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May El Barachi
University of Wollongong in Dubai

Assane Lo
University of Wollongong in Dubai

Sujith Samuel Mathew
Zayed University, sujith.mathew@zu.ac.ae

Kiyan Afsari
University of Wollongong in Dubai

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A Novel Quality and Reliability-Based Approach for Participants' Selection in Mobile Crowdsensing

MAY EL BARACHI[1], ASSANE LO[1], SUJITH SAMUEL MATHEW[2], AND KIYAN AFSARI[1]
[1]Faculty of Engineering and Information Sciences, University of Wollongong in Dubai, Dubai 20183, United Arab Emirates
[2]College of Technological Innovation, Zayed University, Abu Dhabi 144534, United Arab Emirates

Corresponding author: May El Barachi (maielbarachi@uowdubai.ac.ae)

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ABSTRACT With the advent of mobile crowdsensing, we now have the possibility of tapping into the sensing capabilities of smartphones carried by citizens every day for the collection of information and intelligence about cities and events. Finding the best group of crowdsensing participants that can satisfy a sensing task in terms of data types required, while satisfying the quality, time, and budget constraints is a complex problem. Indeed, the time-constrained and location-based nature of crowdsensing tasks, combined with participants' mobility, render the task of participants' selection, a difficult task. In this paper, we propose a comprehensive and practical mobile crowdsensing recruitment model that offers reliability and quality-based approach for selecting the most reliable group of participants able to provide the best quality possible for the required sensory data. In our model, we adopt a group-based approach for the selection, in which a group of participants (gathered into sites) collaborate to achieve the sensing task using the combined capabilities of their smartphones. Our model was implemented using MATLAB and configured using realistic inputs such as benchmarked sensors' quality scores, most widely used phone brands in different countries, and sensory data types associated with various events. Extensive testing was conducted to study the impact of various parameters on participants' selection and gain an understanding of the compromises involved when deploying such process in practical MCS environments. The results obtained are very promising and provide important insights into the different aspects impacting the quality and reliability of the process of mobile crowdsensing participants' selection.

INDEX TERMS Data quality, mathematical modeling, mobile crowdsensing, participants' reliability, participants' selection.

I. INTRODUCTION

FOR many years, Wireless Sensor Networks (WSNs) [1] have been considered as the main solution to contextual information acquisition and sensing activities, in various domains such as environment/habitat monitoring, healthcare applications, home automation, and traffic control. However, recently, with the widespread use of smartphones and the continuous increase of their capabilities, a new sensing paradigm has emerged: mobile crowdsensing. The concept of crowdsensing implies the reliance on the crowd to perform sensing tasks and collect data about a phenomena of interest (e.g. traffic conditions and accidents' occurrence) [2].

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The process of acquiring crowd sensed information involves the publishing of a sensing task within a geographic location to a network of participants and the real time management of responses from interested participants. Typically, the publishers of sensing tasks (or data consumers) specify the type and location of the event of interest (e.g. fire accident at location X,Y), the minimum quality level required for the task (e.g. min. quality level of 7.5), the maximum budget allocated (e.g. max. budget of 30$), and the maximum time window to satisfy the request (e.g. max. time window of 5 minutes). The crowdsensing process poses many interesting research challenges, specifically in the areas of: overall system architecture, task publishing techniques, participant selection methodologies, responses' validation and analysis, incentives and data monetization, security and privacy preservation, and management of the physical infrastructure. Selecting the optimal group of crowdsensing participants that can collect the data types required, while meeting the specified time, quality, and budget constraints is a challenging problem. Indeed, the time-constrained and location based nature of crowdsensing tasks, combined with participants' mobility and unpredictable behavior render the task of MCS participants' selection a complex task. The dynamic nature of the MCS environments is a key factor that affects the quality and reliability of the sensory information generating valuable knowledge for critical applications. Our research focus is on this challenge of MCS participants' selection, taking into account the quality and reliability of the sensory information required.

In the literature, selection of crowdsensing participants is mainly dependent on the characteristics of the area of interest (AoI), the capabilities of the sensing devices, and the characteristics of the participants [3]. Each of these dimensions have many associated factors like the density of population or the lack thereof in a particular AoI, or number of participants with required sensors, or the cost of uploading sensory data, or the past behavior and reputation of participants. These factors affect the quality and reliability of the crowdsensing process and it is therefore important to consider them when selecting suitable MCS participants. From the participants' perspective, they are required to submit sensory information either periodically (e.g. traffic incident monitoring) or continuously (e.g. pollution levels monitoring), while satisfying the data types, quality level, time and budget constraints. Recent research contributions on MCS participants' selection have included some of these factors [3]–[17]. While these contributions have their merits, they often lack comprehensive and practical models to fully capture the complexity of the MCS participants' selection process. Moreover, such approaches overlook some important factors that may impact the selection process, such as participants' malicious behavior, time requirement for task satisfaction, country in which the task is taking place, and others. Furthermore, there is a lack of extensive testing and experimental results that give deep insights about the parameters impacting the participants' selection process or the compromises it entails.

In this work, we propose a novel and comprehensive mathematical model for representing the problem of MCS participants' selection. Our model relies on a large number of parameters that can have an impact on the selection result, in addition to using realistic benchmarking for quantifying sensors quality scores, concrete distributions of phones' brands across geographical regions, and practical events types with varying sensory data requirements. Matlab simulations were used to extensively test the proposed model and demonstrate its merits and the insights it provides in the area of MCS participants' selection.

We present our work in the sections that follow, where Section 2 discusses the related work review, and Section 3 describes our novel approach for participant selection, including the description of the mathematical model and the proposed participants' selection algorithm. In Section 4, we present and analyze our extensive simulation results. Finally, in Section 5, we present a summary of our findings and highlight future work.

II. RELATED WORK

The selection of the participants in MCS is a research challenge that directly affects the quality and reliability of the sensory information and hence there are several selection models suggested in the literature. In this section we discuss the state-of-the-art in MCS participants' selection and the various factors that are considered in those approaches.

One of the common criteria used for MCS participants' selection is the coverage or density of participants within a given Area of Interest (AoI). How would the system get maximum coverage of participants in the AoI for a minimal cost? One of the approach used is to determine the historical data of participants' spatiotemporal availability in an AoI, and use those historical traces to send sensing requests to participants with high-probability of availability in the AoI [4]–[6]. In [4], The dynamic tensor analysis algorithm is used to learn the time-series of trajectories so as to predict the future user's mobility path. Since, getting the information from each individual participant and processing it separately was not efficient, the participants were grouped based on certain criteria, such as grouping participants with similar spatiotemporal historical patterns. The group is then ranked and a participant from the group is selected (based on energy and trust scores) to transmit the sensory data required. Similarly, the work presented in [5] focuses on the participants' mobility model and coverage probability by assuming that a participant's historical locations are known and the time slot for mobility prediction is short. This approach models participants according to a discrete Markov model and selects individual participants based on the coverage estimation. The number of participants selected is the sum of all selected sets of participants. In [6], the selection algorithm relies on taxi trajectories and considers the inter-cover time for urban sensing. One drawback of this approach is that taxi trajectories only capture a small subset of the actual participants. Since vehicles move at high speeds, it would be difficult to identify participants within an AoI. Moreover, the stay of the participants within a sensing area would be too short to accomplish given tasks and therefore this approach is non-optimal for most MCS tasks. In [3], Azzam *et al.* proposed a dynamic selection model that increases or decreases the number of participants selected to achieve a highly stable group composition. To motivate participants to provide sensory data, the model utilizes cooperative game theory. In this approach, stability is an important factor to measure the effect of participants' collaboration. However, dynamic models are known to require additional computation and introduce overhead due to frequent modifications of groups' composition.

Another MCS participants' selection factor is the cost incurred to collect sensory data. An optimal minimum threshold for the number of participants and a fixed cost for the duration of the transmission of sensory data needs to be specified to better estimate the overall budget for getting the sensory data. An approach that was considered for reducing the sensing cost is to understand the incentives expected by interested participants [7], [8]. In this approach, the participants announce their expected price for providing sensory data and the system selects the minimal cost, based on the available budget. If the required coverage of participants is not achieved, then the missing information is extrapolated from the available data. In [9], a system called CrowdRecruiter minimizes incentive payments while ensuring that coverage constraint is met. The targeted application in this case is air quality monitoring and sensing tasks are fulfilled using phone calls. CrowdRecruiter first predicts the coverage probability of each mobile user based on historical records, then computes the joint coverage probability of multiple users and selects the near-minimal set of participants. However, this approach is limited by the calls of mobile participants. If the recruited participants make no calls during specified sensing cycles, it will lead to responses delay. In [10], based on the prediction of the probability of calls made at a particular time and location, offline and online greedy algorithms are proposed to dynamically select a subset of participants to perform the tasks. The optimization goal is to minimize the total cost while ensuring different levels of coverage for multiple tasks.

The capabilities of the participant's sensing device constitute another important criterion when selecting MCS participants [11], [12]. The availability of required sensors on a mobile device and the availability of device's resources for computation, storage, and communication are attributes that are typically used when selecting MCS participants. Moreover, the quality of the sensors is an important factor to consider. To achieve that, a budget is usually used as a reward to participants in sensing tasks based on the quality of their phone sensors. If there are multiple participants in the same AoI, the sensing tasks are divided to ensure efficient energy consumption and fairness. Zhao *et al.* [13] considered fair and energy-efficient task allocation in MCS by solving a min-max aggregate sensing time problem. He *et al.* [14] considered social surplus maximization for location-dependent task scheduling. They formulated a task scheduling problem, where the objective is to maximize the overall net reward of all the participants, subject to the time of each user and the redundancy of sensing tasks.

Recent research contributions also considered factors like, participant reputation, domain expertise, social attributes, trust factors, and risk factors, in the selection process. In [15], a truthful, individually rational, and computationally efficient mechanism was designed to maximize the social welfare for single-minded combinatorial models. This approach relies on an approximation ratio and assumes a linear quality model. Moreover, an iterative mechanism with individual rationality for multi-minded combinatorial models was proposed as part of this work. The study in [16] presents a selection process that chooses appropriate participants based on a reputation scheme to evaluate the trustworthiness of the submitted data. The approach in [17] included a preferred list of potential participants to select the most appropriate subset. This list could be system generated to contain the participant's friends who have been endorsed to be trustworthy or could be manually created by the requester. A blocked list is also created which lists participants that are not endorsed to be trustworthy.

A. DISCUSSON

While the existing approaches have their merits, they usually rely on specialized mathematic models that only represent some of the aspects impacting the MCS participants' selection process or are geared toward specific MCS applications. Comprehensive, generic, and practical models that capture the most important aspects for MCS recruitment are needed. Moreover, none of the existing approaches present extensive testing results that give true insights about the parameters impacting the participants' selection process or the compromises it requires.

For instance, some approaches model users' reliability based on the percentage of tasks they completed in the past versus the total number of tasks assigned, thus focusing on a historical measure of interactions. Due to the complexity of human behavior in crowdsensing environments, participants' reliability for a sensing task can be impacted by many factors, both historical and instantaneous, including their proximity from event of interest, their phones' residual battery level, the quality of their phone sensors, and their history of malicious activity. Malicious activities may include different undesired behaviors, which may be intentional or unintentional, and impact the quality of the data collected. Such behaviors can range from individual pollution attacks (intentionally manipulating reports to give wrong information), to malicious denial of service attacks (accepting sensing request and not returning results to prevent other honest users from participating in the sensing activities), to honest but selfish denial of service attacks (accepting all sensing requests, but completing them over an extended period of time to save resources), to orchestrated pollution attacks (group of malicious users agreeing to give conflicting reports that are far from the truth value, to impact the reliability of the output). Therefore, participants' reliability cannot be solely based on historical contributions, but should rather include both instantaneous factors and historical factors, capturing both past and current behavior. This is required since participants with good behavior in the past can start misbehaving in the present.

Furthermore, in existing approaches, devices' data quality is typically measured using parameters such as sensors' availability and sampling frequency. While those aspects play a role in the quality of the data collected by devices, there is a need for a concrete and practical benchmark to provide an accurate and quantifiable measure of phones' sensors quality. Finally, some other parameters that may impact the participants' selection process are often not considered in existing approaches, such as the country in which sensing task is taking place, the time window allowed for the task, the total population size and the number of available participants, the size of the AoI and the population density in it.

In the coming section, we present a novel and comprehensive MCS participants' selection approach that consider all the important parameters needed to model the complexity of the participants' selection problem. In our approach, participants' selection takes into consideration four categories of factors, namely: 1) Social characteristics of the participant who owns the mobile device; 2) AoI related factors; 3) Cost related factors; and 4) Risk related factors. In our model, 19 parameters were used to model the quality and reliability aspects, and extensive testing was conducted to study the impact of those parameters on the participants' selection process, in order to gain insights on the compromises involved when deploying such process in practical MCS environments.

III. A NOVEL PARTICIPANTS' SELECTION APPROACH FOR MOBILE CROWDSENSING

This section presents the crowdsensing participants' selection problem statement, details the system model and the mathematical model and mathematical formulation, and describes the proposed participants' selection algorithm.

