Impact of Users' Mobility on the Quality of Edge Sensing Systems

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***Abstract*—Edge sensing (ES) is rising as a potential solution for remote sensing challenges, as it exploits the proliferation of smartphones, leverages their embedded sensors to collect data from users' surrounding environments and uses their processors to perform edge computing tasks. Moreover, it is characterized by its low cost and time efficiency. Tremendous efforts have been dedicated to ES systems' quality of data (QoD) and coverage to enhance its performance. Since users incentivization plays a crucial role in enhancing the system's performance, the research community concentrated on improving incentives schemes. In this paper, we evaluate the effect of users' mobility on ES systems' quality of data and coverage, and propose a users' distribution-based dynamic-incentive scheme. In particular, we use a 2-dimensional random waypoint (RWP) model to emulate the randomness of users' mobility and velocity. The proposed incentive scheme aims to eliminate the negative impact of mobility on the QoD; by considering different factors to determine users' incentives and creating users' attraction areas in the targeted cells.**

***Index Terms*—Edge sensing; Quality of data; Mobility; Incentive; Random waypoint.**

I. Introduction

On the grounds of the prevalence of smartphones among users, mobile crowd-sensing (MCS) evolved as a sensing paradigm that leverages the smartphones' built-in sensors to collect data from users' surrounding environment [1]. The role of MCS is limited to sensing and sharing data, however with the advances introduced to smartphones' processors, there is a need for an innovative technology that allows maximizing the utilization of the advancements installed in smartphones. Edge-sensing (ES) is a recent paradigm that, in addition to sensing and sharing data, involves computations and processing on the edge (i.e., users' smartphones). Therefore, ES can be used for a wider range of applications such as environment monitoring, safety, and smart cities applications [2]. However, concerns arise regarding the ES systems' performance as it faces challenges in having proper task allocation, cost minimization, and data quality maximization. Recruiting ample participants is a preeminent way to improve quality and coverage. However, recruitment results in cost increment, and subsequent cost-quality trade-off. Sparse edge sensing reduces the number of tasks allocated by dividing the area of interest (AoI) into spatiotemporal cells [3].

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The challenges of improving sensed data quality and enhancing the system's spatiotemporal coverage are very critical for every ES application. The problem stems from the fact that users who share the data have varying levels of expertise and are barely controllable [4]. The contributed data could be inaccurate or corrupted because of the users-centric architecture, which could affect the QoD dramatically [5]. The fact that the objective of any ES system is to have a realistic representation of users' surrounding environment makes QoD and system coverage critical factors for any ES administrator. This is particularly essential as the aim exceeds completing the tasks to completing it with an acceptable QoD, and to have full coverage to eliminate the risk of blind spots within the system.

ES exploits the mobility of users to have extensive coverage. Unlike wireless sensors networks (WSN), the architecture of ES depends on mobile users' smartphones instead of the stationary sensors to complete the required sensing tasks. The mobility of users helps in reflecting a more realistic image of the targeted area. Moreover, users' mobility enables ES to be an optimal solution for a wide range of applications. However, users' mobility can affect the QoD, task assignments, and system's performance [6]. Furthermore, the movement of users is associated with some costs such as transportation costs and users' resources consumption such as mobile battery and data usage, all these costs should be compensated to guarantee proper system performance.

The core of any ES system is the users or participants who are responsible for executing the sensing tasks, where incentivizing participants to do the required task is extremely critical. However, ES systems work with a constrained budget, hence, incentive schemes should be optimized for each system to guarantee the system's performance within the minimum budget [7]. Incentives come in two main forms: monetary incentives and non-monetary incentives such as services provided for the users. These forms can be further sub-categorized into fixed and dynamic incentives.

