancy factor set
RR	Participants' Redundancy-Reputation factor set
S	Set of primary winners (selected users)
S^{MCDB}	Set of winners (selected users) in the MCDB algorithm
S^R	Set of redundancy winners
S^s	Set of secondary winners (selected users)
T	Set of all campaign tasks
T_i	Set of tasks done by user i
T_S	Set of tasks done by users in set S
$T_i^{\text{MCDB}}(S^{\text{MCDB}})$	Set of tasks allocated for MCDB winner i over the set S^{MCDB}
$T_i^s(S^s)$	Set of tasks allocated for secondary winner i over the set S^s
v_j	Value of task j
$v_i^r(S)$	Reputational value for user i over set S
$v_i^u(S)$	Reputational-Redundant value for user i over set S
W_t	Priority weight for task t
Y_{ij}	Flag if the platform choses user i to perform the bidded task j or not, $Y_{ij} \in \{0, 1\}$
$\{B^c\}$	Set of collective bids by participants
$\{\mathcal{P}\}$	The set of payments
V	Values of set of tasks

III. PREVIOUS WORK ON MAXIMIZING CLEARANCE RATE

This section overviews the recent literature of CR-maximized auctions. For the convenience of the reader, and for the sake of a self-contained presentation, all the algorithm listings for previous work is given in Appendix A and Appendix B. Also, a summary of the symbols and the notations that are used throughout this work is given in Table 1. Given the platform's budget, the methods highlighted in this section select winners using either descriptive bidding or a combination of descriptive and collective bidding (hybrid bidding) [24], [25]. Similar to a typical auction, in order to save the budget to accomplish as many tasks as possible, the goal is to choose the least expensive bids that cover the tasks at hand. For descriptive bidding and hybrid bidding, we start by linking the number of sensing tasks to the platform's budget as given by

$$\mathcal{B} = \mathcal{V}, \tag{1}$$

where the budget, $\mathcal{B}$, is equal to the sum of all the values of the tasks in the campaign, $\mathcal{V}$. This means that the available platform's budget will certainly have to increase as M–the number of sensing tasks in a campaign–increases. Whilst the sensing tasks are assigned to winners, the budget is updated as:

$$\mathcal{B}_{new} \leftarrow (\mathcal{B}_{old} R) - \mathcal{P}, \tag{2}$$

which means that the budget decreases as payments, $\mathcal{P}$, are made to winners. The update in Eqn. 2 is motivated by the notion that not all users should have equal access to the budget, i.e., low reputable users should see a low platform's budget and vice versa. This is why the budget is weighted by the reputation. It also helps the platform avoid using its valuable budget to pay for malicious users.

A. REPUTATION-AWARE DESCRIPTIVE BIDDING (DB-RA)[2]

This algorithm maximizes the CR by minimizing the payments given to the winners according to the optimization function given by

$$\min \sum_{j \in M, i \in N} b_{ij}(1 - r_i), \tag{3}$$

where r_i is the reputation of user i, and b_{ij} is the descriptive bid of user i for task j. This function chooses the least bids for the most reputable users, i.e., the higher the reputation the lower the second term. The steps are shown in algorithm listing A.1 in Appendix A. The algorithm commences by calculating the budget, then comparing the bids sent by users for each task. Accordingly, as long as the budget permits, it chooses the least bid for every task. After task-participant matching, the winners' payments are computed before the users' reputation are updated (using an outlier detection algorithm) for the following auctions.

On the contrary to collective (wholesale) bidding, one main advantage of descriptive bidding is that it enables the demanders to assign priorities to each task individually. Weights for prioritizing tasks can be embedded in Eqn. 3 as follows:

$$\min \sum_{j \in M, i \in N} \frac{b_{ij}}{W_j}(1 - r_i), \tag{4}$$

where W_j is the weight representing the priority of task t. The summation of the per-task user bids for the user i is the payment that will be made to that user, and it is given by

$$B_i = \sum_{j=1}^{M_i} Y_{ij} b_{ij}, \tag{5}$$

where the $Y_{ij} \in [0, 1]$ factor is the platform decision whether user i will be assigned task j or not, depending on his bid. For the Reputation-Unaware (RU) version of the algorithm, $r_i = 1$ for user i.

[2]The code is publicly avialable through: bitbucket.org/isl_aast/descriptive-bidding-ccnc-2019/src/master/

B. MAX CONTRIBUTION DESCRIPTIVE BIDDING (MCDB)

Following [13], [26], and as indicated in algorithm listing A.2 in Appendix A, the MCDB algorithm chooses its winners according to the maximum user contribution rather than the least bid. The user contribution of a user is the net (overall) work added by the user to the platform, i.e. the additional value added to the platform by the sensing tasks of this user minus the bid which the platform will–in return–pay to this user. For reputation-unaware bidding, the value of the user i is calculated as [26]:

$$v_i(S) = v(S \cup \{i\}) - v(S), \tag{6}$$

such that:

$$v(S) = \sum_{t \in T_S} v_t \tag{7}$$

In the reputation-aware versions, though, the user's value–user's reputational value–is calculated as [13]:

$$v_i^r(S) = v^r(S \cup \{i\}) - v^r(S), \tag{8}$$

such that:

$$v^r(S) = \sum_{t \in T_S} \sum_{k \in \Gamma_t} \frac{v_t r_k}{|\Gamma_t|}, \tag{9}$$

where v_t is the value of task t, S is the set of winners, and $|\Gamma_t|$ is the cardinality of the set of participants handling the task t.

Unless the bidder is interested in only one task, the sum of the descriptive bids is usually more than the collective bid. Hence, descriptive bidding are very budget demanding, and although motivating to participants, paying all tasks in descriptive bidding would consume the platform's budget without reaching the desired clearance rate. To ameliorate the budget demanding characteristic of DB and MCDB, during assigning the tasks to winners, the platform ensures that a task would not be covered more than once.

Another approach to avoid the high budget demand of descriptive bidding is to adopt a *hybrid bidding* procedure. That is: For a campaign with a set of tasks T, with cardinality $|T| = M$, every potential participant, who is interested in a subset of tasks $T_i \subset T$, sends two types of bids to the platform namely, a collective bid and a descriptive (per-task) bid. In hybrid bidding algorithms, the platform starts by running the auction and making payments according to the collective bids sent by the participants. Then, the remaining tasks that were not covered by collective bids are assigned/paid according to descriptive bids. Hybrid bidding results in an average CR increase of 4% compared to descriptive bidding. Nevertheless, the former requires more interaction, as the participants need to submit another bid beside the descriptive list. Arguably, this is less user-friendly than the traditional collective bidding [13] and the descriptive bidding.

Following previous work in the literature [13], hybrid bidding algorithms start by calculating the marginal contribution (or marginal value) for each participant, then subtracting their collective bids from the resultant value (line 3 in algorithm listing B.1 in Appendix B). Afterwards, tasks are allocated to a set of winners, S, called *primary winners* (lines 5,6 in algorithm listing B.1 in Appendix B), based on the maximum users' contribution. In this formulation, namely, the reputation-aware (*RA*) formulation, the collective bid of user i, b_i^c, is weighted by the user's reputation score r_i, such that a high reputation score would result in lowering the bid, and consequently increases the odds of selecting that user. Following the payment calculation for the primary winners, given by algorithm listing B.2 in Appendix B, the remaining budget for the platform is calculated by:

$$\mathcal{B} = \mathcal{V} - \mathcal{P} \tag{10}$$

where $\mathcal{V}$ and $\mathcal{P}$ are the sum of values of the campaign tasks and the sum of payments to primary winners respectively. Given the remaining budget of the platform, the margin that is available (before getting a negative utility) to accomplish the tasks that had not been covered by primary winners can be determined.