A. PROBLEM STATEMENT, ASSUMPTIONS, AND NOTATIONS

As shown in Figure 1, we consider a system model that consists of a set of data consumers (interested in crowd-sensed data), data collectors (i.e. crowdsensing participants collecting the requesting data using their phone sensors), and a crowdsensing platform acting as broker between data consumers and data collectors. The broker collects status information (i.e. updated location and sensors' availability) from data collectors on a regular basis, to keep track of all available data types and the associated quality levels that can be offered at any given moment, to data consumers. The data consumers send their requests to the broker, which then uses the request requirements and the available data collectors' status information to find the appropriate set of collectors/participants who can answer the request. When a data consumer sends a request to the broker, this request should specify the type and location of the event of interest (e.g. car accident in GPS lo-cation 41.40338, 2.17403). This can be achieved through

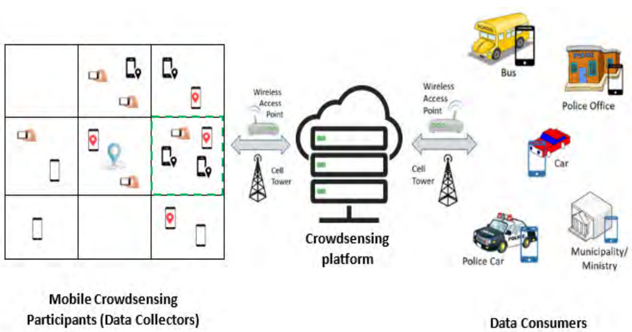


FIGURE 1. Mobile crowdsensing system overview.

interaction with the crowdsensing mobile app, in which a map is shown, and the data consumer can selection a point of interest along with a diameter around it – thus representing an area of interest (AoI) centered around an Event of Interest (EoI), along with a menu to choose the type of event of interest (e.g. car accident, fire incident, storm incident...etc). In addition to specifying the type and location of the event of interest, the data consumer should also specify the minimum quality level required for the task, the maximum budget allocated, as well as the maximum time window required for the task (e.g. Car accident at location X,Y, min. quality level of 8, max. budget of 20$, max. time window of 5 minutes).

It should be noted that, unlike other approaches that rely on individual participants' selection [4]–[6], we adopt a group-based selection approach in which a group of participants collaborate to fulfil sensing tasks using the combined capabilities of their devices. More specifically, we consider the area of interest (i.e. area at the center of which lies the event of interest) as a grid, that is divided into a number of sites – each site containing a group of participants. The main objective of our participants' selection approach is to find the best combination of sites that can be used to collect the types of data requested, while satisfying the specified constraints (i.e. max. time allowed for task, max. budget allocated, minimum level of quality required). More specifically, our approach aims at satisfying the task requirements, while achieving the highest data quality and participants' reliability possible. Moreover, the solution also attempts to minimize the number of participants selected per task, in order to reduce redundancy and minimize the data collection time and the price to be paid for the task.

Assumptions: Once the broker selects a group of participants for a sensing task, the sensing request is forwarded to the selected participants who can accept or reject the request. In the case of request acceptance, each crowdsensing participant (data collector) offers the sensing capabilities of his/her mobile device, depending on the data types required for the sensing task.

In our model, we have the following assumptions about the crowdsensing environment:

- There is a specific sensing service/event associated to each sensing task that is given by the task creator. The types of data/sensors required depend on the sensing service/event.
- There is a specific time window for each sensing task given by the task creator.
- There is a minimum data quality level for each sensing task given by the task creator.
- We assume a cooperative environment, in which a group of participants collaborate to fulfil sensing tasks. Furthermore, the types of data/sensors required for each sensing task should be fulfilled by the aggregated capabilities of a group of participants, not by each individual participant.
- A task may require the use of one or more sensors of a single participant's phone.

- Each participant can handle multiple sensing tasks simultaneously.
- The area of interest is represented as a grid, consisting of a number of sites – each site encompassing a number of participants, based on the participants' locations with respect to the event.
- This variety of the sensors a site offers depends on the phone brands/models carried by the participants in the site.
- Each site is characterized by: 1) the number of participants in the site; 2) the variety of the sensors it offers; 3) the price of the service it offers; 4) its proximity from the event of interest; 5) its average battery level; and 6) its average sensors quality with respect to the sensing task.

Notations: Our model includes several parameters, which are summarized, along with their notations, in table 1.

TABLE 1. Notations.

Variables	Descriptions
Λ	The Area of interest (AoI) represented as a square lattice centred around the Event of Interest.
$side$	The length of a side of the area of interest.
P	Total population within area of interest.
N	Total number of available participants in the area of interest.
γ	the participants' density in the area of interest.
T_Λ^i	Sensing task i occurring in area Λ.
D_Λ^i	The required sensing data types for sensing task i occurring in area Λ.
σ_Λ^i	The maximum time window permitted for obtaining the sensing data, for task i occurring in area Λ.
Q_Λ^i	The required data quality level for task i occurring in area Λ.
N_j	The number of participants in site j.
B_{ij}^Λ	Max budget allocated to site j for task T_Λ^i.
R_{ij}^Λ	Reliability score of site j with respect to task T_Λ^i.
p_{ij}^Λ	Price for carrying task T_Λ^i at site j.
DSR_{ij}^Λ	Data satisfaction ratio provided by site j for task T_Λ^i.
V_{ij}^Λ	The probability of task satisfaction of a given site j
$\kappa_{j,\Lambda}$	Site $j's$ total quality score, with respect to task T_Λ^i.
d^j	The proximity of site j from the event of interest
h^j	The average battery level in site j
s^j	The average sensors' quality in site j with respect to the sensing task
M_j	malicious participants in site j
M_j^c	Non-malicious participants in site j
ε	The strength of price competition among the participants in a site.
D_Λ^{ij}	Number of task i data types supported by site j.
K_{ij}^Λ	Site j selection score with respect to task T_Λ^i.
C	Country in which the sensing task is taking place.
ET	Event type to which the sensing task is related.

B. SYSTEM MODEL AND MATHEMATICAL FORMULATION

We begin by considering a geographic system $\Lambda \subseteq Z^2 (AoI = \Lambda \subseteq Z^d, d \geq 1)$ which can represent a city, a country, a road, a shopping center ... etc.

The Area of interest (AoI) Λ will be chosen to be a square lattice centered at the event of interest (EoI) which we will denote by site J and that the distance between two sites is equal to l.

Let $T_\Lambda^i = (D_\Lambda^i, \sigma_\Lambda^i, Q_\Lambda^i)$ denote a sensing task i where D_Λ^i represents the required sensing data types (which are mapped from different event types), σ_Λ^i is the maximum time window permitted for obtaining the sensing data, and Q_Λ^i is the required data quality level for the task.

Given a set of tasks $T_\Lambda = (T_\Lambda^i)_{i\in I}$, we shall denote by l; the maximum distance from J within which all tasks T_Λ^i can be accomplished.

Next, we take Λ to be the square lattice with diameter *side* centered at J with spacing l between each two sites. Given the length of a side of the area of interest (*side*) along with the participants' density γ in that area, we can determine the spacing of the grid $l$as follows:

$$\gamma = \frac{N}{P} \tag{1}$$

where:

P= Total population within area of interest
N= Total number of available participants in the area of interest (i.e. users who are logged in to the crowd-sensing mobile app.)

$$\gamma l = side.(1-) \tag{2}$$

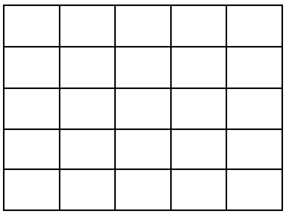
Therefore, the number of sites generated in one area (n) is directly proportional to the size of the area and the population density as shown below.

$$n = (\frac{side}{l})^2 \tag{3}$$

To ensure that the spacing calculated does not result in sites' fractions, for spacing results with fractions, we round the spacing calculated to the nearest divisor of the side. For instance, if the side = 20 meters, the total population = 100 and the number of participants = 62, then $\gamma = 62/100 = 0.62$. $l = 20 \times (1 - 0.62) = 7.6$. The closest divisor of 20, to 7.6 is 5. Therefore, n = $(20/5)^2$ = 16 sites. Furthermore, in the case where the number of participants = total population (e.g. 100 participants in a population of 100), the same approach is used, resulting in the following: $\gamma = 100/100 = 1$. $l = 20 \times (1-1) = 0$. The closest divisor of 20, to 0 is 1. Therefore, n = $(20/1)^2$ = 400 sites. Therefore, the spacing in that case will always equal to 1, and the number of sites will equal to the square of the side of the area of interest.

We shall assume that the participants are located at the sites $j's$ of the lattice Λ and that the distance between two sites is equal to $side.(1-\gamma)$

We shall also assume that the participants are close enough to cooperate effectively and that the task publisher will select sites rather than a particular individual participant in a site.



$$AoI = \Lambda \subseteq Z^d$$

Put:

$$\Lambda = \Lambda_{side.(1-\gamma)}$$

Observe that the variety of sensors at a site j for T^i_Λ is a non decreasing function of N_j. Each site has a Data satisfaction ratio DSR^Λ_{ij} that represents the ratio of data types satisfied by the site, with respect to data types required for the task. DSR^Λ_{ij} is a non decreasing function of N_j. Also, because of a possible competition between participants in a site, the price p^Λ_{ij} for T^i_Λ at site j is a non increasing function of N_j.

We assume that the task publisher can assign to each site j a perceived probability of satisfying the minimum required quality information for T^i_Λ, V^Λ_{ij}. V^Λ_{ij} should be a non decreasing function of N_j

We assume that the participants at a given site j can be partitioned into malicious participants M_j (those who have the intention to deliberately provide wrong information) and non-malicious participants M^c_j

We define the reliability of the site j with respect to T^i_Λ, R^Λ_{ij} to be the probability of satisfaction given that the information comes from non-malicious participants in site j

We assume that at each site j, the task publisher has a maximum budget B^Λ_{ij} that he is willing to spend for T^i_Λ

The Equations of the model: We first begin with the required data types (D^i_Λ) and the required data quality level for the task Q^i_Λ, at site j. We will denote by K^Λ_{ij} the site selection score, based on which it is decided whether or not the task requirements are satisfied by task j, as follows:

$$K^\Lambda_{ij} = (B^\Lambda_{ij}.R^\Lambda_{ij} - p^\Lambda_{ij}).DSR_{ij} \tag{4}$$

where:

B^Λ_{ij} = Max budget allocated to site j for task XT^i_Λ
R^Λ_{ij} = Reliability score of site j with respect to task T^i_Λ
p^Λ_{ij} = Price for carrying task T^i_Λ at site j
DSR^Λ_{ij} = Data satisfaction ratio provided by site j for task T^i_Λ

The probability of task satisfaction of a given site j with N_j participants, is given by equation (5).

$$V^\Lambda_{ij} = 1 - e^{\frac{-N_j}{\kappa_{j,\Lambda}}} \tag{5}$$

N_j represents the number of participants in the site j. $\kappa_{j,\Lambda}$ represents site $j's$ total quality score, with respect to task T^i_Λ. The total quality score will vary from site to site, depending on the sensing capabilities offered in each site. $\kappa_{j,\Lambda}$ will be small (smaller than 1) for tasks in which the site's participants carry devices with high sensing capabilities (i.e. high residual battery level, high sensors' quality) and are located in close proximity to the event of interest. $\kappa_{j,\Lambda}$ will be large (larger than 1) for tasks in which the site's participants carry devices with low sensing capabilities (i.e. low residual battery level, poor sensors' quality) and are located far from the event of interest. The total quality score for site j is given by equation (6).

$$\kappa_{j,\Lambda} = \frac{1 + d^j}{d^j + h^j + s^j} \tag{6}$$

where:

d^j = Site $j's$ distance to the event of interest. $(0 \leq d^j \leq 2l)$
h^j = The average battery level at site j. (h^j is given in percentage)
s^j = The average sensors' quality score at site j. (s^j is given in percentage)

R^Λ_{ij}, which represents site j's reliability score, is modeled as the probability of task satisfaction given that the information comes from non-malicious participants in site j The site's reliability score is represented by equation (7).

$$R^\Lambda_{ij} = P(V^\Lambda_{ij}/M^c_j) \tag{7}$$

Using Bayes' Theorem, we have:

$$R^\Lambda_{ij} = \frac{P(M^c_j/V^\Lambda_{ij})V^\Lambda_{ij}}{P(M^c_j)} \tag{8}$$

The price of the service offered by the site is represented by equation (9). This expression of the price is based on the circular city model, presented in [18].

$$p^\Lambda_{ij} = \frac{\sigma^i_\Lambda}{\kappa_{j,\Lambda} N^\in_j} \tag{9}$$

where:

σ^i_Λ represents the maximum amount of time required (in minutes) to accomplish task T^i_Λ
N_j represents the number of participants in the site j
$\kappa_{j,\Lambda}$ represents to total quality score for site j
ε is an exponent reflecting the strength of price competition among the participants in a site. If $\varepsilon = 0$, then there is no competition – all participants are isolated (each in one site) or demand the same price.

The site's data satisfaction ratio (DSR) is calculated using equation (10). The higher the value of a site's data satisfaction ratio, the higher the chance of that site being selected for the task.

$$DSR^\Lambda_{ij} = \frac{D^{ij}_\Lambda}{D^i_\Lambda} \tag{10}$$

where:

D^{ij}_Λ = Number of task$i$ data types supported by site j
D^i_Λ = Number of data types required for task T^i_Λ

Finally, the site's quality satisfaction ratio (QSR) is calculated using equation (11).

$$QSR_{ij}^{\Lambda} = \kappa_{j,\Lambda} - Q_{\Lambda}^{i} \tag{11}$$

where:

$\kappa_{j,\Lambda}$ = Site j total quality score with respect to task T_{Λ}^{i}
Q_{Λ}^{i} = the minimum required data quality level for the task T_{Λ}^{i}

Sites that cannot deliver a data quality level that is equal to or above the quality level requested for the task will have a negative QSR, and will be eliminated from the final selection. Furthermore, all malicious sites, which produce a reliability of 0, will be assigned a negative value in the final score and will be eliminated from the final selection. The sites with highest final selection scores (i.e. that achieve the highest reliability, highest DSR, and lowest price), will be selected.