In this paper, we aim to study the effect of users' mobility on QoD, where the random waypoint (RWP) model is adopted to emulate the users' mobility and velocity. A users' distribution-

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based dynamic-incentive scheme is proposed to eliminate the negative impact of mobility on QoD. The rest of the paper is organized as follows. Section II includes a brief literature review. The mobility model effect on QoD is addressed in Section III. After that, the QoD incentive scheme is proposed in Section IV. Simulation and performance evaluation are explored in Section V and conclusions are drawn in Section VI.

II. Related Work

Data Quality: The authors in [8] introduce a cross-validation technique in which validating the crowd is required to verify the sensor data provided by participants. Validation outcome is used to reshape data into a more realistic representation of the ground truth. The work in [9] aims to assess the reliability of the sensed data based on social network theory, the participants are modeled as nodes in a social network where common tasks are assigned to them. The trustworthiness is assessed by a combined centralized reputation-based assessment and a vote-based collaborative reputation value. EndorTrust, proposed in [10] to evaluate and predict the reliability of the participants' contributions, by using machine learning to investigate an inter-worker connection for reliability prediction enhancement, while also taking into consideration the heterogeneity of both participants and tasks. In [7], a metric that uses the difference in centrality estimate to find the quality of source in small data cases is introduced.

Users Mobility: With a restricted budget, [11] proposed a vehicular edge sensing system that incentivizes vehicle agents to match the sensing distribution of the sampled data to the intended target distribution. The authors designed the incentive problem as a novel type of non-linear multiple-choice knapsack problem, with the dissimilarity between the gathered data distribution and the desired distribution as the objective function, to make the system adjustable to various desired target distributions. To make the most of the money, a personalized incentive that combines monetary incentives with a prospective task (ride) demands at the destination was presented. The purpose of the work presented in [12] is to investigate some of the mobility characteristics of a real-world ES dataset ParticipAct, to describe how these characteristics might be used to organize a successful ES data collecting campaign. Authors examine mobility traces gathered using ParticipAct and explain how the data obtained help an ES task.

Incentives Schemes: A greedy algorithm-based recurrent reverse auction incentive mechanism is proposed in [13], that picks a representative subset of users based on their location given a fixed budget. While in [14], a budget constrained incentive mechanism that uses the user's previous data is presented, to mainly determine the user's preferences. Subsequently, a sub-module approximation algorithm is designed to greedily pick the data contributor while staying within the budget.

To the best of our knowledge, the impact of users' mobility on QoD has not been conducted yet in ES systems. The literature addresses the challenges of users' mobility and QoD separately. However, the mobility does not only affect the quality of service (QoS), but the users' mobility could also result in decreasing the number of measurements in the cell, which will have an impact on the QoD. In this paper, we aim to study the effect of users' mobility on the quality metric proposed in [7] and to propose a users' distribution-based dynamic-incentive scheme.

III. Mobility Model Effect on QoD

The considered system model includes N_{total} number of users distributed over and area of $X_m \times Y_m$ dimensions. Such AoI is divided into square cells to study the distribution of users over the whole AoI.

To evaluate the repercussion of mobility, the users are considered to follow a RWP mobility model. The location of a user performing RWP movement on a line $[0, X_m]$ can be expressed using the following probability density function (PDF) [15]

$$f_X(x) = -\frac{6}{x_m^3}x^2 + \frac{6}{x_m^2}x \tag{1}$$

However, the previously described 1D PDF considers line movement, thus, it should be changed into 2D PDF to reconcile with the square-shaped cells. This is done by considering two 1D movements one on the x-axis and the other on the y-axis, as follows

$$\int_{y^\circ}^{y^\circ+\bigtriangledown} \int_{x^\circ}^{x^\circ+\bigtriangledown} \left(\frac{-6x^2}{{x_m}^3} + \frac{6x}{{x_m}^2}\right)\left(\frac{-6y^2}{{y_m}^3} + \frac{6y}{{y_m}^2}\right) dxdy \tag{2}$$

Solving Eqn. (2) gives the PDF of users' distribution over the square cells. Where y°, $y^\circ + \bigtriangledown$, x° and $x^\circ + \bigtriangledown$ define the borders of the cell. We obtain Eqn. (3) at the top of next page, showing the resultant PDF of users' distribution over the AoI.