Unless the set of M tasks have been covered by the primary winners, the platform proceeds to determine another set of winners–the secondary winners, S^S. Using the descriptive bids, the platform chooses the secondary winners to whom the uncovered tasks are allocated. At the expense of the budget, the platform pays the secondary winners according to their descriptive bids to motivate them in order to achieve a higher CR. This happens either because of them being the only bidders for some tasks, or because of their unique location near to particular tasks afar from the crowd. The steps for choosing the secondary winners and computing their payments are given by algorithm listing B.3 in Appendix B.

C. HYBRID BIDDING

While Hybrid Descriptive Bidding (HDB) is a combination of *TSCM* [13] and *Descriptive Bidding (DB)* [24], Hybrid Max Contribution Descriptive Bidding (HMCDB) is a combination between *TSCM* and *Max Contribution Descriptive Bidding (MCDB)*. Hence, for HDB and HMCDB, the primary winners will be chosen according to the highest user contribution using their collective bids. Afterwards, the secondary winners will be chosen according to the least descriptive bid for HDB, and according to the users contribution for HMCDB. The steps for choosing primary winners and computing their payments are given by algorithm listings B.1 and B.2), respectively, and the steps for choosing and paying the secondary winners in HMCDB is shown by algorithm listing B.4. **It is worth mentioning that Hybrid Bidding was referred to as 2SB (two-stage bidding) in [24] and [25]**.

The rest of this section presents a comparison between the reputation-aware versions of the aforementioned algorithms. The comparison covers various auction characteristics including the number of tasks, the number of participants, and the number of auctions. Figure 2 shows the impact of varying the number of tasks on the CR. The performance of pure (non-hybrid) descriptive bidding algorithms (i.e., MCDB and DB) deteriorates as the number of tasks increases. This is because the sum of the descriptive bids list (for one participant) is directly proportional with the number of tasks. Increasing the sum leads to a negative marginal contribution and forces the platform to exclude the user. Hybrid bidding algorithms (HMCDB and HDB) and collective bidding algorithms (TSCM), though, demonstrates an increase in the CR as M increases.

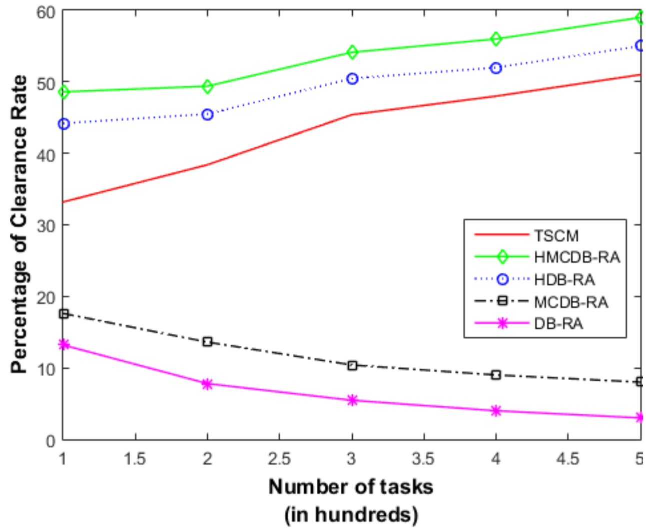

FIGURE 2. The impact of varying the number of tasks on the performance of the reputation-aware (RA) versions of HMCDB, HDB, DB and MCDB.

The impact of varying the number of participants on the CR is shown in Fig. 3. As the number of participants increases, the performance of all the algorithms increases. This is because increasing the number of participants enlarges the pool of candidates from which the platform chooses winners. Meanwhile, since the per-task algorithms use descriptive bids only, which is budget-demanding, and since MCDB and DB have fixed budget because the number of tasks is constant ($M = 100$ in this case), the CR increases slowly as the number of participants increases, and they perform poorly compared to other algorithms.

Figure 4 shows the impact of varying the number of auctions and, along the same lines with the previous comparison, using the maximum user contribution rather than the least bidding demonstrates higher CR, i.e., HMCDB and MCDB performed better than the HDB and DB respectively. The least bidding algorithms proceed greedily, task by task in order; hence, they are well-posed to handle tasks with priorities. However, least bidding algorithms consume the budget on a fewer tasks when compared to algorithms that incorporate the user contribution. This is because the latter family of methods benefit from a more comprehensive look at all the tasks, and they choose the users that can cover many tasks.

IV. PROPOSED WORK

We start the discussion of the proposed work by introducing a new auctioning procedure, *Reactive Auctioning*, that is a simple extension of the MCDB and HMCDB algorithms, which were discussed in the previous section. Afterwards, we present the main contributions of this research, namely the

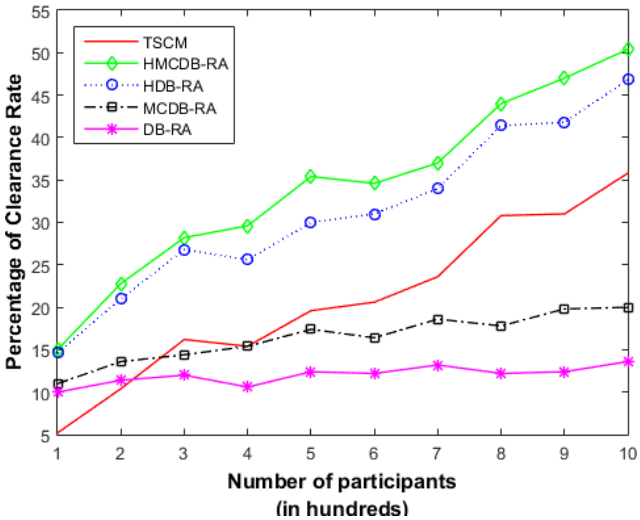

FIGURE 3. **The impact of varying the number of participants on the performance of HMCDB, HDB, DB and MCDB with their reputation-aware (RA) versions.**

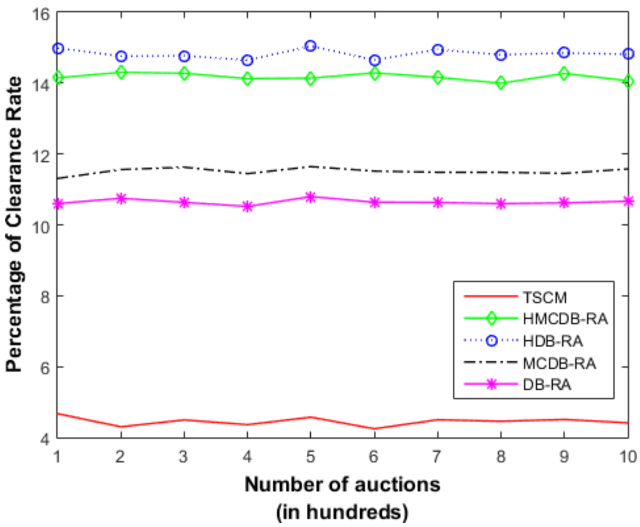

FIGURE 4. **The impact of varying the number of auctions on the performance of HMCDB, HDB, DB and MCDB with their reputation-aware (RA) versions.**

Look-back Auctioning and the *Redundancy Penalization Auctioning*. In section V, we show how Look-back Auctioning and Redundancy Penalization Auctioning can significantly enhance the performance of Reactive Auctioning with regards to the attained clearance rate.