The final expression for the site selection score is given by equation (12).

$$K_{ij}^{\Lambda} = (Budget_{site}.Reliability_{site} - Price_{site})\,.DSR_{site}$$

$$K_{ij}^{\Lambda} = (B_{ij}^{\Lambda}.R_{ij}^{\Lambda} - p_{ij}^{\Lambda}).DSR_{ij}^{\Lambda}$$

$$K_{ij}^{\Lambda} = \left(B \cdot \frac{P\left(M_j^c / V_{ij}^{\Lambda}\right) \cdot \left(1 - e^{-\frac{N_j}{\kappa_{i,\Lambda}}}\right)}{P\left(M_j^c\right)} - \frac{\sigma_{\Lambda}^{i}}{\kappa_{i,\Lambda} \cdot N_j^{\varepsilon}} \right) \cdot DSR_{ij}^{\Lambda} \tag{12}$$

Subject to the following constraints:

$$QSR_{ij}^{\Lambda} \geq 0 \tag{C1}$$

$$\sigma_{\Lambda}^{i} < \sigma_{\Lambda} \tag{C2}$$

Constraint C1 implies that sites with a negative QSR will be eliminated from the selection process as they cannot satisfy the requested quality level. Constraint C2 implies that the time window to achieve the task by the site should be less than the total allowed time window for the task.

C. CROWDSENSING PARTICIPANTS' SELECTION ALGORITHM

Our proposed crowdsensing participants' selection algorithm is described in Algorithm 1.

The process starts when a data consumer sends a sensing task request to the crowdsensing platform, specifying: 1) The type of event of interest; 2) the location and size of the area of interest; 3) the minimum quality level required; 4) the maximum budget allocated for the task; and 5) the maximum time window to satisfy the request. Since our algorithm was tested in a simulated environment, we also specified some input configuration parameters that were required to run the selection process, including: the total population in the area of interest; the number of available participants in the area of interest; the country where the task is taking place; and the percentage of malicious participants. In a real-life deployment, this information would be collected dynamically

Algorithm 1 Participants' Selection Algorithm

1. **Input:** Sensing task details & initial configuration values – Country (Region), Total population (P), # of participants (N), Task budget (B), Size of area of interest (side), time window for task (time), required information quality level (quality), % of malicious participants (mp).
Output: selected site(s) that can satisfy the sensing task requirements & constraints

2. *[side,P,N,Region,time,event,Quality,B,mp]* = **get_input**();//get all the required input parameters
3. $[L, n, y]$ =**get_dist**(*side,N,P*); // calculate sites' dimensions/spacing & form grid
4. *Phone_Battery*= **Random**(1-100); // Generate phones' battery levels
5. *Phone_Location*= **Random**(0-side); // Generate participants' locations
6. *[device_sensors,participant_phones]*=**assign_phones**(N,Region); //assign phone models to participants, based on country's statistics
7. *N_ID*= 1:N; // assign ID to each participant
8. *sensor_table*= **read_sensors_data**('Sensors'); //read from the database values of sensors' quality scores
9. *Malicious_participants* = **Random**(mp%);// randomly assign malicious participants according to maliciousness % (mp)
10. *Event_location* = [side/2 side/2];// Set event location at the center of the grid
11. *Event_data_types* = '1001101100'; // represent event data types required in binary
12. Compare event type to availability of data type on the phone
13. Determine list of participants per site, based on the participants' locations in the grid.
14. Count the *number of participants* in each site;
15. Identify *phone models* in each site;
16. Calculate *phones_Sensors_quality* with respect to event; // average quality of sensors required for the event, per phone, based on sensors quality DB.
17. *Site_sensors_quality* = **average**(*phones_sensors_quality* in site); //quality of site sensors quality is the average of individual phones sensors quality in that site.

Algorithm 1 *(Continued.)* Participants' Selection Algorithm

18. *Site_Maliciousness_score*(M) = **average**(*malicious participants in site*);
19. *Site_battery* = **average**(*individual battery levels in site*);
20. *Site_data_types* = **SUM** (*site_devices_data_types*) //the data types a site can handle is the aggregation of the data types that can be provided by individual phones in the site.
21. *DSR* = *site_data_types/Event_data_types*; //Calculate sites' data satisfaction ratios
22. Set *price competition value*: //Calculate price competition values in sites
    if ($y < 0.33$)
        $eps = 0$;
    else if ($y < 0.66$)
        $eps = 0.5$;
        else
            $eps = 1$;
        end
23. Calculate *sites' distances from the event* ($\mathbf{d^j}$);
24. Calculate sites' total quality scores (*kappa*), based on *distances from event, average sites battery* ($\mathbf{h^j}$), *and sites' sensors quality scores* ($\mathbf{s^j}$);
25. Calculate *price* and *probability of task satisfaction* per site;
26. Calculate *sites' Reliability Scores(R);*
27. If site:M > 0// Assign a reliability of zero to sites with malicious participants
    site:$R = 0$;
    Add_to_malicious_sites_list(*site*);

    else
    site:R = site:V;
28. Calculate *Total sites' final selection scores* = (B∗ R − p)∗*DSR*;
29. if (*Required_Quality* > *Site_Quality*)
        eliminate(*site*); **//eliminate site that does not pass quality check**
        add_to_eliminated_sites_list *(site)***;**
30. Rank sites from highest to lowest final selection scores: *ranked_sites_list* = **sort_descending_order**(*Scores*);

Algorithm 1 *(Continued.)* Participants' Selection Algorithm

31. Select site with *highest final selection score* as *top_selected_site*;
32. If (*top_selected_site_DSR* == 100) //if selected site satisfied all data types, while satisfying the constraints, display that site information as final result
        Set selected_sites_list = *top_* selected_site;
    Else
        Add *top_selected_site* to *selected_sites_list*;
        Event_data_type = − *Selected_Site_data_types*; // reduce task to the data types that were not provided by selected site(s)

    Repeat (steps 16 to 32);
33. **Display** *selected_sites_list***;**
    Display eliminated_sites_list;
    Display malicious_sites_list;

by the system (e.g. country would be identified from the event's GPS coordinated, the % of malicious participants would be determined based on the history of previous interactions with the users, and the population and participants' pool size would be determined based on real users' locations tracked by the system). Once those configuration parameters specified, the selection algorithm consists of 4 key stages, namely:

- ➢ Stage 1: Grid Formation and Participants' distribution
- ➢ Stage 2: Individual participants' parameters generation
- ➢ Stage 3: Sites' parameters generation & scores computation
- ➢ Stage 4: Final sites' selection

Stage 1: Once the input parameters specified, the first step of the selection process consists in dividing the AoI into sites and generating some realistic parameters related to the participants and their devices. More specifically, the number of sites in which the AoI will be divided is calculated based on (3), the sites dimensions are computed as per (2), and the grid is formed. Gridlines are drawn on the AoI to differentiate each site, and participants are placed in their respective sites according to their randomly generated location. Since the location of individual participants have a 4 decimal point precision, no participant will belong to two adjacent sites. To illustrate the grid formation operation, we take as example a scenario with the following input configuration:

- Side = 30m (area size = 30m × 30m)
- P = 100 (total population of 100 in AoI)
- N = 65 (# of available participants within AoI is 65 out of 100)

For that scenario, the values of γ, n, and l, calculated using equations 1, 2, and 3 are as follows:

- $\gamma = \frac{N}{P} = \frac{65}{100} = 0.65$
- $l = side \times (1-\gamma) = 30 \times (1-0.65) = 10.5$. The closest divisor of 30, to 10.5 is 10
- $n = (\frac{side}{l})^2 = (\frac{30}{10})^2 = 9$

Accordingly, the AoI (of 30 × 30 m) is divided into a 3 × 3 grid, with a total of 9 sites, in which the 65 available participants are distributed randomly, as shown in figure 2.

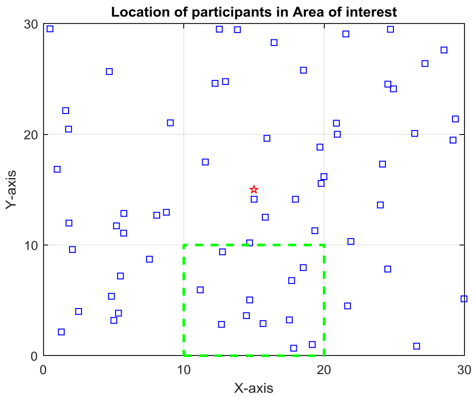


FIGURE 2. Grid formation example.

Stage 2: In addition to being assigned with a random location within the 2D grid, individual participants are also assigned random battery levels. Similarly, malicious users are randomly chosen based on the specified percentage of malicious users. Furthermore, individual participants are assigned specific smartphones, out of 32 chosen phone brands, that we determined based on statistics related to the most commonly used smartphones in 21 countries worldwide [19]. Those countries were selected from every continent to represent a variety of smartphone penetration rates, such as: high penetration rate (e.g. UAE), medium penetration rate (e.g. Argentina), and low penetration rate (e.g. Nigeria). The full list of countries considered in our simulation is shown in Table 2. In real-life deployment, information about smartphone brands carried by participants would be determined dynamically by the platform based on users' registration and login interactions.

The next step consists in computing the participants' phones quality scores with respect to the event, as well as the sites' sensors quality scores. To accurately represent phone quality scores, we relied on two sensor benchmarking databases to accurately quantify the quality of individual sensors associated with each of the 32 smartphone models considered, namely: SensMark [20] and Dxomark [21]. Dxomark is an independent benchmarking tool that scientifically assesses and scores the quality of smartphone lenses and cameras, while SensMark relies on a mobile app. running on the smart phone to evaluate and benchmark the various phone sensors (e.g. GPS, accelerometer, temperature sensors) and provide a total score for the tested sensors with respect to the accuracy and quality of the data offered. Finally, an N-by-6 matrix is constructed for N participants, in which each participant is represented by: 1) *The Participant ID; 2) The x coordinate; 3) The y coordinate; 4) The participant maliciousness; 5) The participant's battery level; and 6) The participant's phone model.*

TABLE 2. List of countries considered in our simulated environment.

No.	Region	No.	Region
1	US	12	Brazil
2	UK	13	Argentina
3	Germany	14	India
4	France	15	Japan
5	Spain	16	Malaysia
6	Italy	17	Australia
7	Ireland	18	South Africa
8	Poland	19	Egypt
9	Russia	20	Nigeria
10	Sweden	21	UAE
11	Canada		

Stage 3: In this work, we investigated six types of events for sensing tasks, assuming that events occur at the center of the AoI and that each event requires its unique data types as shown in table 3.

TABLE 3. Data types required per event.

	Description	Temperature	Light	Accelerometer	Ambient Temp.	Pressure	Proximity	Relative humidity	GPS	Camera	pulse
1	Traffic Condition	0	0	0	0	0	0	0	0	1	0
2	Traffic accident	0	1	0	1	0	1	0	0	1	1
3	Fire incident	1	0	0	1	0	0	0	0	1	1
4	Storm Incident	1	1	0	1	0	0	1	0	1	1
5	Heart attack	0	0	0	0	0	0	0	0	1	1
6	Volcanic Eruption	1	1	0	1	1	1	1	1	1	0

The required data types of event form a 10-bit binary number (event_data_type), similar to each site's data type parameter (site_data_type) representing the data types needed for this event, that can be obtained from the collection of phones within this site. A logical **and** operation between site_data_type and event_data_type is performed in order to compute the number of data types that are: a) available in the site and b) required by the event. The result of the logical operation is divided by the number of data types required per event (number of ones) and produces a data satisfaction ratio (DSR) for each site per event.

Let us take as example an event requires the following data types: Temperature, GPS, Camera, and Pulse.

- ➢ The event_data_type produced will be <u>**1000000111**</u> number_of_event_data = 4
- ➢ Site 1 can provide these data types: <u>**1000000101**</u>
- ➢ Site 2 can provide these data types: <u>**1000011111**</u>
- ➢ event_data_type AND site1_data_type = <u>**1000000101**</u> ∗missing camera
- ➢ number_of_data_site1 = 3
- ➢ DSR_site 1 = number_of_data_site1/ number_of_event_data = 3/4.
- ➢ event_data_type AND site2_data_type = <u>**1000000111**</u> All data types are satisfied
- ➢ number_of_data_site2 = 4
- ➢ DSR_site 2 = number_of_data_site2/ number_of_event_data = 4/4.

Another sites' parameter that is calculated for each site is the site sensors' quality score, as follows: Based on the sensors' quality scores obtained from the benchmarking databases, the algorithm computes the phones' quality scores with respect to the event as well as the sites' sensor quality scores, as follows: a) calculate the phone quality score per event (average value of quality scores of sensors related to event only, and which are supported by the phone) for the phones in each site; b) For each site, calculate the site's quality score by using the formula: Site quality score (Si) = average of phones quality scores (for phones in the site). For example, if event 1 requires camera and GPS data:

- ***Step 1:*** Identify the phone models in each site
- ***Step 2:*** Extract the GPS and camera quality for each phone model available to produce an average representing the phone quality Score for Event 1/site
- ***Step 3:*** for all the phone models available in a site, take the average of individual phone quality that represents site quality score

The next step consists of calculating the sites total quality scores based on (6), as well the sites' prices based on (9). Subsequently, the sites' probability of task satisfaction, the sites' reliability scores, and the sites' data satisfaction ratios and quality satisfaction ratios are calculated based on equations (5), (7), (10), and (11) respectively.