In order to rely on the users' smartphones, their mobility must be tackled in the analysis. While the users are moving, the task completion (e.g., sensing or picturing some area) is mainly spatio-temporally constrained, and therefore, a proper approach is needed to account for mobility impact on Eqn. (3). Taking into account that the users mobility will make them not always available for task completion [16], a way to measure mobility impact is by considering users not available the whole duration of the sensing task, due to mobility. Therefore, we propose a new parameter which is the corrected number of users N_c, to assure the completion of the task.

Assuming that the travelled distance by a user within the cell is uniformly distributed from D_{min} to D_{max}, which is the maximum distance that could be traveled within a cell. Users travel at a constant speed then the duration spent by the user in the cell will be inversely proportional to their velocity. A time threshold to ensure the task completion should be determined based on the application of the ES system. For instance, emergency applications impose a strict deadline for sensing when compared to environment monitoring. The time threshold can be actually converted into a velocity threshold as well.

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$$f(x,y)=\left(\left(\frac{-2((y^{\circ}+\bigtriangledown)^3-(y^{\circ})^3)}{{y_m}^3}+\frac{3((y^{\circ}+\bigtriangledown)^2-(y^{\circ})^2)}{{y_m}^2}\right)\right)\left(\left(\frac{-2((x^{\circ}+\bigtriangledown)^3-(x^{\circ})^3)}{{x_m}^3}+\frac{3((x^{\circ}+\bigtriangledown)^2-(x^{\circ})^2)}{{x_m}^2}\right)\right) \quad (3)$$

Therefore, considering a velocity threshold for users velocity is necessary to enhance the system's performance through assigning tasks to users who will spend enough time to complete the task. The corrected number of users will improve the performance of the quality metric, as it will give a more realistic number of users by excluding users with higher velocity and lower task completion rate. The corrected number of users N_c is then formulated as

$$N_c = N_{\text{total}} \left(1 - \frac{V_{\max} - V_{th}}{V_{\max} - V_{\min}}\right) \quad (4)$$

where V_{max} and V_{min} are the maximum and minimum velocities of users respectively, and V_{th} is the velocity threshold.

The probability p of the presence of the user in the cell is obtained by substituting the cell coordinates (x, y) in Eqn. (3). It is required for the calculation of the probability of having N users in a certain cell ($P(N)$), as

$$P(N) = \binom{N_c}{N} p^N q^{N_c-N} = \frac{N_c!}{(N_c - N)!N!} p^N q^{N_c-N} \quad (5)$$

where q is the complementary probability $1 - p$.

Several quality metrics have been proposed in literature, where the one in [7] can reliably quantify samples as little as $N_{min} = 11$. With above obtained results, we can formulate the probability of unsatisfying the quality metric for any N_{min} value as

$$P(N < N_{\min}) = \sum_{N=0}^{N_{\min}} \binom{N_c}{N} p^N q^{N_c-N} \quad (6)$$

IV. QoD Incentive Scheme

To deal with the effect of mobility shown in section 3, we propose a users' distribution-aware dynamic-incentive scheme. After the task's location is determined and to guarantee acceptable QoD, a necessity factor (nf) might be needed [17]. The necessity factor indicates the need for an incentive to finish the task with an acceptable QoD. As an example, in a scenario where there are enough users and QoD is satisfied, the $nf = 0$. Multiple scenario parameters can be taken into consideration to find the optimal necessity factor. This factor is used to calculate a dynamic incentive for each situation which will result in changing users' distribution over cells, by creating attraction areas within the targeted cells. Our proposed nf is proposed as

$$nf^k = w_1 x_{i1}^k + w_2 x_{i2}^k + w_3 x_{i3}^k \quad (7)$$

where x_{i1}^k, x_{i2}^k and x_{i3}^k reflects the impacts of probability of satisfying the quality metric, task fulfilment and deadline on the necessity factor, respectively. The weight of each parameter can be fixed by the administrator based on the importance of each parameter to the task goal, where their summation is equal to 1.