A. REACTIVE AUCTIONING

In reactive auctions, the platform goes extensively through the stages of both, HMCDB and MCDB. Then, based on which algorithm achieves higher CR, it assigns tasks to participants. Because the decision on whether to adopt HMCDB or MCDB is not done *proactively*, e.g., by means of models learned from previous auctioning data,[3] this new auctioning procedure seems to combine HMCDB and MCDB by *reacting* to their attained CR, hence the name. Throughout the upcoming part of this work, we refer to Reactive Auctioning using the abbreviation EA. It is worth mentioning that Reactive Auctioning combines HMCDB and the MCDB due to their effectiveness compared to HDB and DB, respectively, which is the insight that concluded the previous section. The stages of Reactive Auctioning are as follows:

1) HMCDB Algorithm
   a) Primary Winners Selection
   b) Primary Winners Payment Determination
   c) Secondary Winners Selection and Payment Determination
   d) CR^{HMCDB} Calculation
2) MCDB Algorithm
   a) MCDB Winners Selection
   b) MCDB Payment Determination
   c) CR^{MCDB} Calculation
3) Comparison of the CRs and determining the winners who will be assigned the tasks accordingly

Reactive auctioning is inspired by the recent literature [24] where the performance evaluation for different algorithms highlighted that MCDB and HMCDB exchange the superiority according to the auction parameters. **In [24], per-task bidding (PTB) and two-stage bidding (2SB) represented MCDB and HMCDB respectively**. In the rest of this document, we use the terms Reactive Bidding and Reactive Auctioning interchangeably. In fact, Reactive Auctioning is the auction management procedure that adopts Reactive Bidding.

Further analysis on the cases where Reactive Auctioning's CR failed to reach M–the total number of tasks in the campaign–highlighted that the platform, in many scenarios, runs out of budget, and is not capable of choosing more participants to be winners. This is due to the platform's negative utility constraint, i.e., the platform is not allowed to lose during any sensing campaign. Those users who were not chosen (as winners) by the platform would, otherwise, have significantly increased the clearance rate. However, the challenge is that they bid more than what the platform can afford. Accordingly, we have been motivated to figure out other resources for increasing the platform budget without compromising neither the platform's negative utility constraint nor the requirement of reputation awareness. In the rest of this section, we present new bidding procedures that adopt Reactive Auctioning for managing the sensing campaign, while simultaneously exploit practical and real-life scenarios to augment the platform budget.

B. LOOK-BACK AUCTIONING

Classically, auctions have been viewed as separate events. In practice, however, auctions are often a part of larger transactions. Without the loss of generality, we argue that an auction does affect its subsequent events, including other auctions. Based on this observation, and assuming that the platform performs many auctions successively, which is a realistic assumption, we propose to increase the platform

[3]This is a future research direction.

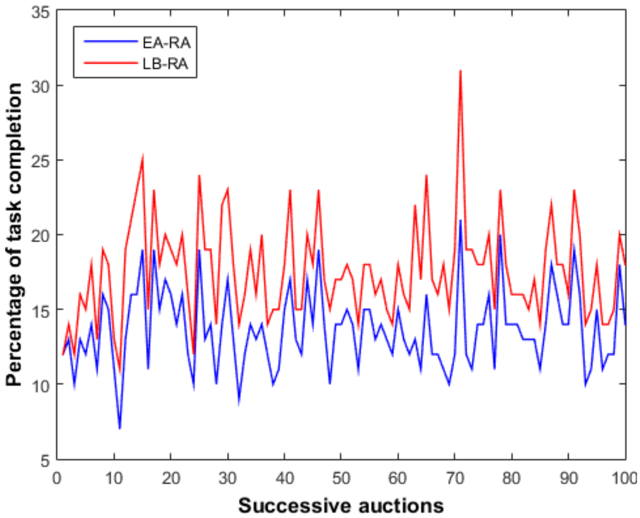

FIGURE 5. The CR performance of EA-RA and LB-RA in a sample of 100 successive auctions.

budget in one auction by employing the profit made by the platform in preceding auctions, i.e., by looking back in time at previous auctions, hence the name. To the best of our knowledge, this research is the first to: 1) benefit from considering successive auctions, and 2) use budget transfer towards the goal of budget augmentation. Compared to the case of holding Reactive Auctions as individual events, Reactive Look-back auctions (LB) results in an average CR increase of 4%. Figure 5 shows a comparison between the reputation-aware versions of Reactive Look-back auctions (LB-RA) and Reactive Auctioning (EA-RA). Over 100 successive auctions, by taking M = 100 and N = 100, an average of 99 auctions recorded higher Clearance Rate using LB-RA than EA-RA. We elaborate on their performance analysis in the next section.

The idea of increasing the budget in the current auction from previous ones is realized after choosing every secondary winner and determining its payment. Particularly, the budget in the current auction is comprised of the following: the sum of the tasks' values in the current auction **plus** the remaining budget from prior auctions **plus** the platform utility that was attained in previous auctions, such that the platform utility [26] is given by

$$\tilde{u}_0 = v(S) - \sum_{i \in S} \mathcal{P}_i, \tag{11}$$

where $v(S)$ is the total value of tasks done by S, and $\mathcal{P}_i$ is the payment to user i. While the look-back algorithm outperforms all the methods in Section III and the Reactive Auctioning in terms of CR, its superiority stems from the accumulated budget from previous sections. Meanwhile, a steady increase/gain in budget is not guaranteed. We argue that the increase is predictable, though, given previous cases/data to learn from.[4]

[4]This is a future research direction

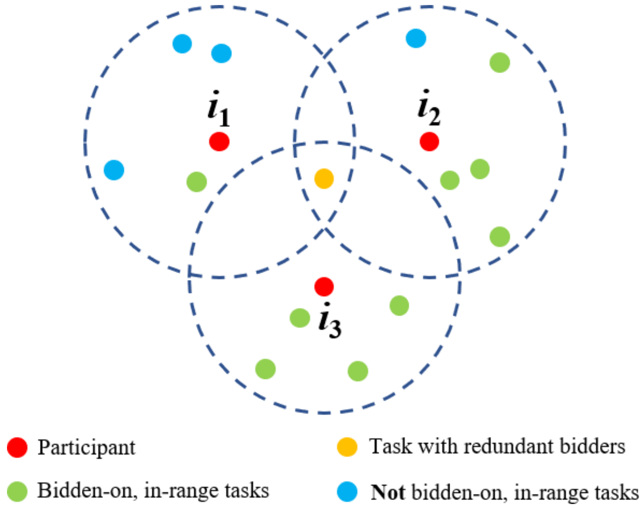

FIGURE 6. An illustration of three participants i_1, i_2, and i_3, bidding redundantly on a task (yellow circle). Blue circles represent tasks that are not bidden-on, yet lie within the range of interest of the three participants. Green circles represent bidden-on tasks within the range of interest of the three participants.

C. REDUNDANCY-PENALIZING BIDDING (RPB)

Since this research addresses CR maximization, one absolute concern is to figure out and mitigate possible reasons for budget drainage, which impacts CR negatively. A principal reason for such a drainage is redundant task assignment. The redundancy here refers to the bidders, i.e., a task bidden-on by many participants is said to be demonstrating a case of redundant bidding. Redundancy might happen due to a variety of scenarios, one of which is the easiness of accomplishing the task, for example, due to its favorable location.