Stage 4: Finally, the sites' final selection scores are calculated based on (12). To obtain the final list of selected site(s), all sites with a negative final selection scores (i.e. sites with malicious participants), or sites with a negative quality satisfaction ratio (i.e. sites that do not meet the min. level of quality required) are eliminated from the selection, and moved to the eliminated sites list. The remaining sites are ranked based on their final selection scores, from highest to lowest values. For the highest scoring site, if its data satisfaction ratio is 100% (i.e. can satisfy all data types required for the task), this site it marked as selected, and the process is terminated. If the data satisfaction ratio of the top scoring site is not 100% (i.e. some of the request's data types are not supported by the site), the request's requirements are reduced by removing the data types that are already satisfied (in this round), and reducing the time window required, then repeating the selection steps again to find additional sites that would meet the remainder of the request's requirements. Finally, the program displays the selected site(s), the eliminated sites, and the remaining sites as final output.

IV. EXPERIMENTAL RESULTS

A. SIMULATION ENVIRONMENT, INPUT PARAMETERS, AND TEST SCENARIOS

We implemented our proposed participants' selection algorithm using Matlab, and used the following parameters as input configuration values to our simulation: 1) event types; 2) Geographical areas; 3) Most popular phone models per geographical area; 4) sensors' quality scores.

Six event types were defined (as shown in table 4), along with associated data types and sensor types, to experiment with different scenarios using our simulation. Those types were chosen to represent requests with different sensing data requirements. It should be noted that our model is extendible and can support additional event types as well.

TABLE 4. Types of events considered in our simulation.

No.	Events	Data Types
1	Traffic condition	GPS
2	Traffic accident	Light, Temperature, Proximity, GPS, Camera, Pulse
3	Fire incident	Temperature, Ambient Temperature, Camera, pulse
4	Storm incident	Temperature, Light, Ambient temperature, Relative Humidity, Camera, Pulse
5	Heart attack	Camera, pulse
6	Volcanic eruption	Light, Temperature, ambient temperature, Proximity, relative humidity, GPS, Camera

The ***twenty-one countries*** presented in table 2 were also considered as potential regions for our simulation. For each country, the five most used phone brands were identified based on 2017 smartphone market penetration statistics [19], resulting in a list of ***32 phone brands*** that were considered in our simulation. Those brands are shown in table 5. Each of the 21 countries considered was associated with five of those phone brands, according to the statistics used [19]. Table 6 shows the top five smartphone brands used in the USA in 2017, as well as their % penetration rate.

TABLE 5. Smartphone brands considered in our simulation.

'iphone7'	'GalaxyS6'	'Galaxy j7'	'lyf Jio F90M'
'iphone6'	'GalaxyA5'	'j1 Ace'	'Iphone X'
'iphone6s'	'default'	'j2Prime'	'J3'
'iphone6sp'	'GalaxyJ5'	'J7Metal'	'Oppo37'
'iphone6p'	'Huaweip8'	'J7Prime'	'GalaxyS8'
'iphone7p'	'iphone5s'	'Lyf LF 2403N'	'Generic Anroid'
'iphoneSE'	'Huawei P9'	'Xiaomi Note 4'	'Nokia105'
'GalaxyS7'	'S7Edge'	'j2'	'Nokia 108'

Another input parameter used consists in the ***sensors quality scores*** for each sensor, for each of the 32 smartphones models considered. This information was collected using the SensMark and Dxomark sensors benchmarking databases [20], [21]. Since the sensors' quality score is a relative factor, the highest score found in the database was marked as a perfect 10, and all other scores were normalized according to the following expression: $SensorScore = \frac{Score}{MaxScore} * 10$. Table 7 shows the normalized sensors' quality scores associated with five different phones, based on the sensors' benchmarking results. If a sensor does not have a score, it implies that this sensor is not supported by this phone brand. The table shows the variation in the availability

TABLE 6. Top smartphones used in the US in 2017.

Country	Rank	Phone Model	% Usage by population
USA	1	iPhone 7	11.52%
	2	iPhone 7 Plus	9.78%
	3	iPhone 6S	7.88%
	4	iPhone 6	6.52%
	5	iPhone 6S Plus	4.41%

TABLE 7. Sample of sensors' quality scores for five smartphones' models.

Phone / Sensors	'iphone7'	'GalaxyS6'	'S7Edge'	'Huawei P9'	'Lyf LF 2403N'
'Temperature'	7.2851615	7.2516	7.98512	-	-
'Light'	3.795	5.72	6.7116667	3.333333333	-
'Accelerometer'	6.884714	6.4984156	7.129923	6.035913686	-
'Ambient Temperature'	6.84151	7.06541	7.152	-	-
'Pressure'	-	7.2305864	7.8843106	-	-
'Proximity'	5.151	5.35125	6.15841	4.9521	-
'Relative Humidity'	-	-	9.5	-	-
'GPS'	10	10	10	10	10
'Camera'	7.7981651	7.5229358	8.1651376	7.339449541	1.651376147
'Pulse'	-	9	10	-	-

and quality of sensors from one phone brand to another. For instance, the S7 Edge phone encompasses all 10 sensors with relatively high sensors' quality scores, while the iPhone 7 only supports 7 out of the 10 sensors, and the LyfLF 2403 N (a phone brand that is popular in India) only supports 2 sensors.

B. EVALUATION STRATEGY AND METRICS

The objectives of the experiments we conducted are to assess whether our model functions as planned, and analyze the impact of different variables on the five main parameters of our model, namely: 1) the site quality score; 2) the site reliability score; 3) the site's price; 4) the site's probability of task satisfaction; and 5) the site's final selection score. To achieve those goals, a number of testing approaches and metrics were used, as summarized in table 8. The detailed analysis of the conducted tests will be presented in the coming sections.

C. IMPACT OF VARIOUS PARAMETERS ON SITE QUALITY SCORE ($\kappa_{i,\Lambda}$)

The first set of experiments we conducted focused on evaluating the impact of the geographic area and event type on sites' quality scores. Since each geographic area is characterized by some specific phone brands which are widely used in it, different areas implies different phone brands, and thus varying availability and quality of sensors. In this set of experiment, we varied the event type requested and country in which request is taking place, and kept the other simulation parameters constant, as shown in table 9.

Table 10 and figure 3 shows the obtained results for the first scenario – a fire incident in Germany. In this scenario, the area of interest was divided into 25 sites, 19 of which contained participants. The site selected in this scenario was site 11 (highlighted in green), which had an average sensors' quality score of 7.76 (the highest sensor's quality score out

TABLE 8. Testing strategies and metrics.

Test Category	Performance Metric	Description of how metric was measured/ calculated	Test scenarios used
Impact on site quality score	- Site total quality score	Site quality score: calculated using equation 6	We varied the following parameters, to illustrate their impact on the site quality score: 1. Site average battery level 2. Site proximity to area of interest 3. Site sensors quality measure
Impact on site reliability score	- Site reliability score	Site reliability score: calculated using equation 7	We varied the following parameters, to illustrate their impact on the site quality score: 1. Site maliciousness 2. Site quality score 3. # of participants in site
Impact on site price	- Site price	Site price: calculated using equation 9	We varied the following parameters, to illustrate their impact on the site price: 1. Task time, 2. The site quality score, 3. The total number of site participants 4. The price competition among participants
Impact on site probability of task satisfaction	- Site probability of task satisfaction	Site probability of task satisfaction: calculated using equation 5	We varied the following parameters, to illustrate their impact on the site price: 1. The site quality score, 2. The total number of site participants 3. The task time 4. % of maliciousness
Impact on site final selection score	- Site final selection score	Site final selection score: calculated using equation 12	We varied the following parameters, to illustrate their impact on the site final selection score: 1. Type of event 2. Participants' maliciousness 3. Requested quality level 4. Country 5. Number of participants 6. Total population 7. Size of area of interest 8. Budget allocated for task

of all sites), a proximity of 0 from the event of interest (i.e. centered at the event of interest, as shown in figure 3), and an average site's residual battery level of 75%. The total site's quality score obtained was 0.655238 – representing the lowest value and thus the highest site quality levels. It should be noted that the sites highlighted in yellow (sites: 2, 6, 7, 8, 9, 10, 12, 17, and 18) were eliminated from the selection, since they did not meet the min. required information quality level (4.5 in that case). Moreover, none of the sites contained

TABLE 9. Test configuration parameters – Site quality score experiment.

Type of event(s) & country – these are variable in this test set	Germany/fire, Italy/fire, India/Traffic accident, Malaysia/storm
Total population	60
Participants	46
Budget	100
Area size	50*50
Time window for task	1
Required information quality level	4.5
% of malicious participants	0

TABLE 10. Sites' quality score results – fire incident in Germany scenario.

Germany / Fire Incident				
Site	Site's Sensors Quality	Site's proximity from EoI	Site's battery level	**Site quality score (Kappa)**
1	8.214996904	28.28427125	24	**0.943567**
2	4.293577982	22.36067977	42	**1.172811**
3	5.165019297	20	52.66666667	**0.959396**
4	5.80092843	22.36067977	43	**0.990224**
5	6.890430724	28.28427125	61.5	**0.771796**
6	4.293577982	22.36067977	0	**2.26327**
7	4.293577982	14.14213562	53	**1.041749**
8	4.293577982	14.14213562	45	**1.135022**
9	4.293577982	22.36067977	47	**1.10919**
10	4.293577982	10	59.5	**0.976451**
11	7.761637891	0	75	**0.655238**
12	4.293577982	10	60.5	**0.967102**
13	4.781552179	20	42.25	**1.107907**
14	5.383080275	14.14213562	35	**1.123765**
15	4.656745413	10	62.16666667	**0.920407**
16	4.683957339	14.14213562	58.6	**0.949093**
17	4.293577982	22.36067977	70	**0.887683**
18	4.293577982	28.28427125	6	**1.986477**
19	5.81565156	22.36067977	47.66666667	**0.946111**

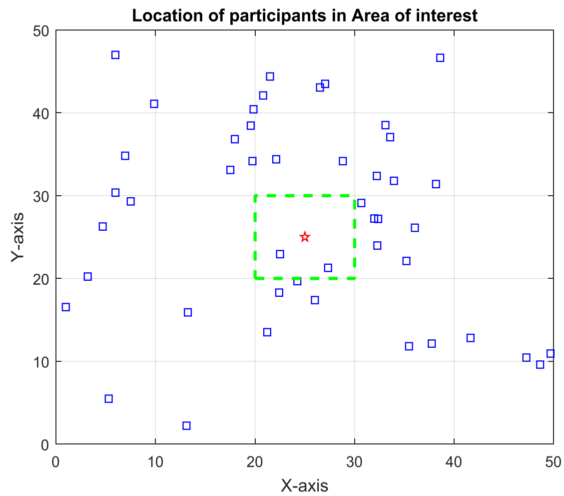


FIGURE 3. Selection result – fire incident in Germany scenario.

TABLE 11. Sites' quality score results - traffic accident in India scenario.

India / Traffic accident				
Site	Site's Sensors Quality	Site's proximity from EoI	Site's battery level	**Site quality score (Kappa)**
1	4.445714	28.28427	44	1.126448
2	4.293578	22.36068	60	0.972086
3	4.293578	20	21	1.54696
4	4.265669	22.36068	46.66667	1.116609
5	4.23776	14.14214	55	1.026545
6	4.293578	10	19	1.60481
7	3.765138	14.14214	15.2	1.868849
8	4.293578	10	11	1.83851
9	4.293578	0	63	0.943968
10	3.765138	10	51.6	1.119097
11	4.293578	20	17	1.646867
12	4.293578	22.36068	30.33333	1.354027
13	2.972477	14.14214	60.5	1.106671
14	4.209851	10	38.5	1.237768
15	3.862253	14.14214	55.75	1.05875
16	1.651376	22.36068	10	3.556058
17	4.293578	28.28427	6	1.986477
18	4.749986	22.36068	47	1.056857
19	4.293578	28.28427	60	0.972242

malicious participants, since the % of malicious users was set to 0% in that test case. Finally, Figure 3 shows the area of interest, divided into 25 sites, the distribution of participants in the area, and the site what was selected for the sensing task (site at the center, with the green dashed borderline).