Probability of satisfying the quality metric: The probability of satisfying the quality metric differs from one cell to another. This difference should be considered in the incentive scheme to assure the completion of all tasks regardless of their location.

$$x_{i1}^k = \ln(2 - P(N_{\min})) \quad (8)$$

where $P(N_{\min})$ is the probability of satisfying the quality metric with the least number of available users N_{min}, obtained from Eqn. (5). As a result of the mobility model, center cells have a higher probability of satisfying the quality metric compared to cells on edge, thus, this parameter is crucial in the process of determining the necessity factor. Notice that the probability of satisfying the quality metric is inversely proportional to the necessity of incentives, where a decrease in $P(N_{\min})$ will drive a larger x_{i1}^k value.

Task fulfilment: To achieve an acceptable QoD, the minimum number of sensing samples should be reached. Therefore, the number of measurements affects the necessity of incentives.

$$x_{i2}^k = \ln\left(2 - \frac{ST}{TT}\right) \quad (9)$$

where ST represents the number of the submitted sensing samples and TT is the total number of the required sensing samples to fulfil the task. Assuming the availability of minimum number of users, TT is calculated using $TT = N_{min} U_{st}$ where U_{st} is the number of sensing samples that each user can submit. It is noticeable that there is less need for incentives with the increased number of submitted samples.

Deadline: Deadline is a critical parameter that should be considered to assure completing the tasks within the specified period. The closer the deadline, the higher the necessity of incentives to guarantee the completion of the sensing task.

$$x_{i3}^k = \ln\left(1 + \frac{1}{t - k - 1}\right) \quad (10)$$

where t is the deadline of the task, we can see that as round k gets larger, the value of x_{i3}^k increase then the need for an incentive is higher.

A. Attraction area

From the previous subsection we have $0 \le x_{i1}^k \le \ln(2)$, $0 \le x_{i2}^k \le \ln(2)$, $0 \le x_{i3}^k \le \ln(2)$ and $w_1 + w_2 + w_3 = 1$, then $0 \le nf^k \le \ln(2)$. So the normalized necessity factor can be calculated as follows

$$\overline{nf^k} = \frac{nf^k}{\ln(2)} \quad (11)$$

The aim of calculating the necessity factor is to implement it in the creation of an attraction area in the targeted cell, this

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can be done as follows

$$g(x,y) = \left(1 - \overline{nf^k}\right) A_t + \left(\frac{\overline{nf^k}}{p}\right) A_c \qquad (12)$$

where A_t represents all the points within the AoI is

$$A_t = \left(u\left(x_d + x_m\right) - u\left(x_d - x_m\right)\right) \cdot \left(u\left(y_d + y_m\right) - u\left(y_d - y_m\right)\right) \qquad (13)$$

while A_c corresponds to all the points within targeted cell as

$$A_c = \left(u\left(x_d - x_{c,\max}\right) - u\left(x_d - x_{c,\min}\right)\right) \cdot \left(u\left(y_d - y_{c,\max}\right) - u\left(y_d - y_{c,\min}\right)\right) \qquad (14)$$

In Eqn. (13) and Eqn. (14), Heaviside unit step functions are used to examine the x and y coordinates of each point. Using Heaviside unit step functions allows the separation of points within the targeted cell from points within the AoI.

Eqn. (12) is used to scale the distribution of users' locations by creating an attraction area in the cell $[x_{(c,min)}, x_{(c,max)}][y_{(c,min)}, y_{(c,max)}]$, while $\overline{nf^k}$ is the normalized necessity factor between 0 and 1. A higher $\overline{nf^k}$ will result in more users attraction to the cell. p is the probability of having users in the cell under normal conditions. The multiplication of Eqn. (12) and Eqn. (3) will give the new users' distribution which is considered as a response to the need for more users in the targeted cell to accomplish the sensing task.