Figure 6 shows a case of redundant task assignment, i.e., multiple participants simultaneously bid on a particular task. The figure also features cases for tasks that are not bidden-on even though they lie within the range of interest of the participants, and other cases for bidden-on tasks that are within the range of interest of the corresponding participants. The range of interest for each participant is shown as a dashed circle with a red circle (the participant) at its center.

Being concerned with CR maximization, we propose a new objective function that penalizes redundant task assignment. On one hand, this ameliorates budget drainage, which saves resources for accomplishing more tasks. On the other hand, it promotes the completion of *unpopular tasks* with a few number of bidders, that would otherwise be dropped, assuming that the more the bidders on a task, the higher the probability it is going to be accomplished. This algorithm is comprised of the following four stages: 1) Primary Winners Selection, 2) Redundancy Winners Selection, 3) Winners Filtration and Payment Determination, and 4) Secondary Winners Selection and Payment Determination. Stages 1 and 2 are given by algorithm listing 1. Since the first function in algorithm listing 1 (for Primary Winners Selection) is identical to the algorithm listing B.1, we omitted its details for brevity. Stage 3 and stage 4 are realized by the algorithm listings 2 and 3 respectively.

Algorithm 1 Identifying Redundancy Winners

function Get Primary Winners(V, B^c, R, P)
  $\vdots$
  return S
end function
Compute U for participants
function Get Redundancy Winners(V, B^c, S, U, P)
  $S^R \leftarrow \Phi$
  $h \leftarrow \underset{i \in \mathcal{I}}{\operatorname{argmax}}\, v_i^u(S^R) - \frac{b_i^c}{u_i}$
  while $\frac{b_h^c}{u_h} < v_h^u \bigwedge S^R \neq P$ **do**
    $S^R \leftarrow S^R \cup h\ ,\ S_{tasks} \leftarrow T_h$
    $h \leftarrow \arg \max_{i \in \mathcal{I} \setminus S^R} v_i^u(S^R) - \frac{b_i^c}{u_i}$
  end while
  $S^R = S^R \setminus (S^R \cap S)$
  return S^R
end function

Algorithm 2 Compute Payments for Winners

function Get Winners Payments(V, B^c, S, S^R, R, U)
  for $i \in \mathcal{I}$ **do**
    $p_i \leftarrow 0$
  end for
  for $i \in S$ **do**
    $S' \leftarrow S \setminus \{i\}, \Theta = \Phi$
    repeat
      $q \leftarrow \arg \max_{\mathcal{V} \in S' \setminus \Theta} (v_{\mathcal{V}}^r(\Theta) - \frac{b_{\mathcal{V}}^c}{r_{\mathcal{V}}})$
      $p_i \leftarrow \max(p_i, \min\{v_i^r(\Theta) - (v_q^r(\Theta) - \frac{b_q^c}{r_q})\})$
      $\Theta \leftarrow \Theta \cup \{q\}$
    until $\frac{b_q^c}{r_q} \geq v_q^r \bigvee \Theta = S'$
  end for
  for $i \in S^R$ **do**
    $S' \leftarrow S^R \setminus \{i\}, \Theta = \Phi$
    repeat
      $q \leftarrow \arg \max_{\mathcal{V} \in S' \setminus \Theta} (v_{\mathcal{V}}^u(\Theta) - \frac{b_{\mathcal{V}}^c}{u_{\mathcal{V}}})$
      $p_i \leftarrow \max(p_i, \min\{v_i^u(\Theta) - (v_q^u(\Theta) - \frac{b_q^c}{u_q})\})$
      $\Theta \leftarrow \Theta \cup \{q\}$
    until $\frac{b_q^c}{u_q} \geq v_q^u \bigvee \Theta = S'$
  end for
  return P
end function

In stage 2, where we identify redundancy winners, highlights the main contribution in Redundancy-Penalizing Bidding (RPB). We introduce a new redundancy factor that is

Algorithm 3 Secondary Winners Selection and Payment Computation - Maximum Contribution

$\mathcal{B} = \mathcal{V} - \mathcal{P}$
if $S_{tasks} \neq T$ **then**
  $S^s = \Phi, T^s = \Phi$
  for $i \in \mathcal{I} \setminus \{S \cup S^R\}$ **do**
    for $t \in T_i$ **do**
      if $t \in S_{tasks}$ **then**
        $T_i = T_i \setminus t$
      else if $t \in T \setminus S_{tasks}$ **then**
        $P^s \leftarrow P^s \cup \{i\}$
      end if
    end for
  end for
  $h \leftarrow \underset{i \in \mathcal{I}^s}{\operatorname{argmax}}(v_i^r(S^s) - \frac{b_i(S^s)}{r_i})$
  while $\frac{b_h}{r_h} + (r_h \times \mathcal{B}) \geq 0 \bigwedge S^s \neq P^s \bigwedge S_{tasks} \neq T$ **do**
    $S_{tasks} \leftarrow S_{tasks} \cup T_h^s(S^s)$
    $S^s \leftarrow S^s \cup \{h\}$
    for $i \in \mathcal{I}^s \setminus S^s$ **do**
      for $t \in T_i$ **do**
        if $t \in T_h^s$ **then**
          $T_i = T_i \setminus t$
        end if
      end for
    end for
    $\mathcal{B} = (\mathcal{B} \times r_h) - \frac{b_h}{r_h}$
    $h \leftarrow \arg \max_{i \in \mathcal{I}^s \setminus S^s} (v_i^r(S^s) - \frac{b_i(S^s)}{r_i})$
  end while
end if
Outlier_Detection(S, S^R, S^s)
for $s \in \{S \cup S^R \cup S^s\}$ **do**
  update r_s
end for
return S^s

given by

$$d_i = 1 - max_{t \in T_i}\{\frac{1}{|\Gamma_t|}\}, \tag{12}$$

where d_i is the redundancy factor of user i, and $|\Gamma_t|$ is the cardinality of the set of participants who are bidding on the task t. The essence is that we need to increase the opportunity of user i (of being selected) if i is interested in a task $t \in T_i$ for which there are a few bidders, i.e., if d_i is small. Hence, the more participants bidding on a task, the less priority it gets. Towards this goal, the platform adopts a procedure that is similar to the primary winners selection procedure. Particularly, in order to choose the set of redundancy winners S^R, the platform uses a weighted version of the reputation score, as shown in the second function of algorithm listing 1.

This **weighted reputation score** is named the **redundancy-reputation factor** and is given as:

$$u_i = \frac{r_i}{d_i}, \tag{13}$$

where r_i is the reputation of user i and u_i is the redundancy-reputation factor of user i. The higher the u_i, the higher the opportunity of user i to be selected as a winner in the auction. Penalizing redundant task assignment can be seen in the objective functions in lines 8 & 11 of algorithm listing 1. The significant impact of the redundancy-reputation factor on the attained clearance rates will be shown and discussed in the Results and Discussion section. It is worth mentioning that for reputation-unaware (RU) bidding, $r_i = 1$ for user i. Finally, the set of reputation values, redundancy factor values, and redundancy-reputation factor values for all participants are referred to as R,D, and U respectively.

In stage 3 of Redundancy-Penalizing Bidding, the platform proceeds with the payment calculation for both sets of winners, namely the primary winners and the redundancy winners. While the start of algorithm listing B.2 and algorithm listing 2 look similar, the latter features additional loop over S^R for computing the payments of redundancy winners. Another noteworthy point is that the comparison between line 9 with line 17 in algorithm listing 2 shows that the payments computed using the *redundancy-reputation* factors are higher than the payments calculated by the reputation factor. This is one principal reason for adding the update step of the *redundancy winners* in line 13 in algorithm listing 1, since we are concerned with minimizing the payments in general.