Table 11 and figure 4 shows the obtained results for the second scenario – a traffic accident in India. Similar to the first scenario, the area encompassed 19 sites with participants and 6 empty sites. Site 18 was selected in that case, with a site quality score of 1.0568, a residual battery level of 47%, a proximity level of 22.36 meters from the event of interest, and a sensors' quality score of 4.749. In comparison to the first scenario occurring in Germany, in which the most popular phone brands are the Samsung Galaxy S7, Samsung Galaxy A5, iPhones 6, 6S, and 7 [19] – i.e. brands with high variety and high quality sensors, the second scenario took place in India, with phones containing less sensors with lower sensor quality scores (e.g. Lyf Jio F90M, Samsung Galaxy J2, Xiaomi Redmi Note 4, Lyf LF-2403N, Samsung Galaxy J7 Prime [19]). This resulted in 18 out of 19 sites being eliminated from the selection, due to the inability to meet the

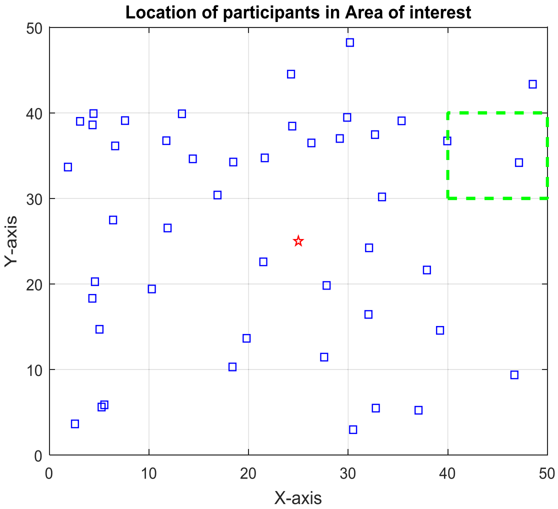


FIGURE 4. Selection result – traffic accident in India scenario.

minimum required information quality level – i.e. 4.5 in that case. The only site that was able to meet that requirement was site 18, with a sensors' quality score of 4.749, and thus it was selected despite its low residual battery level and poor overall quality score. Figure 3 highlights the location of the selected site in this scenario.

Finally, Table 12 and figure 5 shows the obtained results for the third scenario – a storm incident in Malaysia. In that scenario, site 8 was selected with a close proximity from the event of interest (10 meters), a high residual battery level (of 73.5%), and a sensors quality score exceeding the required level (4.865). Due to the mixed nature of popular phones in Malaysia, 11 out of 18 sites were not selected due to lack of ability to meet information quality requirements (see sites high-lighted in yellow). Figure 5 illustrates the location of the selected site in the area.

Illustrating the impact of different parameters on the site's total quality score (Kappa), we plotted three graphs, presented in figure 6-a, 6-b, and 6-c. Figure 6-a depicts the inversely proportional linear relation between the site's average battery level and the site's total quality score. Indeed, the more the battery level increases, the lower the site kappa score becomes – indicating higher sensing capabilities. Similarly, there exists an inversely proportional linear relation between the sensors' quality level in the site and the site's total quality score (kappa), as shown in figure 6-b. The higher the sensors' quality level, the lower the total quality score – indicating higher sensing capabilities. Finally, as shown in figure 6-c, the site's total quality score increases in a logarithmic fashion, with the increase in the site's distance from the event of interest. For instance, when the site is very close to the event of interest (close to zero), the site's kappa score is very low (0.77). For sites that are far away from the event of interest (e.g. 30 meters), the site's kappa score increases (i.e. its quality level de-creases) to 0.98. The kappa value stabilizes, tending to 1, for distances bigger than 50 meters from the event, since beyond this level, the participant is too far to capture meaningful information about the event. We can conclude that sites with higher residual battery and higher sensors' quality scores have a higher chance of being selected for sensing tasks. Consequently, the geographic region and its associated phone brands/supported sensors have an important impact on the

TABLE 12. Sites' quality score results – strom incident in Malaysia scenario.

Malaysia / Storm				
Site	Site's Sensors Quality	Site's proximity from EoI	Site's battery level	**Site quality score (Kappa)**
1	4.293578	28.28427	84	0.792425
2	6.146789	22.36068	74	0.742434
3	4.293578	20	66	0.919451
4	4.293578	28.28427	66	0.920048
5	4.998196	14.14214	51.66667	0.984004
6	4.293578	22.36068	40.5	1.193345
7	4.293578	20	70	0.887452
8	4.865168	10	73.5	0.820127
9	4.726728	0	63	0.906887
10	4.293578	10	24.5	1.475836
11	4.293578	20	55.5	1.015574
12	4.293578	14.14214	4	2.097502
13	4.437961	10	39.33333	1.192262
14	6.559633	14.14214	13.5	1.259639
15	4.716349	22.36068	58.6	0.946634
16	5.247706	22.36068	45.33333	1.021886
17	5.533945	20	42	1.026782
18	4.293578	22.36068	35	1.275212
19	4.293578	28.28427	57.25	0.998197

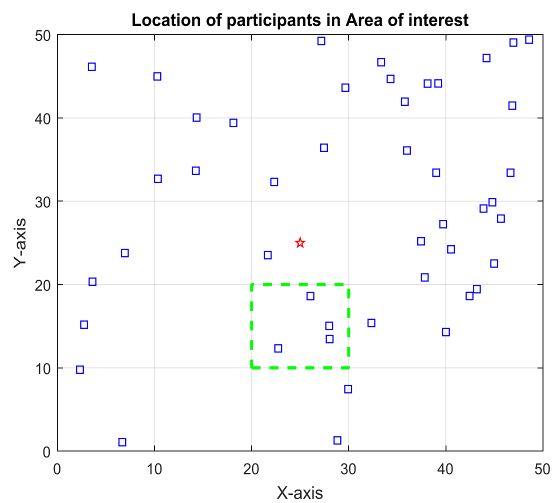


FIGURE 5. Selection result – storm incident in Malaysia scenario.

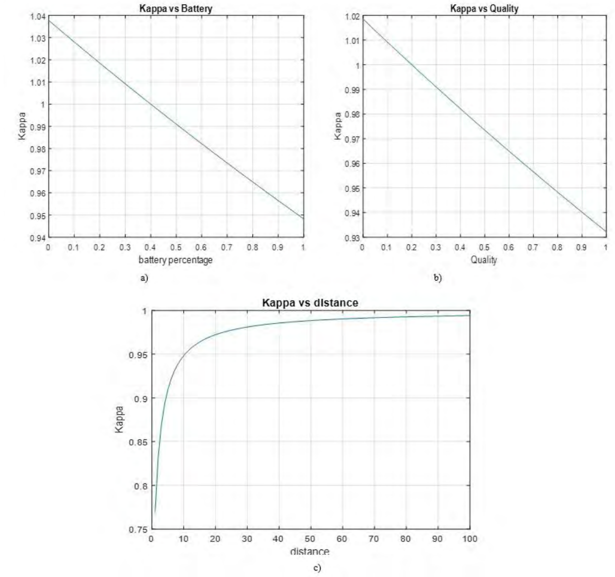


FIGURE 6. **Impact of various parameters on site's total quality score (Kappa): a) impact of residual battery level on site's quality score; b) impact of sensors' quality level on site's quality score; c) impact of proximity from event of interest on site's quality score.**

participants' suitability for sensing tasks, since more sophisticated phones support more sensors and ones that have higher quality scores. Finally, the closer the site from the event of interest, the higher its chance of being selected – noting that the proximity has a lower impact on the selection than the battery level and sensors' quality scores. The proximity from the event has a stronger positive impact for sites close to the event, showing little variation for sites beyond a certain distance which are considered as out of reach with respect to the event.

D. IMPACT OF VARIOUS PARAMETERS ON SITE RELIABILITY SCORE (R_{ij}^{Λ})

The second set of experiments we conducted focused on evaluating the impact of the % of malicious participants; the event type; the country; the total number of participants; and the task time on sites' reliability scores. In this set of experiment, we varied those 5 parameters, through 5 different scenarios. Table 13 shows the obtained results. In the table, M represents the site maliciousness; K the site's total quality score, N the site's participant number, and R the site reliability score.

In the 5 scenarios, the area of interest was divided into 4 sites. In scenario 1, the configuration parameters were as follows: Country = Poland; Event = Traffic accident (event 2); Task time = 2 minutes; # of participants = 60 participants; Maliciousness % = 2%, min. information quality = 4.5. Site 1 was selected for the task, with a reliability score of 1, a total quality/kappa score of 1.0293 (the lowest in the 4 sites), 0% of malicious participants, and 17 total participants. Site 2 was eliminated since it could not meet the min. information quality requirements, and site 4 was eliminated since it contained malicious participants. We note that

TABLE 13. **Sites' reliability score results.**

Test scenarios / Sites Reliability parameters and Scores	Site_1 reliability parameters and score				Site_2 reliability parameters and score				Site_3 reliability parameters and score				Site_4 reliability parameters and score			
	M	K	N	R	M	K	N	R	M	K	N	R	M	K	N	R
Scenario 1: Country = Poland; Event = Event 2; Task time = 2 minutes; # of participants = 60 participants; Maliciousness % = 2%, Q=4.5	0.00%	1.0293	17	1	0%	1.0293	14	1	0%	1.0384	17	1	5%	1.0259	10	0
Scenario 2: Country = Germany; Event = Event 3; Task time = 4 minutes; # of participants = 30 participants; Maliciousness % = 20%	18.00%	1.0198	11	0	13%	1.0341	8	0	20%	1.0515	5	0	17%	1.0287	6	0
Scenario 3: Country = Brazil; Event = Event 4; Task time = 5 minutes; # of participants = 50 participants; Maliciousness % = 10%	0	1.0361	10	0.999	21%	1.0341	14	0	0%	1.0441	13	1	15%	1.0363	13	0
Scenario 4: Country = Malaysia; Event = Event 6; Task time = 3 minutes; # of participants = 60 participants; Maliciousness % = 15%	0	1.0321	19	1	18%	1.0289	17	0	11%	1.0321	9	0	27%	1.02501	15	0
Scenario 5: Country = South Africa; Event = Event 5; Task time = 2 minutes; # of participants = 30 participants; Maliciousness % = 0%	0	1.025	6	0.9971	0%	1.0404	8	0.9995	0%	1.0282	8	0.9996	0%	1.0406	8	0.9995

maliciousness has a direct impact on sites' reliability – since malicious sites are given zero as reliability score. In the second scenario, the configuration parameters were as follows: Country = Germany; Event = Fire incident (event 3); Task time = 4 minutes; # of participants = 30 participants; Maliciousness % = 20%, min. information quality = 4.5. Due to the high % of malicious participants, all four sites were eliminated due to presence of malicious users in them, and thus no selected could be made for this task. In scenario 3, the following configuration parameters were used: Country = Brazil; Event = Storm incident (event 4); Task time = 5 minutes; # of participants = 50 participants; Maliciousness % = 10%, min. information quality = 4.5. In that scenario, 2 out of the four sites contained malicious participants and thus were eliminated. Site 1 could not meet the information quality requirement, and site 3 was selected with a reliability score of 1, 13 participants, 0% maliciousness, and a total quality score of 1.0441.

In Scenario 4, the configuration was as follows: Country = Malaysia; Event = volcanic eruption (event 6); Task time = 3 minutes; # of participants = 60 participants; Maliciousness % = 15%, min. information quality = 4.5. In that case, 3 out of 4 sites contained malicious participants and were eliminated, while site 1 was selected with a reliability score of 1, 19 participants, 0% maliciousness, and a total quality score of 1.0321. Finally, scenario 5 represented the following: Country = South Africa; Event = heart attack (event 5); Task time = 2 minutes; # of participants = 30 participants; Maliciousness % = 0%, min. information quality = 4.5. In that scenario, non of the sites were eliminated due to maliciousness. Site 2 was selected with a reliability score of 0.9995, 8 participants, 0% maliciousness, and a total quality score of 1.0404.

Illustrating the impact of different parameters on the site's reliability score (R), we plotted three graphs, presented in figure 7-a, 7-b, and 7-c. Figure 7-a shows that any maliciousness percentage > 0% is associated with a zero reliability score, as per equation 7. Figure 7-b shows an exponentially decreasing relation between kappa and

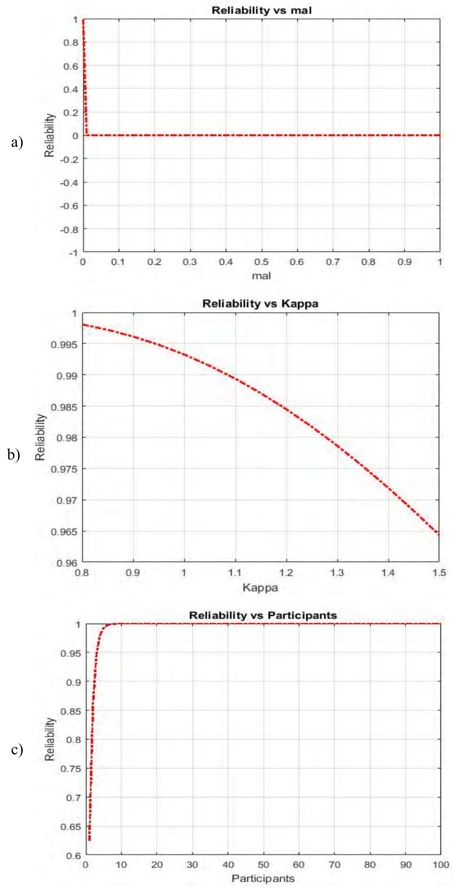


FIGURE 7. Impact of various parameters on site's reliability score (R): a) impact of maliciousness % on site's reliability score; b) impact of site's quality level on site's reliability score; c) impact of number of participants on site's reliability score.

the site's reliability. This implies that the more kappa increases (i.e. the quality decreases), the more the reliability of the site will decrease exponentially. This illustrates the importance of the site's sensing capabilities on its reliability for the task. Finally, figure 7-c shows an increasing logarithmic relation between the number of participants in the site and the site's reliability. Indeed, sites with a small number of participants (less than 10 participants) have lower reliability, since they represent fewer sources of information. Some of those sources could reject the request, or suffer from dying batteries or erroneous readings, thus impacting the reliability of the site. On the other hand, when the number of participants in a site increases, there are better chances that the needed information can be collected. For sites with more than 10 participants, we notice that the reliability stabilizes at 1, since having a very large number of readings would not bring additional value due to the high level of redundancy.