V. Simulation and Performance Evaluation

A. Simulation set-up

To test the mathematical formulas derived in this paper, a ES system with various conditions is simulated and the simulation results are explored in this section. The system consists of 9 square-shaped cells with N number of moving users. The users' mobility is following the RWP, specifically, 2D model movement. Users travel within the system's AoI which is considered to be $[0, x_m][0, y_m]$. Users' velocity is uniformly distributed with $1 \leq v \leq 20$.

B. Simulation results

It is shown in Table I that the derived PDF succeeded in estimating the number of users in each cell as the results from the simulation align with the results from the PDF. Fig. 1 shows users' distribution over the system cells. It is noticeable that the users are not uniformly distributed over the cells as a result of the RWP mobility model. As shown in Fig. 1 the center cell has higher users density which can affect the system drastically. The probability of unsatisfying the quality metric

TABLE I
Comparison of users' distribution math and simulation results

Cell number	Cell 1	Cell 5	Cell 8
Estimated N (math)	6.03	20.88	11.25
Average N (simulation)	6.17	21.29	11.10

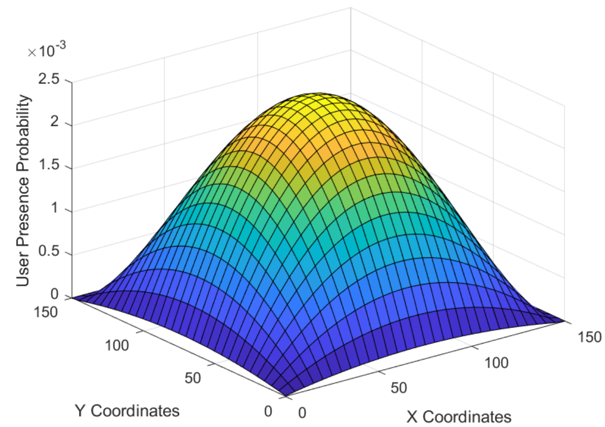

Fig. 1. Users' distribution over the cells

in edge cells is expected to be much higher than itself in center cells. Consequently, the AoI edges could become blind spots causing a failure in having a full coverage. Fig. 2 shows these probabilities.

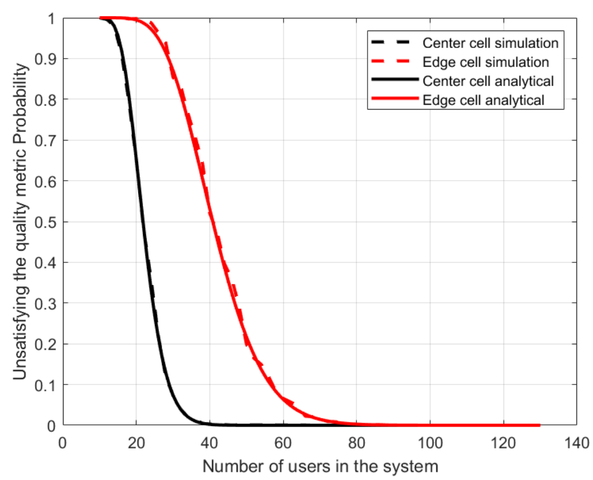

Fig. 2. Cell location effect on the quality metric

Moreover, from Fig. 1 and Eqn. (3) it is noticeable that the probability of satisfying the quality metric can be affected by the size of the cell. Fig. 3 plots how the size of the center cell affects the probability of satisfying the quality metric. It is noticeable from Fig. 3 that larger cells have a higher probability of satisfying the quality metric as the probability of having more users increases.

Fig. 4 shows how V_{th} affects the corrected number of users which shows that velocity may not affect the distribution of the users, however, it affects the number of eligible users to do the sensing task.