Because the reputation-aware version of the proposed algorithm, *RPB-RA*, results in higher payments (lines $16-18$ in algorithm listing 2), we argue that it also motivates participants to bid for the unpopular tasks. The reputational user value can be calculated as given in Eqn. 14. The main difference between Eqn. 9 and Eqn. 14 is that the latter adopts the user's redundancy-reputation, u_i, while the former adopts the user's reputation, r_i. This results in better payments for participants. Given the budget of the platform as in Eqn. 10, we can determine the remaining budget that is available–before getting a negative utility–to accomplish the tasks that have not been covered by the chosen winners. Unless the set of M tasks have been covered by the primary and redundancy winners, the platform proceeds to the final stage of the algorithm. Using the descriptive bids, the platform determines the secondary winners.

$$v^u(S) = \sum_{t \in T_S} \sum_{i \in \Gamma_t} \frac{v_t u_i}{|\Gamma_t|}, \tag{14}$$

where v_t is the value of task t, S is the set of winners, and $|\Gamma_t|$ is the cardinality of the set of participants handling the task t.

For stage 4: Although algorithm listing B.4 and algorithm listing 3 look similar, line 4 of the latter algorithm (unlike algorithm listing B.4) indicates a loop over all participants excluding the primary winners and the redundancy winners.

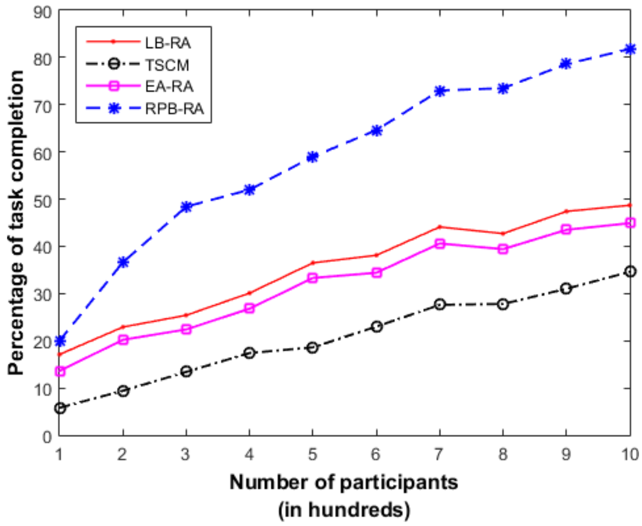

FIGURE 7. The impact of varying the number of participants on the CR for the proposed algorithms compared to TSCM.

It is worth mentioning that previous research in the literature [33] proposed to set a level of acceptable redundancy for data reliability purposes. While our procedure lends itself well to include such an adjustable redundancy, our objective function already incorporates reputation awareness, which ensures data reliability without resorting to redundant task assignment.

V. RESULTS AND DISCUSSION

The simulations presented in this section were done using Matlab® 2015, on a PC with Intel Core-i7 2GHz processor and 4GB of RAM. Also, whenever a design choice had to be made, *the values of the parameters were set to be either identical or close to their values in other research in the literature* [11], [13], [24], in order to facilitate the comparison.

To show the influence of the campaign area on the CR performance, three area settings were used–1000 $m \times 1000$ m, 600 $m \times 600$ m, and 200 $m \times 200$ m. The participants and the tasks are uniformly distributed in the campaign area, and each participant is surrounded by an area of interest of 30 m radius as depicted in Fig. 1. The value of each task and the participants' collective bids vary uniformly in the range [1,5] and [1,10] respectively, akin to [13]. Similarly, the per-task bids vary uniformly in the range $[v_j - \alpha, v_j + \alpha]$. We set $\alpha = 2$ in our simulations, and the participants' reputations are varied uniformly from 0.6 to 0.9. We also mapped the redundancy factor to the range [0.5, 1] in order to be close to the range of the reputation to have nearly equal influence. In the simulations, three aspects are considered (allowed to vary) which are: the number of auctions, the number of tasks, and the number of participants. Table 2 summarizes the simulated scenarios and their corresponding parameter values.

For evaluating the effectiveness of the proposed algorithms, namely Reactive Auctioning (EA), Look-Back Auctioning (LB), and Redundancy-Penalizing Bidding (RPB),

TABLE 2. A summary of the different simulated scenarios and their corresponding parameter values.

	Impact of #Auctions		Impact of #Tasks		Impact of #Participants	
Parameters	*Values*	*Case*	*Values*	*Case*	*Values*	*Case*
#Tasks	100	Constant	100-500	Increasing by 100	100	Constant
#Participants	100	Constant	1000	Constant	100-1000	Increasing by 100
#Auctions	100-1000	Increasing by 100	5 for each tasks case	Constant	5 for each participants case	Constant

we compare their performance to TSCM [13] as a representative of reputation-aware techniques, ***all of which are online techniques***, i.e., they require an established connectivity between the platform and the participants. It is worth recalling that Reactive Auctioning selects the best from HMCDB-RA and MCDB-RA [24]. Since the former performs better than the latter (in terms of CR) in most of the cases, which was shown by the authors of [24], the CR performance of Reactive Auctioning is always better than, or identical to that of HMCDB-RA. Hence, while presenting and analyzing the performance of the proposed algorithms, we chose not to include HMCDB-RA, and to limit the discussion to TSCM, Reactive Auctioning, Look-Back Auctioning, and Redundancy-Penalizing Bidding. Finally, it is worth mentioning that TSCM adopts collective bidding only for managing the auction, and that our previous work [24] was, to the best of our knowledge, the first in the literature to adopt the concept of descriptive (per-task) bidding.

Increasing the number of participants with a constant budget ($M = 100$) means a larger pool of candidates becomes available for the platform to choose from. Hence, generally speaking, the probability of finding a better set of winners increases as the number of participants increases. This increases the CR as shown in Fig. 7 which compares the reputation-aware versions of the proposed algorithms with TSCM. The Redundancy-Penalizing Bidding attains consistently higher CR compared to the other techniques. This increase is approximately four times the CR of TSCM and almost linear in the range of $100 - 500$ participants. Budget-related insights can be drawn from Fig. 8 which presents the CR attained by the proposed algorithms with varying number of tasks. Recalling Eqn. 10, a small number of tasks means a small budget. In such a budget-constrained scenario, it is expected that budget transfer from an auction to the one following it (in time) becomes critical for attaining high CR. This can be seen in the gap between Look-Back Auctioning and Reactive Auctioning in Fig. 8. Similar to the case of varying the number of participants, RPB-RA outperforms TSCM, Reactive Auctioning and Look-Back Auctioning across a wide range for the number of tasks. The CR slightly exceeds *90%* in case the number of tasks slightly exceeds 200 tasks.