E. MPACT OF VARIOUS PARAMETERS ON SITE PRICE (P^{Λ}_{ij})

The third set of experiments we conducted focused on evaluating the task time, the site quality score, the total number of site participants and the price competition among participants on sites' prices. In this set of experiment, we varied the country, the event type, the number of participants and the task time, through 4 different scenarios. Table 14 shows the obtained results.

TABLE 14. Sites' price results.

Test scenarios (Q=5, M=2%)		Scenario 1: Country = Germany; Event = Storm; # of participants = 120/200; Task time = 2 minutes	Scenario 2: Country = South Africa; Event = Heart attack; # of participants = 40/120; Task time = 5 minutes	Scenario 3: Country = Sweden; Event = Traffic condition; # of participants = 35/60; Task time = 10 minutes	Scenario 4: Country = Nigeria; Event = Fire Incident; # of participants = 80/200; Task time = 15 minutes
Site_1	Site quality score:	1.023	1.0244	1.0287	1.0218
	Site participants #:	14	10	3	30
	Site price score:	0.5225	1.543	5.6125	3.5603
Site_2	Site quality score:	1.0161	1.0266	1.0154	1.0234
	Site participants #:	13	5	4	21
	Site price score:	0.5459	2.1781	4.9241	3.1983
Site_3	Site quality score:	1.0253	1.0242	1.0241	1.0168
	Site participants #:	9	14	3	12
	Site price score:	0.6502	1.3048	5.6379	4.2584
Site_4	Site quality score:	1.0235	1.0208	1.0144	1.0273
	Site participants #:	18	11	6	17
	Site price score:	0.4606	1.4776	4.0246	2.6659
Site_5	Site quality score:	1.024		1.0179	
	Site participants #:	18		2	
	Site price score:	0.4603		6.94	
Site_6	Site quality score:	1.0246		1.0343	
	Site participants #:	11		5	
	Site price score:	0.5886		4.323	
Site_7	Site quality score:	1.0214		1.034	
	Site participants #:	11		1	
	Site price score:	0.5904		9.67	
Site_8	Site quality score:	1.0221		1.0267	
	Site participants #:	12		6	
	Site price score:	0.5649		3.97	
Site_9	Site quality score:	1.024		1.0213	
	Site participants #:	14		5	
	Site price score:	0.522		4.3971	

In scenario 1, the configuration parameters were as follows: Country = Germany; Event = Storm (event 4); Task time = 2 minutes; # of participants = 120 participants out of 200 users' population. The area of interest was divided into 9 sites in that case, and site 3 was selected for the task, with a site price score of 0.6502, 9 participants, and a site kappa score of 1.0253. Sites 4 and 5 were eliminated due to malicious participants, and all other sites could not meet the minimum quality requirement. Figure 8-d illustrates the location of the selected site in this scenario.

In scenario 2, the configuration parameters were as follows: Country = South Africa; Event = Heart attack (event 5); Task time =5 minutes; # of participants = 40 participants out of 120 users' population. The area of interest was divided into 4 sites in that case, and site 3 was selected for the task, with the lowest price score among the 4 sites (i.e. a score of 1.3048), as well as 14 participants, and a site kappa score of 1.0242. None of the other sites were eliminated in that case, thus showing the that lower the site's price, the higher its chance of getting selected. Figure 8-c illustrates the location of the selected site in this scenario.

In scenario 3, the configuration parameters were as follows: Country = Sweden; Event = Traffic condition monitoring (event 1); Task time = 10 minutes; # of participants = 35 participants out of 60 users' population. The area of interest was divided into 9 sites in that case, and site 8 was selected for the task, with the lowest price score among the 9 sites (i.e. a score of 3.97), as well as 6 participants, and

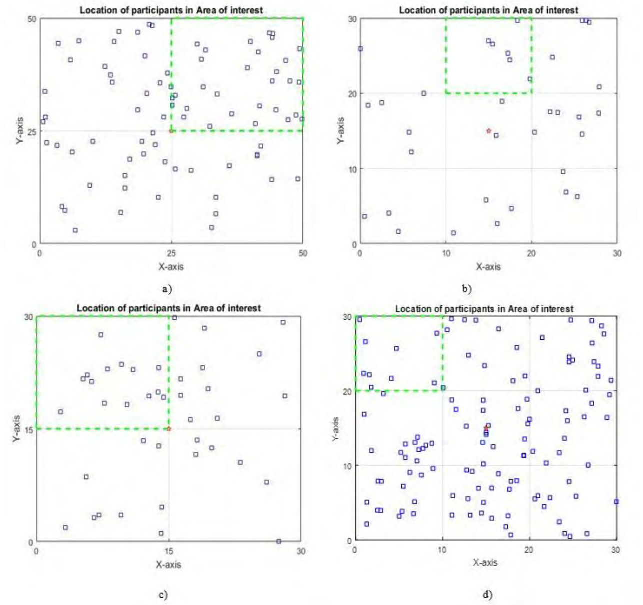


FIGURE 8. Selection results: a) Nigeria scenario; b) Sweden scenario; c) South Africa scenario; and d) Germany scenario.

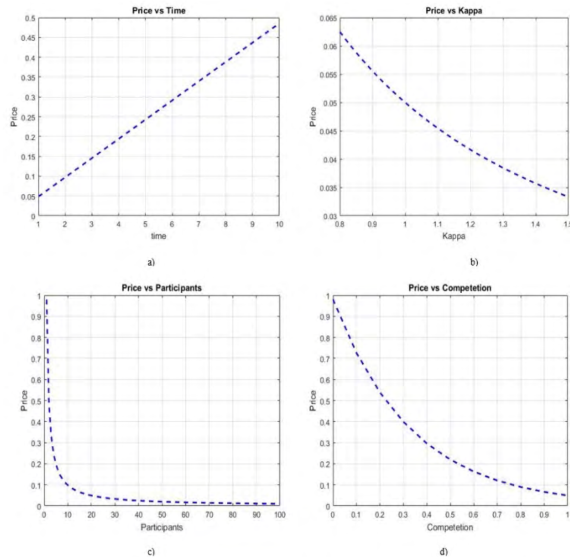


FIGURE 9. Impact of various parameters on site's price: a) impact of request time window on site's price; b) impact of site's quality level on site's price; c) impact of number of participants on site's price; d) impact of price competition on site's price.

a site kappa score of 1.0267. None of the other sites were eliminated in that case. Figure 8-b illustrates the location of the selected site in this scenario.

Finally, scenario 4 pertained to a fire incident in Nigeria, with a task time of 15 minutes, and 80 participants of a population of 200 users. The area was divided into 4 sites, as shown in figure 8-a and site 1 was selected with a price score of 3.5603, 30 participants, and a kappa score of 1.0218. Sites 2 and 3 could not meet the minimum quality requirements, and site 4 was eliminated due to malicious participants.

Illustrating the impact of different parameters on the site's Price score (P), we plotted four graphs, presented in figure 9-a, 9-b, 9-c, and 9-d. Figure 9-a shows a linearly increasing relation between the task time and the site's price, since long lived tasks would require more resources and the commitment of the users to remain in the same area for the duration of the task. Therefore, we expect that time recurrent tasks or continuous sensing tasks would be associated with higher sensing prices. Figure 9-b shows the relation between Kappa (reflecting the sites' sensing capabilities and quality level) and the site's price. In this case, we observe that the site's price decreases in an exponential fashion with the decrease of the site's sensing capabilities. Indeed, sites with lower sensing capabilities and lower quality levels would be associated with lower prices, in comparison to sites with higher sensing capabilities and better quality levels. In figure 9-c, we notice that the site's price decreases rapidly (at an exponential rate) with the increase of the number of participants' in the site. Since the availability of many participants in the same area implies the availability of multiple sources for the information, the competition between those sources drives the site's price down. This is confirmed by figure 9-d in which the site's price decreases exponentially with the increase in the price competition between participants. The higher the price competition between the participants, the lower the site's price will be due to the abundance of sources for the same information.

F. IMPACT OF VARIOUS PARAMETERS ON SITE PROBABILITY OF TASK SATISFACTION(V_{ij}^{Λ})

The fourth set of experiments we conducted focused on evaluating the impact of the site's total quality score and the total number of site participants on sites' probability of task satisfaction. In this set of experiment, we varied the country, the event type, the number of participants, the task time and the % of maliciousness, through 4 different scenarios. Table 15 shows the obtained results.

In scenario 1, the configuration parameters were as follows: Country = Germany; Event = traffic condition; Task time = 10 minutes; # of participants = 26 participants out of 60 users' population; % of maliciousness = 0%. The area of interest was divided into 4 sites in that case, and site 2 was selected for the task, with the highest probability of task satisfaction out of the 4 sites (0.9999), 10 participants, and a site kappa score of 1.0128. None of the sites were eliminated in that case, thus showing the that higher the site's probability of task satisfaction, the higher its chance of getting selected.

In scenario 2, the configuration parameters were as follows: Country = Spain; Event = traffic accident; Task time = 3 minutes; # of participants = 46 participants out of 60 users' population; % of maliciousness = 5%. The area of interest was divided into 16 sites in that case (1 of which was empty). Site 4 was selected in that case, with a probability of task satisfaction of 0.8546, 2 participants, and a site kappa score of 1.0371. Two sites were eliminated due to malicious

TABLE 15. Sites' probability of task satisfaction results.

Test Scenarios		Scenario 1: Country = UK; Event = Traffic Condition; # of participants = 26/60; Task time = 10 minutes; Maliciousness % = 0%	Scenario 2: Country = Spain; Event = Traffic Accident; # of participants = 46/60; Task time = 3 minutes; Maliciousness % = 5%	Scenario 3: Country = Argentina; Event = Fire Incident; # of participants = 60/100; Task time = 1 minute; Maliciousness % = 5%	Scenario 4: Country = Poland; Event = Storm; # of participants = 50/100; Task time = 1 minute; Maliciousness % = 7%
Site_1	Site quality score:	1.010427205	1.0524	1.028	1.0415
	Site participants #:	6	4	17	9
	Site Prob. Of Satisfaction:	0.9974	0.9777	1	0.9998
Site_2	Site quality score:	1.0128	1.0483	1.0282	1.02
	Site participants #:	10	3	14	10
	Site Prob. Of Satisfaction:	0.99999	0.9428	1	0.9999
Site_3	Site quality score:	1.03888	1.0493	1.0445	1.0374
	Site participants #:	4	2	15	15
	Site Prob. Of Satisfaction:	0.9787	0.9967	1	1
Site_4	Site quality score:	1.030116177	1.0371	1.0394	1.0449
	Site participants #:	6	2	14	16
	Site Prob. Of Satisfaction:	0.997	0.8546	1	1
Site_5	Site quality score:		1.0222		
	Site participants #:		4		
	Site Prob. Of Satisfaction:		0.98		
Site_6	Site quality score:		1.0413		
	Site participants #:		5		
	Site Prob. Of Satisfaction:		0.9918		
Site_7	Site quality score:		1.0438		
	Site participants #:		4		
	Site Prob. Of Satisfaction:		0.9783		
Site_8	Site quality score:		1.0309		
	Site participants #:		4		
	Site Prob. Of Satisfaction:		0.9793		
Site_9	Site quality score:		1.0257		
	Site participants #:		2		
	Site Prob. Of Satisfaction:		0.8577		
Site_10	Site quality score:		1.0208		
	Site participants #:		2		
	Site Prob. Of Satisfaction:		0.859		
Site_11	Site quality score:		1.0469		
	Site participants #:		2		
	Site Prob. Of Satisfaction:		0.852		
Site_12	Site quality score:		1.0467		
	Site participants #:		2		
	Site Prob. Of Satisfaction:		0.899		
Site_13	Site quality score:		1.0453		
	Site participants #:		3		
	Site Prob. Of Satisfaction:		0.9433		
Site_14	Site quality score:		1.0484		
	Site participants #:		2		
	Site Prob. Of Satisfaction:		0.8516		
Site_15	Site quality score:		1.122		
	Site participants #:		1		
	Site Prob. Of Satisfaction:		0.5961		

participants, and 7 sites did not meet the minimum quality requirements.

In scenario 3, the configuration parameters were as follows: Country = Argentina; Event = fire; Task time = 1 minutes; # of participants = 60 participants out of 100 users' population; % of maliciousness = 5%. The area of interest was divided into 4 sites in that case, and site 2 was selected, with a probability of task satisfaction of 1, 14 participants, and a site kappa score of 1.0282. The 3 other sites were eliminated due to malicious participants.

In scenario 4, the configuration parameters were as follows: Country = Poland; Event = storm; Task time = 1 minutes; # of participants = 50 participants out of 100 users' population; % of maliciousness = 7%. The area of interest was divided into 4 sites in that case, and site 2 was selected, with a probability of task satisfaction of 0.9999, 10 participants, and a site kappa score of 1.02. Two sites were eliminated due to malicious participants, and one site could not meet the minimum quality requirements.

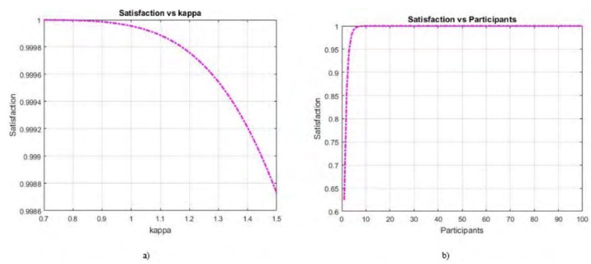


FIGURE 10. Impact of various parameters on site's probability of task satisfaction: a) impact of site's quality level on site's probability of task satisfaction; b) impact of number of participants on site's probability of task satisfaction.