In Fig. 9, we highlight the impact of considering the reputation in the bidding process. The shown curves depict the CR performance of the Reputation-Aware versus the Reputation-Unaware versions of the proposed algorithms. We conclude from the figure that there is a **reputation/clearance rate trade-off**, i.e., the proposed algorithms can attain higher CR by dropping the reputation from the objective function; however, this may impact negatively the quality of the sensed data. In addition to LB auctioning and RPB auctioning, the figure also highlights the impact of combining both, i.e., *penalizing redundant task assignment in temporally consecutive auctions*. It can be seen that their combined impact further enhances the clearance rate compared to the performance of any of them individually. *We also investigated varying the number of tasks, rather than varying the number of participants, and a conclusion similar to that is shown in Fig. 9 was obtained.*

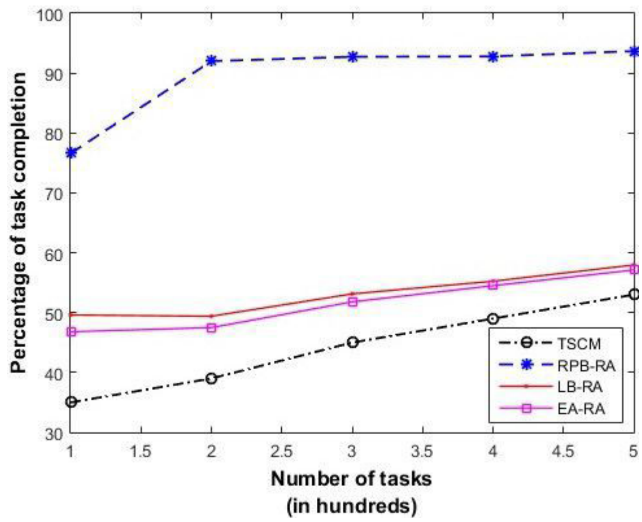

FIGURE 8. The impact of changing the number of tasks on the CR for the proposed algorithms compared to TSCM.

We have also varied the number of auctions and the geographical area in which the auctions take place, and we conclude the following. As shown in Fig. 10, compared to TSCM, a consistent improvement in CR has been obtained by the proposed algorithms across different areas of the simulation setup. We have used two settings for the area of simulation, namely, $200\ m \times 200\ m$ and $1000\ m \times 1000\ m$. Obviously, higher CRs were reached in the former case because the tasks and participants are confined in a smaller area, so the probability of the users having more tasks in

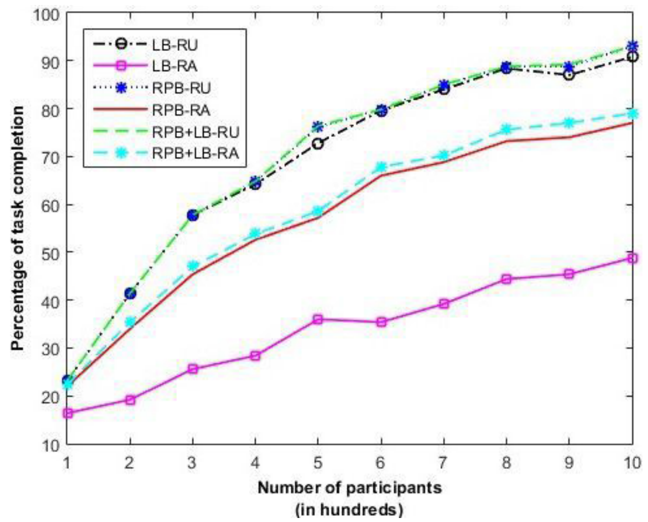

FIGURE 9. The impact of changing the number of participants on the CR for the reputation-aware and reputation-unaware versions of the proposed algorithms.

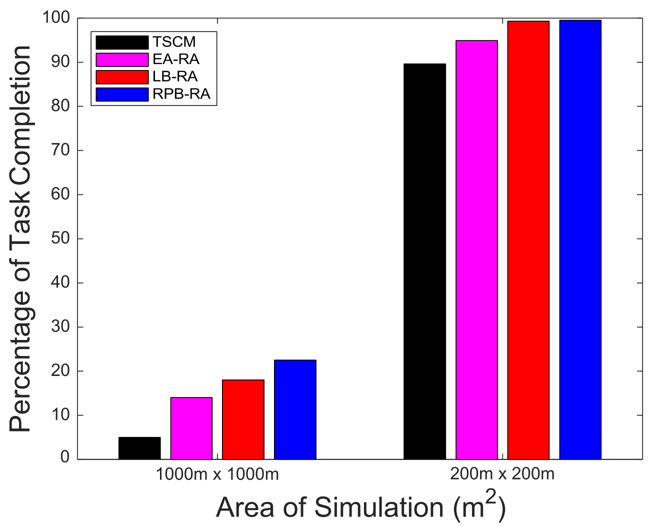

FIGURE 10. Comparing the CR attained the reputation-aware versions of the proposed algorithms–Reactive Auctioning, Look-Back Auctioning, and Redundancy-Penalizing Bidding–with a reputation-aware algorithm from the recent literature. The figure shows a consistent superiority for RPB over other algorithms across different campaign areas.

their area of interest (30 m radius) increases. The impact of varying the number of auctions on the CR is shown in Table 3 which presents the average percentages of task completion attained by the reputation-aware versions of different algorithms. Particularly, we computed the average CR attained by each algorithm over H auctions, and we allowed H to vary according to Table 2. The average CR is found to be nearly constant, regardless the number of held auctions. The LB could benefit from successive auctions; hence, it attained an increase of 4% in the average CR compared to Reactive Auctioning. RPB results in a significant increase in clearance rate, that is close to five times (500%) that of the TSCM and two times that of Reactive Auctioning.

This significant increase in CR is justified by the fact that other techniques aim at maximizing the user utility and the platform utility using only one stage of bidding (collective bidding). However, the proposed algorithms comprises two rounds of bidding. Also, RPB starts by giving higher priority to the unpopular tasks, then proceeds to another round of bidding (corresponding to secondary winners) to make the best out of the platform budget, and better satisfy service demanders. We will also discuss the impact of the procedure adopted by RPB on the computational time later in this section. It is important to mention that RPB does not increase the budget of the platform, but it uses it efficiently.

TABLE 3. Average task completion percentages of different Reputation-Aware algorithms, over H auctions, in a geographical area of (1000 m × 1000 m), M = 100 and N = 100. Please see text for more details.

Method	*TSCM*	*EA-RA*	*LB-RA*	*RPB-RA*
Clearance Rate	*5%*	*14%*	*18%*	*22.5%*

TABLE 4. A comparison between LB-RA and RPB-RA, with varying number of participants and HMCDB as a reference. The figures in the first row indicate how much improvement in CR was attained by each algorithm, and the second row shows the time required for that improvement to take place. Please see text for more details.

Method	*LB-RA*	*RPB-RA*
$\Delta CR(\%)$	*4%*	*8.5%–32%*
$\Delta Time(s)$	*3–30*	*6–65*

TABLE 5. A comparison between LB-RA and RPB-RA, with varying number of tasks and HMCDB as a reference. The figures in the first row indicate how much improvement in CR was attained by each algorithm, and the second row shows the time required for that improvement to take place. Please see text for more details.

Method	*LB-RA*	*RPB-RA*
$\Delta CR(\%)$	*4%*	*30%–40%*
$\Delta Time(s)$	*0.2–70*	*-20–0.1*

TABLE 6. A comparison between the proposed techniques showing the number of accomplished tasks from a total of 24 coverable tasks. The coverable tasks are the tasks within the area of interest of the participants. Please see text for more details.

Method	*MSensing*	*TSCM*	*LB-RA*	*RPB-RA*	*LB+RPB-RA*
Accomplished Tasks	*4*	*2*	*11*	*20*	*21*

In Table 4, we present a comparison between the Reputation-Aware versions of LB and RPB, with the reference being HMCDB [24]–one of the most recent methods in the literature that aimed at maximizing the CR. Particularly, we show how much enhancement in CR (ΔCR) has been attained by each of the proposed algorithms, compared to that of HMCDB, and the computational time cost to achieve that increase ($\Delta Time$). For a varying number of participants (according to the values given in Table 2), the CR attained by LB-RA is approximately 4% higher than that of HMCDB ($\Delta CR = 4\%$), and the time required was 3–30 seconds longer than that required by HMCDB, depending on the number of participants. For RPB-RA, though, the CR increase

TABLE 7. **The strength points for each of the proposed algorithms.**

Technique	*HMCDB*	*HDB*	*MCDB*	*DB*	*EA*	*LBA*	*RPB*
High CR	✔					✔	✔
Task Priorities		✔		✔			✔
High Platform Budget						✔	
High User incentive			✔	✔			✔
High CR at high N and M							✔
User contribution	✔		✔		✔	✔	✔

ranged from $8.5\% - 32\%$ at a time cost that ranged from $6-65$ seconds, depending on the number of participants. Similarly, Table 5 shows that comparison for a varying number of tasks (according to the values given in Table 2). As indicated in the table, RPB-RA could attain *negative values* for $\Delta Time$, i.e., it takes less time than HMCDB, and achieves higher CR. Our insight is that RPB, instead of leaving unpopular tasks uncovered until the stage of selecting secondary winners, it covers these tasks first. Hence, on one hand, it pays for the redundancy winners using the collective bids which are cheaper than the descriptive bids. And on the other hand, it reaches the *secondary winners stage* with less uncovered tasks, which translates to less descriptive bidding loops, i.e., less time to complete an auction.

So far, the CR has been shown as a percentage of the total number of tasks in the campaign. However, as mentioned earlier, some tasks are already *uncoverable* because they are out of the area of interest of all the participants. This means that a technique may not be able to accomplish all the tasks in the campaign, yet it is able to accomplish most the coverable tasks. Such a comparison further highlights the effectiveness of the proposed algorithms. We present in Table 6 the number of accomplished tasks by different techniques, from a total of 24 coverable tasks, where the coverable tasks are the tasks within the area of interest of the participants. Among the shown techniques is the composite Reputation-Aware LB+RPB algorithm, i.e., the bidding procedure that penalizes redudant task assignment, considers the participants' reputation, and transfers the budget from previously held auctions.

A Final Remark: We are aware that there are a multitude of parameters that could be considered in our simulations. For clarity and conciseness of presentation, we could not include all the parameters that can vary in a real-life scenario. Two examples of such parameters are the arrival time of users' bids and the quorum (if required by the service demander). We argue, though, that our simulations behave as if the bid arrival time is not a constraint, which is an acceptable and realistic scenario given the typical time to hold an auction. Furthermore, our proposed approaches are not at odds with any of these parameters that were not allowed to vary in our simulations. Lastly, running our simulations on a realistic map is among the points of future investigation. To facilitate the application of the proposed algorithms in real-life scenarios, Table 7 summarizes the characteristics/points of strength of each algorithm.

VI. CONCLUSION

This research aimed at increasing the quality of MCS auction-based campaigns. Particularly, we addressed the satisfaction of service demanders through maximizing the number of accomplished tasks during auctions–the clearance rate (CR). A consistent-and-significant increase in CR was obtained using extensive simulation and performance evaluation of new bidding procedures that handle various real-life scenarios. A look-back budget management strategy was presented to handle temporally successive auctions, and its positive impact on the CR was shown under varying system parameters. Along the same lines, we proposed a new objective function that features a new redundancy penalization factor. On one hand, this increases the CR by increasing the odds of accomplishing tasks with a few bidders, that would otherwise be dropped. On the other hand, this increases the CR by saving the budget to accomplish more tasks. The governing objective functions for all the proposed techniques were shown to lend themselves well to reputation-aware auctioning. Hence, they are not at odds with the existing techniques,

Algorithm A.1 Reputation-Aware Descriptive Bidding

$\mathcal{B} = \mathcal{V}$
$S = \Phi$
$S_{tasks} \leftarrow \Phi$
for $t \in T \setminus S_{tasks}$ **do**
  for $p \in P^t$ **do**
    $h \leftarrow \underset{p \in P}{\operatorname{argmin}}(B_{pt}(1 - R_p))$
  end for
  if $B_{ht} < \mathcal{B}R_h$ **then**
    $S_{tasks} \leftarrow S_{tasks} \cup t$
    $S \leftarrow S \cup \{h\}$
    $Y_{ht} = 1$
    $\mathcal{B} \leftarrow \mathcal{B}R_h - B_{ht}$
  end if
end for
for $i \in S$ **do**
  $\mathcal{P}_i = \sum_{j=1}^{M_i} Y_{ij}B_{ij}$
end for
$Outlier\_Detection(S)$
for $s \in \{S\}$ **do**
  update R_s
end for
return $(S, \mathcal{P}, R)$

but enhance their performance. According to the presented comparisons with the former state-of-art techniques, a CR increase that ranges from $50\% - 500\%$ was achieved. Future research directions would target the formulation of a combined objective function for energy efficiency and CR maximization. We also look forward to adopting knowledge priors about geographic correlation patterns among sensed data. This would enable us to estimate the outcome of a sensing campaign without holding it; hence, saving the budget for more auctions.

APPENDIX A ALGORITHM LISTINGS-DESCRIPTIVE BIDDING

See Algorithms A.1 and A.2.

Algorithm A.2 Reputation-Aware Max Contribution Descriptive Bidding

$\mathcal{B} = \mathcal{V}$
$S^{\text{MCDB}} = \Phi$, $T^{\text{MCDB}} = \Phi$, $S_{tasks} \leftarrow \Phi$
$h \leftarrow \underset{p \in P}{\text{argmax}}(V_p^R(S^{\text{MCDB}}) - \frac{B_p(S^{\text{MCDB}})}{R_p})$
while $R_h \mathcal{B} \geq B_h \bigwedge S^{\text{MCDB}} \neq P \bigwedge S_{tasks} \neq T$ **do**
    $T^{\text{MCDB}} \leftarrow T^s \cup T_h^{\text{MCDB}}(S^{\text{MCDB}})$
    $S_{tasks} \leftarrow S_{tasks} \cup T_h^{\text{MCDB}}(S^{\text{MCDB}})$
    $S^{\text{MCDB}} \leftarrow S^{\text{MCDB}} \cup \{h\}$
    $\mathcal{P}_h = B_h$
    for $p \in P \setminus S^{\text{MCDB}}$ **do**
        for $t \in T_p$ **do**
            if $t \in T_h^{\text{MCDB}}$ **then**
                $T_p = T_p \setminus t$
            end if
        end for
    end for
    $\mathcal{B} \leftarrow \mathcal{B}R_h - B_h$
    $h \leftarrow \arg \underset{p \in P \setminus S^{\text{MCDB}}}{\max}(V_p^R(S^{\text{MCDB}}) - \frac{B_p(S^{\text{MCDB}})}{R_p})$
end while
Outlier_Detection(S^{MCDB})
return $(S^{\text{MCDB}}, \mathcal{P}, R)$

Algorithm B.1 Determining Primary Winners

function Get Primary Winners(V, B^c, R, P)
    $S \leftarrow \Phi$, $S_{tasks} \leftarrow \Phi$
    $h \leftarrow \underset{i \in \mathcal{I}}{\text{argmax}}\, v_i^r(S) - \frac{b_i^c}{r_i}$
    while $\frac{b_h^c}{r_h} < v_h^r \bigwedge S \neq P$ **do**
        $S \leftarrow S \cup h$, $S_{tasks} \leftarrow T_h$
        $h \leftarrow \arg \underset{i \in \mathcal{I} \setminus S}{\max}\, v_i^r(S) - \frac{b_i^c}{r_i}$
    end while
    return S
end function