Illustrating the impact of different parameters on the site's probability of task satisfaction (V), we plotted two graphs, presented in figure 10-a and 10-b. Figure 10-a shows an exponentially decreasing relation between the site's kappa score and the probability of task satisfaction. The more the site's sensing capability decrease (i.e. kappa increases), the more the probability of task satisfaction decreases, since the site has a higher chance of not containing the sensors required and meeting the minimum level of information quality requested. Figure 10-b shows that the probability of task satisfaction exhibits a logarithmically increasing relation with respect to the site's number of participants. Indeed, for smaller site (containing less than 10 participants), the probability of satisfaction is low. This is due to the smaller probability that a small number of participants could satisfy all the request's requirements. On the other hand, for larger sites of 10 participants and more, the probability of task satisfaction increases significantly and levels out at 1. This is due to the fact that having too many participants would not add more value, since there would be a high level of redundancy in the information collected.

G. IMPACT OF VARIOUS PARAMETERS ON SITE SELECTION SCORE (K_{ij}^{Δ})

The last set of experiments we conducted focused on evaluating the impact of eight of the model's parameters on sites' final selection scores. First, we varied the ***event type requested***, and kept the other simulation parameters constant, as shown in table 16.

TABLE 16. **Test configuration parameters – event type variation.**

Type of event(s) – this is variable in this test set	1, 2, 3, 4, 5, 6
Total population	200
Participants	140
Budget	1000
Area size	20*20=400m^2
Time window for task	1 minute
Required information quality level	5
% of malicious participants	2
Country	16.Malaysia

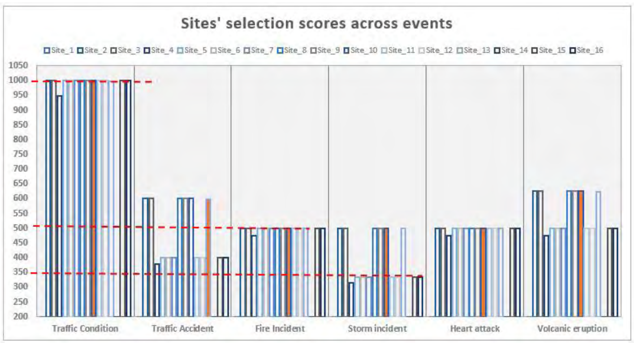


FIGURE 11. **Sites' selection scores across varying event types.**

Figure 11 shows the obtained results, in terms of sites selection with respect to various event types requested. In this test scenario, the area of interest was divided in 16 sites, two of which contained malicious participants (sites 1 and 14). The two malicious sites obtained negative selection scores as shown in the figure, and were therefore eliminated from the selection. Site 10 was selected for five of the six events (traffic condition, fire, storm, heart attack, and volcanic eruption incidents), while site 13 was selected for the traffic accident event. As shown in the figure, the type of event requested had a noticeable impact on sites' selection scores (considering the same set of participants with the same characteristics). This is due to the fact that each event type is associated with specific sensors. Therefore, the event requiring less or more common sensors resulted in higher selection scores. As shown in figure 10-a, traffic condition event (requiring 1 sensor) resulted in scores in the 1000 range, while fire incident (requiring 4 sensors) resulted in scores in the 500 range. Strom incident resulted in the lowest selection scores (350 range) since it requires 6 sensors, including some specialized sensors not commonly available in all phones. Therefore, we can conclude the events requiring more sensors or specialized sensors have lower chances of being satisfied. Moreover, sites with more sophisticated phones supporting all types of sensors have higher chances of being selected, across all types of events.

The second set of experiments we conducted focused on evaluating the impact of ***participants' maliciousness*** on sites' selection scores. In this set of experiment, we varied the % of malicious participants, and kept the other simulation parameters constant, as shown in table 17.

TABLE 17. **Test configuration parameters – participants' maliciousness % variation.**

Type of event	2. Traffic accident
Total population	100
Participants	50
Budget	100
Area size	20*20
Time window for task	1
Required information quality level	4.5
% of malicious participants	2%,5%,10%,25%
Country	8.poland

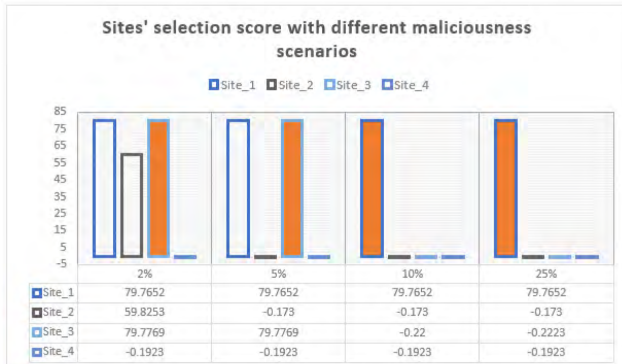


FIGURE 12. **Sites' selection scores across varying maliciousness percentages.**

Figure 12 shows the obtained results, in terms of sites selection with respect to various percentages of malicious participants in the area of interest. In this test scenario, the area of interest was divided in 4 sites. Site 1 was selected for the scenarios with 10% and 25% malicious participants, while site 3 was selected for the scenarios with 2% and 5% malicious participants. As shown in the figure, the more the % of maliciousness increased, the more sites contained malicious participants and were therefore eliminated from the selection. For instance, with 2% maliciousness, 1 out of 4 sites had malicious participants. With 5% maliciousness, 2 out of 4 sites had malicious participants, while for 10% and 25% maliciousness, 3 out of 4 sites had malicious users. We can conclude that the % of maliciousness in the network has a significant impact on the ability to satisfy requests, as it has a direct impact on participants and sites reliability, which is an essential parameter in the final selection score.

The third set of experiments we conducted focused on evaluating the impact of ***the requested quality level*** on sites' selection scores. In this set of experiment, we varied the requested quality level, and kept the other simulation parameters constant, as shown in table 18.

TABLE 18. Test configuration parameters – requested quality level variation.

Type of event	3
Total population	100
Participants	50
Budget	100
Area size	20*20
Time window for task	5
Required information quality level	3, 4, 5, 8
% of malicious participants	2
Country	8.poland

FIGURE 13. Sites' selection scores across varying required quality levels.

Figure 13 shows the obtained results, in terms of sites selection with respect to various quality levels requested. In this test scenario, the area of interest was divided in 9 sites. Site 2 was eliminated since it contained malicious participants. Site 6 was selected when quality levels 3 and 4 were requested, while site 7 was selected when quality level 5 was requested. When quality level 8 was requested, none of the 9 sites were selected, since none could satisfy the quality requirement. We can conclude that the higher the requested quality level, the lower the chance of making a successful selection, since the site's aggregate quality score should be equal to or exceed the required quality level.

The fourth set of experiments we conducted focused on evaluating the impact of ***the country*** in which the sensing task is taking place on sites' selection scores. In this set of experiment, we varied the requested quality level, and kept the other simulation parameters constant, as shown in table 19.

TABLE 19. Test configuration parameters – country variation.

Type of event	6
Total population	50
Participants	20
Budget	10
Area size	20*20
Time window for task	1
Required information quality level	6
% of malicious participants	0
Country	Poland, USA, UAE, Egypt, Nigeria, India, Brazil, Japan

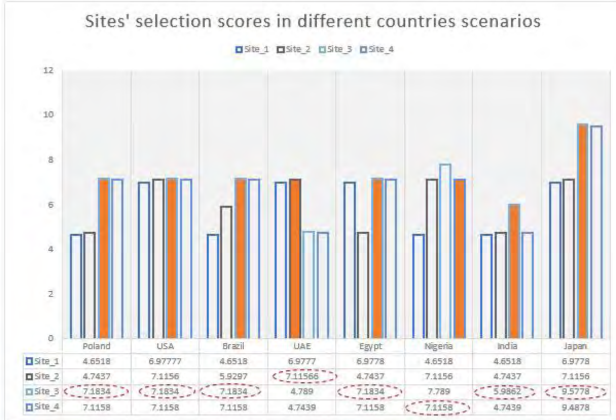


FIGURE 14. Sites' selection scores across varying geographical areas.

Figure 14 shows the obtained results, in terms of sites selection with respect to various geographical. In this test scenario, the area of interest was divided in 4 sites. Since the maliciousness percentage was 0% in that case, non of the sites were eliminated because of malicious participants. Site 3 was selected for six of the eight countries (Poland, USA, Brazil, Egypt, India, and Japan), while site 2 was selected when the country was set to UAE, and site 4 was chosen when Nigeria was the country in question. That specific test case pertained to a volcanic eruption event requiring 7 sensors, namely: Light, Temperature, ambient temperature, Proximity, relative humidity, GPS, Camera. Analyzing the obtained results, when a sophisticated sensing request is made, sites containing the latest phones containing a large variety of sensors would have a high chance of being selected. In this case, site 3 contained such phones and therefore was selected in most tests. On the other hand, in the UAE and Nigeria scenario, a different distribution of phone brands resulted in other sites containing the required sensors, and thus being selected. We can therefore conclude that countries in which there is a high penetration rate of latest smartphone brands supporting many sensors have a better chance of satisfying sophisticated sensing requests, than those supporting more modest phone brands.

The fifth set of experiments we conducted focused on evaluating the impact of ***the number of participants*** on sites' selection scores. In this set of experiment, we varied the number of participants, and kept the other simulation parameters constant, as shown in table 20.

In that experiment, the population size was 100 and the area size was 20 meters X 20 meters. Since the number of sites is impacted by the participants' density (i.e. number of participants / total population), the higher the density the bigger the number of sites in which the area will be divided. As shown in figure 15-a, for 10 participants, the area was divided into only 1 site. For 50 participants, the area was divided into 4 sites. This number increased to 16 sites for 75 participants. The 100 participants case is a special case in which all the population of users are participants. The

TABLE 20. Test configuration parameters – number of participants' variation.

Type of event	3
Total population	100
Participants – this is variable in this test set	10;25;50;75;100
Budget	1000
Area size	20*20
Time window for task	1
Required information quality level	5
% of malicious participants	2
Country	16.Malaysia

number of sites in that case = area size^2 = 20^2 = 400 sites, in which each site contained 1 or 2 participants, as shown in figure 15-e.

In terms of sites' final selection scores, figure 15-b depicts the results for the 10, 25, and 50 participants' scenarios. In the 10 participants' scenario, since they are was divided into 1 site that met the minimum quality requirements and did not contain malicious users, it was selected by default. In the 25 and 50 participants' scenarios, site 3 was selected, since the other 3 sites did not meet the min. quality requirements. Figure 15-c illustrates the results for the 75 participants' scenario, in which the area was divided into 16 sites. In that scenario, site 15 was selected, while site 16 was eliminated due to malicious participants, and all other sites (except site 2) did not meet the minimum quality requirements. Finally, figure 15-d shows the results obtained for the 100 participants' scenario. In this case, the area was divided into 400 sites, 93 of which contained participants. Indeed, since the number of sites was very large in that case, each site contained 1 or 2 participants, thus resulting in 307 empty sites, as shown in figure 15-e. In that scenario, site 13 (containing 2 participants) was selected, and sites 3 and 53 contained malicious users. We can therefore conclude that the participants' density has an important impact on the selection, since it impacts the number of sites and their dimensions. The higher the participants' density, the higher the number of sites and the lower the number of participants in each site. Therefore, higher densities will result in a smaller number of participants being selected for a particular task, since the participants are spread over a larger number of sites. The benefit in this case would be a faster response time. However, there would be little redundancy and limited possibility to obtain the information from multiple sources for validation purposes. On the contrary, smaller densities will result in a smaller number of sites containing more users, and thus a chance for a higher level of redundancy.

The sixth set of experiments we conducted focused on evaluating the impact of ***the total population size*** on sites' selection scores. In this set of experiment, we varied the total population size, and kept the other simulation parameters constant, as shown in table 21.

FIGURE 15. Impact of number of participants on sites' selection scores: a) number of non-empty sites with respect to a varying number of participants; b) sites' selection scores for 10, 25, and 50 participants; c) sites' selection scores for 75 participants; d) sites' selection scores for 100 participants; e) location of selected site for 100 participants' scenario.

TABLE 21. Test configuration parameters – total population size variation.

Type of event	2
Total population – this is variable in this test set	100;250;500;750;1000
Participants	80
Budget	100
Area size	20*20
Time window for task	2
Required information quality level	4.5
% of malicious participants	2
Country	8.poland

In that experiment, the population size was varied (100, 250, 500, 750, and 1000), while the number of participants was kept constant at 80 participants, and the area size was 20 meters X 20 meters. In comparison to the previous test, the total population size had an inverse impact on the number of sites. The higher the population size (with a constant number of participants), the lower the participants' density, and the lower the number of sites in which the area is divided. As shown in figure 16-a, the area was divided into 1 site only for the 80 participants with 500, 750, and 100 populations scenarios. In those cases, those single sites were not selected due to the presence of malicious users in them. Figure 16-b depicts the 80 participants with 250 population size result. In that case, the area was divided into 4 sites, one of which contained malicious participants, two did not meet the minimum quality requirements, and one was selected (site 3). Finally, figure 16-c shows the 80 participants with 100 population size results. Due to the high population density, the area in this case was divided into 25 sites, 2 of which were empty, and one with malicious participants. Site 15 was the one selected in that case. Similar to the number of participants, the total population size has an impact on the selection result, since a higher population with low participants leads to lower density and a smaller number of sites. On the contrary, a large population with a high number of participants leads to a high density and a large number of sites – with smaller number of selected participants.