Algorithm B.2 Compute Payments for Winners

function Get Winners Payments(V, B^c, S, R, U)
    for $i \in \mathcal{I}$ **do**
        $p_i \leftarrow 0$
    end for
    for $i \in S$ **do**
        $S' \leftarrow S \setminus \{i\}$, $\Theta = \Phi$
        repeat
            $q \leftarrow \arg \underset{\mathcal{V} \in S' \setminus \Theta}{\max}(v_{\mathcal{V}}^r(\Theta) - \frac{b_{\mathcal{V}}^c}{r_{\mathcal{V}}})$
            $p_i \leftarrow \max(p_i, \min\{v_i^r(\Theta) - (v_q^r(\Theta) - \frac{b_q^c}{r_q})\})$
            $\Theta \leftarrow \Theta \cup \{q\}$
        until $\frac{b_q^c}{r_q} \geq v_q^r \bigvee \Theta = S'$
    end for
    return $\mathcal{P}$
end function

Algorithm B.3 Secondary Winners Selection and Payments Computation - Least Bid

$\mathcal{B} = \mathcal{V} - \mathcal{P}$
if $S_{tasks} \neq T$ **then**
    $S^s = \Phi$, $T^s = \Phi$
    for $i \in \mathcal{I} \setminus S$ **do**
        for $t \in T_i$ **do**
            if $t \in S_{tasks}$ **then**
                $T_i = T_i \setminus t$
            else if $t \in T \setminus S_{tasks}$ **then**
                $P^s \leftarrow P^s \cup \{i\}$
            end if
        end for
    end for
    for $t \in T \setminus S_{tasks}$ **do**
        for $p \in P^t$ **do**
            $h \leftarrow \underset{p \in P}{\text{argmin}}(B_{pt}(1 - R_p))$
        end for
        if $B_{ht} \leq \mathcal{B}R_h$ **then**
            $S_{tasks} \leftarrow S_{tasks} \cup t$
            $S^s \leftarrow S^s \cup \{h\}$
            $Y_{ht} = 1$
            $\mathcal{B} \leftarrow \mathcal{B}R_h - B_{ht}$
        end if
    end for
end if
for $i \in S^s$ **do**
    $\mathcal{P}_i = \sum_{j=1}^{M_i} Y_{ij} B_{ij}$
end for
Outlier_Detection(S, S^s)
return $(S^s, \mathcal{P}, R)$

APPENDIX B ALGORITHM LISTINGS-HYBRID BIDDING

See Algorithms B.1–B.4.

Algorithm B.4 Secondary Winners Selection and Payment Computation - Maximum Contribution

$\mathcal{B} = \mathcal{V} - \mathcal{P}$
if $S_{tasks} \neq T$ **then**
  $S^s = \Phi, T^s = \Phi$
  for $i \in \mathcal{I} \setminus S$ **do**
    for $t \in T_i$ **do**
      if $t \in S_{tasks}$ **then**
        $T_i = T_i \setminus t$
      else if $t \in T \setminus S_{tasks}$ **then**
        $P^s \leftarrow P^s \cup \{i\}$
      end if
    end for
  end for
  $h \leftarrow \underset{i \in \mathcal{I}^s}{\text{argmax}}(v_i^r(S^s) - \frac{b_i(S^s)}{r_i})$
  while $\frac{b_h}{r_h} + (r_h \times \mathcal{B}) \geq 0 \bigwedge S^s \neq P^s \bigwedge S_{tasks} \neq T$ **do**
    $S_{tasks} \leftarrow S_{tasks} \cup T_h^s(S^s)$
    $S^s \leftarrow S^s \cup \{h\}$
    for $i \in \mathcal{I}^s \setminus S^s$ **do**
      for $t \in T_i$ **do**
        if $t \in T_h^s$ **then**
          $T_i = T_i \setminus t$
        end if
      end for
    end for
    $\mathcal{B} = (\mathcal{B} \times r_h) - \frac{b_h}{r_h}$
    $h \leftarrow \arg \max\limits_{i \in \mathcal{I}^s \setminus S^s} (v_i^r(S^s) - \frac{b_i(S^s)}{r_i})$
  end while
end if
$Outlier\_Detection(S, S^s)$
return $(S^s, \mathcal{P}, R)$

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MAGGIE E. GENDY (Student Member, IEEE) received the B.Sc. and M.S. degrees in electronics and communications engineering from the Arab Academy of Science, Technology, and Maritime Transport (AASTMT), Alexandria, Egypt, in 2016 and 2019, respectively. Since 2017, she has been an Assistant Lecturer of electronics and communications engineering with AASTMT. Her research interests include mobile crowdsensing, optimization approaches, and machine learning.

AHMAD AL-KABBANY (Member, IEEE) received the B.Sc. degree in electronics and communications engineering from the Arab Academy for Science and Technology, Alexandria, Egypt, in 2005, and the Ph.D. degree in electrical and computer engineering from the University of Ottawa, Ottawa, Canada, in 2016.

From 2006 to 2010, he was a Teaching and Research Assistant with the Electronics and Communications Engineering Department, Arab Academy for Science and Technology. In 2010, he was a Graduate Research Intern with the University of Ulster, U.K. From 2010 to 2016, he was a Graduate Research Assistant and then a Postdoctoral Fellow with the VIVA Laboratory, School of Electrical Engineering and Computer Science, University of Ottawa. Since 2016, he has been an Assistant Professor of electronics and communications engineering and a Founding Member with the Intelligent Systems Laboratory, Arab Academy for Science and Technology. He is also the Founder and the CEO of VRapeutic–a research-based software startup specializing in the development of therapeutic AI-enabled virtual reality solutions, with a current focus on learning difficulties and developmental disorders. His research interests include the applications of graph optimization and machine learning in communication networks and N-D signal processing, synthesis, analysis, and communication.

Dr. Al-Kabbany has led VRapeutic to several regional recognitions, including the 1st place at the Global Impact Challenge, in 2019, organized by Singularity University, CA, USA. During his Ph.D. studies, he got two research awards from the University of Ottawa, and one of the algorithms that he co-proposed was ranked, at the time, among the best eight techniques worldwide according to a standard benchmark in image alpha matting.

EHAB F. BADRAN (Senior Member, IEEE) received the B.Sc. (Hons.) and M.Sc. degrees in electrical engineering from Assiut University, Asyut, Egypt, in May 1995 and March 1998, respectively, and the M.Sc. and Ph.D. degrees in electrical engineering from Louisiana State University (LSU), Baton Rouge, USA, in May 2001 and May 2002, respectively. From 1995 to 1998, he was an Instructor with the Department of Electrical Engineering, Assiut University, where he was promoted to an Assistant Lecturer, in May 1998. From January 2000 to May 2002, he was a Teaching and Research Assistant with the Department of Electrical and Computer Engineering, Louisiana State University, during his Ph.D. studies. From September 2002 to August 2003, he was an Assistant Professor with the Department of Electrical Engineering, Assiut University. From September 2003 to May 2007, he has worked as an Assistant Professor with the Department of Electronics and Communication Engineering, Arab Academy for Science, Technology, and Maritime Transport, Alexandria, Egypt, where he was an Associate Professor, from June 2007 to May 2011. In June 2011, he was promoted to be a Professor. His research and teaching interests include wireless communications, signal processing, MIMO systems, image processing, and communication networks.