The seventh set of experiments we conducted focused on evaluating the impact of ***the area size*** on sites' selection scores. In this set of experiment, we varied the area size, and kept the other simulation parameters constant, as shown in table 22.

Figure 17 shows the results obtained when the area size was varied (100, 400, 900, 1600, and 2500). The number of sites was 4, for all cases, except for the 900 square meter area size, which resulted in 9 sites. In the case of 100 square meter, site 3 was selected, and site 1 was eliminated due to malicious participants. In the 400 square meter case, site 4 was selected, and site 1 was eliminated due to malicious participants. For the 900 square meter case, site 6 was selected, and site 1 was eliminated due to malicious participants. For the 1600 square meter case, site 2 was selected, and site 4 was eliminated due to malicious participants. Finally, for the 2500 square meter case, site 4 was selected, and site 2 was eliminated due to malicious participants. We can conclude that the area size has an impact on the number of sites and the number of participants in each site, therefore indirectly impacting the selection results.

The last set of experiments we conducted focused on evaluating the impact of ***the budget allocated to the task*** on sites' selection scores. In this set of experiment, we varied

FIGURE 16. Impact of population size on sites' selection scores: a) sites' selection scores for 80 participants in 750, 500, and 100 population size; b) sites' selection scores for 80 participants in 250 population size; c) sites' selection scores for 80 participants in 100 population size.

TABLE 22. Test configuration parameters – area size variation.

Type of event	2
Total population	100
Participants	60
Budget	100
Area size – this is variable in this test set	100, 400, 900, 1600, 2500
Time window for task	1
Required information quality level	4
% of malicious participants	2
Country	8.poland

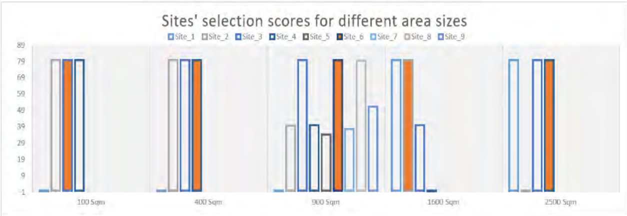


FIGURE 17. Sites' selection scores for different area sizes.

TABLE 23. Test configuration parameters – budget variation.

Type of event	2
Total population	100
Participants	30
Budget – this is variable in this test set	1, 5, 10, 20, 50, 100, 500, 750, 1000
Area size	20*20
Time window for task	10
Required information quality level	4.75
% of malicious participants	2
Country	8.poland

the budget, and kept the other simulation parameters constant, as shown in table 23.

Figure 18 shows the results obtained when the budget was varied (1, 5, 10, 20, 50, 100, 500, 750, 1000). As shown in figure 18-a, when very small budget (e.g. 1$ and 5$) were used, the total selection scores were negative for all sites, indicating that no selection was made due to insufficient budget. When the budget was increased to 10$, 20$ and 50$, site 3 was selected since it obtained the highest selection scores. In those three scenarios, sites 1 and 2 could not meet the minimum quality requirements. Figure 18-b shows the results when large budgets (100, 500, 750, 1000 $) were used.

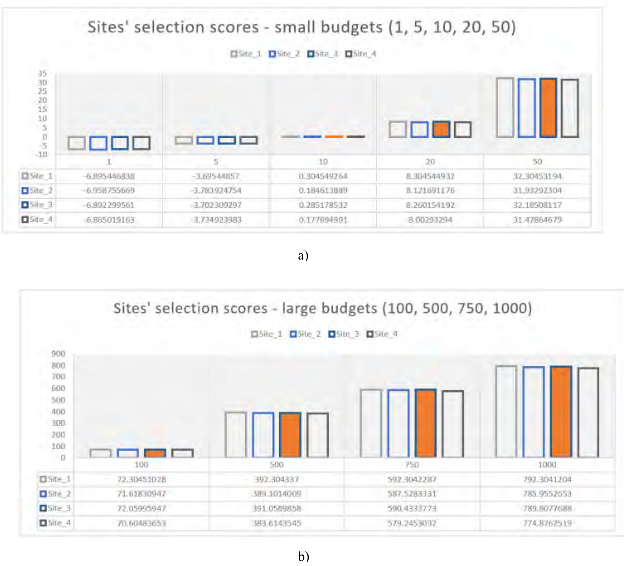


FIGURE 18. Impact of budget on sites' selection scores: a) sites' selection scores for small budgets (1, 5, 10, 20, 50); b) sites' selection scores for large budgets (100, 500, 750, 1000).

The result in those cases remained the same – site 3 selected, and sites 1 and 2 eliminated due to inability to meet the quality requirements. Therefore, beyond a certain threshold, when a sufficient budget is available to meet the price of the selected site, the selection will be made and the selected site will not change. Below this threshold, when the budget is too low, selection will be infeasible. Therefore, it is important to determine the optimal budget to allocate to each task, based on the potential prices of participants/sites.

V. SUMMARY OF FINDINGS AND FUTURE WORK

In this work, we have presented a comprehensive and practical approach to model and address the issue of mobile crowdsensing participants' selection. The proposed approach revolves around the selection of the most reliable group of participants that can provide the best quality possible for the required sensory data. All significant parameters that may have an impact on the outcome of the selection process were included in our model, and realistic benchmarks and statistics results were used to represent a realistic testbed for our approach, which was simulated using Matlab. Furthermore, extensive testing of our model was conducted to gain an understanding of the important aspects affecting the quality and reliability of MCS participants' selection process.

Many important findings and insights were gained from this work, namely:

1) The nature of the MCS application and sensing task impacts the suitability of the participants' being selected. Indeed, sensing tasks requiring many sensors or more sophisticated sensors have a lower chance of being satisfied. Similarly, sites containing more sophisticated phones (supporting all types of sensors) have a higher chance of being selected, across all types of sensing tasks.
2) Malicious activity has a significant impact on the selection process since it directly impacts the participants' and sites' reliability. More sophisticated models for the modeling and detection of malicious sensing activities are needed in the future.
3) The quality level specified in the request impacts the ability to select suitable participants. The higher the requested quality level, the lower the chance of making a successful selection, since the site's (i.e. group of participants) quality score should equal or exceed the requested quality level. Therefore, quality level requirements should be chosen wisely depending on the criticality of the MCS task (e.g. incident or emergency monitoring application should require a higher quality level than noise level monitoring).
4) The geographic area in which the sensing task is required has an impact on the success of the selection process. Since each geographic area is characterized by some specific phone brands which are widely used in it, different areas imply different phone brands, and thus varying availability and quality of sensors. Thus, countries in which there is a high penetration rate

of latest smartphone brands supporting many sensors have a better chance of satisfying sophisticated sensing requests, when compared to less developed countries supporting more modest phone brands.

5) In group-based selection approaches, the area size chosen for a sensing task impacts the number of sites and the number of participants in each site, therefore indirectly impacting the selection results. Moreover, the participants' density in the AoI is found to have an important impact on the selection, since it dictates the number of sites used to form the grid, and the sites' dimensions. Indeed, there exists a compromise between response time and level of redundancy, when considering different participants' densities. Higher densities result in a higher number of smaller sites, and participants being spread over a larger number of sites. Such case could result in faster response time, but limited redundancy, due to the limited possibility of obtaining the information from multiple sources. In contrast, lower densities result in a smaller number of bigger sites, and thus a higher degree of redundancy as well as longer total response time. It should be noted that such compromise does not apply for individual selection approaches.
6) Choosing the optimal budget for a sensing task, that meets the expectations of participants is crucial for the success of the selection process. If the allocated budget is too low, the selection process will fail. If it meets the expectations of participants, it will succeed, leading to efficient budget utilization. It if exceeds the expectations of participants, the selection process will still succeed, but leading to wasted financial resources. Game theoretic approaches and double sided market theory can be used for the calculation of equilibrium conditions leading to optimal budgets per sensing task.
7) In terms of impact on the collected data quality, the following parameters were found to have an important impact: a) Phones' residual battery levels; b) Benchmarked phones' sensors quality scores; and c) phones' proximity from the event of interest. It was found that phones with higher residual battery and higher sensors' quality scores have a higher chance of being selected for sensing tasks. The proximity from the event has a lower impact on the selection than the battery level and the sensors' quality scores. Moreover, we found that the proximity from the event has a stronger positive impact for phones/participants close to the event, showing little variation for participants beyond a certain distance, which are considered as out of reach with respect to the event.
8) In addition to data quality, participants' reliability represents a critical factor in the success of the selection process. Due to the complexity of human behavior in crowdsensing environments, participants' reliability for sensing task can be impacted by many factors, both historical and instantaneous. Sophisticated models are needed to model participants' reliability, in a comprehensive and practical manner. Such models should capture past and present behavior.
9) In our reliability model, we found the following to be important parameters: a) participants' maliciousness; b) participants' data quality score relative to event; c) number of participants collaborating to satisfy the sensing task. The detection of any malicious activity in a site leads to a score of zero as reliability for this site, therefore resulting in its elimination from the selection process, and an impact on its future reputation. On the other hand, the more the participants' data quality score relative to the event increases, the more the reliability increases exponentially. Finally, sites with a smaller number of participants (1 or 2) have lower reliability due to the limited sources of information they offer, while sites with a larger number of participants (5 to 10) are seen as more reliable as they offer better chances to collect and validate the data. Very large sites (10 and more) do not offer more reliability, since the very large number of readings does not bring added value in term of information or redundancy.
10) In term of task price, the following was observed: The longer the sensing task duration the higher the price required for it, since long lived tasks would require more resources and the commitment of the users to remain in the same area for the duration of the task. Therefore, we expect that time recurrent tasks or continuous sensing tasks would be associated with higher sensing prices. On the other hand, sites with lower sensing capabilities and lower quality levels would be associated with lower prices, in comparison to sites with higher sensing capabilities and better quality levels. Finally, we noticed that the site's price decreases rapidly with the increase of the number of participants' in the site. Since the availability of many participants in the same area implies the availability of multiple sources for the information, the competition between those sources drives the site's price down. Indeed, the higher the price competition between the participants, the lower the site's price will be due to the abundance of sources for the same information.
11) Finally, in terms of probability of task satisfaction, we observed that the more the site's sensing capability decreases, the more the probability of task satisfaction decreases, since the site has a higher chance of not containing the sensors required and meeting the minimum level of information quality requested. Moreover, the probability of task satisfaction has an increasing relation with respect to the site's number of participants. Indeed, for smaller sites, the probability of satisfaction is low. This is due to the smaller probability that a small number of participants could satisfy the request's requirements. On the other hand, for larger sites of 10 participants and more, the probability of task satisfaction increases significantly and levels out at 1.

This is due to the fact that having too many participants would not add more value, since there would be a high level of redundancy in the information collected.

As future work, we plan to enhance our participants' selection model by modeling additional aspects of the problem. For instance, we could take into consideration participants' mobility patterns and coverage of the area of interest to ensure the success of long lived and continuous sensing activities. More sophisticated modeling of participants' reliability and participants' malicious activities could be incorporated as well. Finally, optimal pricing models are needed to ensure the efficient utilization of data collection budgets.

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MAY EL BARACHI received the Ph.D. and master's degrees in computer engineering from Concordia University, Canada. She has 12 years' experience in the field with a strong focus on smart and resource efficient systems. During those years, she acquired academic experience as an Associate Professor and has worked as a Researcher with Ericsson Research, Canada. She co-founded and directed a cutting-edge research lab aiming at investigating sensory, cloud, and mobile technologies. She is currently an Associate Professor with the University of Wollongong in Dubai and is involved in several research collaborations with international universities and local industrial partners. She is also a Next-Generation Networking Expert. Her current research interests include mobile crowdsensing, service engineering, quality of service and adaptive resource management, context-awareness, cloud computing models, virtual networks, and next-generation networks.

ASSANE LO received the B.Sc. degree in mathematics, with a minor in physics, from the University of Dakar and the M.Sc. and Ph.D. degrees in mathematics from The University of Arizona, USA. He was a Mathematics Instructor with The University of Arizona. He was an Assistant Professor with the King Fahd University of Petroleum and Minerals (KFUPM). He was evaluated as a Distinguished Professor at KFUPM, from 2007 to 2008 and from 2011 to 2013. He is currently an Associate Professor with the University of Wollongong in Dubai. His main research interests include PDE methods in mathematical physics and statistical physics, and control theory. He is a Registered Member of the American Mathematical Society, the Mathematical Association of America, and the International Association of Mathematical Physics.

SUJITH SAMUEL MATHEW received the Ph.D. degree in computer science from The University of Adelaide, South Australia. He has over 18 years of experience working in both the IT Industry and in IT Academia. He has held positions as the Group Leader, a Technical Evangelist, and a Software Engineer within the IT industry. In academia, he has been teaching various IT related topics and pursuing his research interests in parallel. He is currently with the College of Technological Innovations, Zayed University, Abu Dhabi. His research interest includes ubiquitous and distributed computing, with focus on the Internet of Things.

KIYAN AFSARI received the bachelor's degree (Hons.) from the Electrical and Electronics Engineering Program, University of Wollongong in Dubai, in 2017, where he is currently working as a Laboratory Instructor and a Graduate Research Assistant.