To assess the incentive scheme, Fig. 5 and Fig. 6 are used to evaluate the incentive scheme ability to create an attraction area

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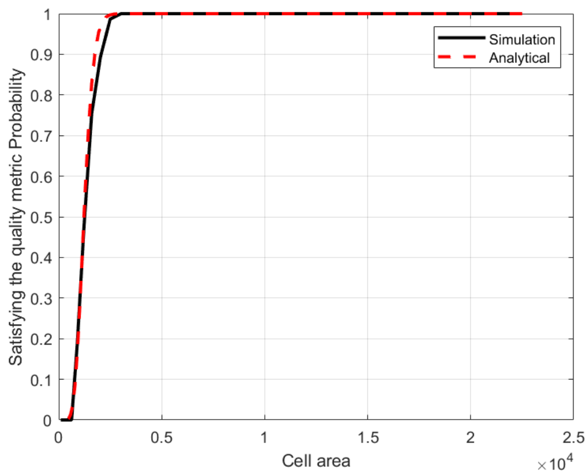

Fig. 3. Cell size effect on the quality metric

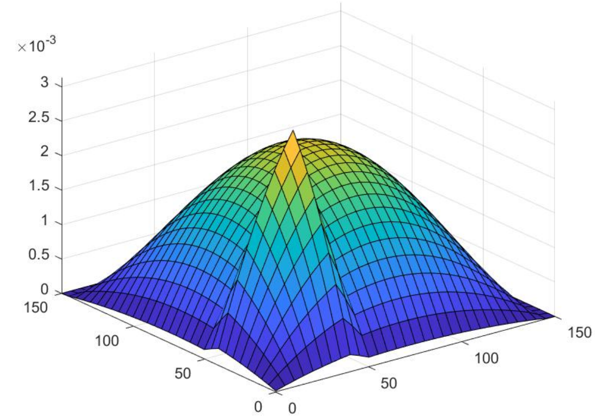

Fig. 5. Attraction area

within a specific cell. As Fig. 5 shows users' attraction area was created in an edge cell which results in increasing users' presence probability. The created attraction area can solve multiple issues faced by ES systems as it enhanced the system coverage by improving users' presence probability in edge cells, which results in increasing the probability of satisfying the quality metric as shown in Fig. 6. Moreover, it shows that the proposed incentive scheme enhanced the system's coverage without the need of recruiting more users which makes it a suitable scheme for budget-constrained scenarios.

VI. Conclusions

The impact of mobile users on ES systems is evaluated in this paper, specifically, the RWP model was considered for users' mobility. Additionally, a location-based dynamic-incentive scheme was proposed to address the challenges caused by users' mobility. The proposed incentive scheme succeeded in creating an attraction area within the targeted cells which results in enhancing the system's coverage and eliminating the negative impact of users' mobility on QoD. The importance of studying the users' mobility lies in the fact that it gives estimation of users' distribution and the overall system coverage, which helps in designing more efficient and reliable incentive schemes. Existing works have focused on designing incentive schemes. However, the joint consideration of users' response to incentive and users' availability is marginally considered in literature.

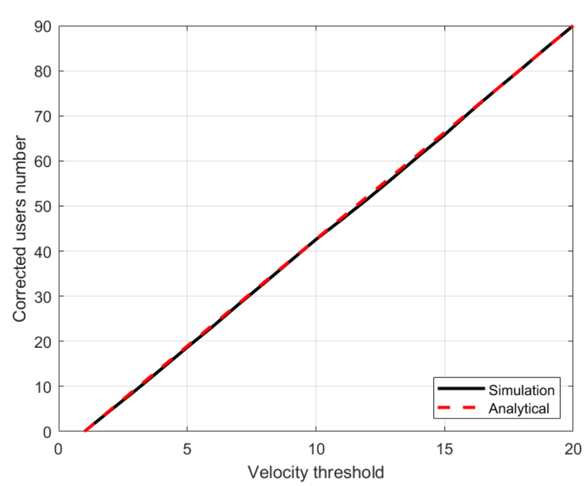

Fig. 4. Velocity threshold effect on corrected number of users

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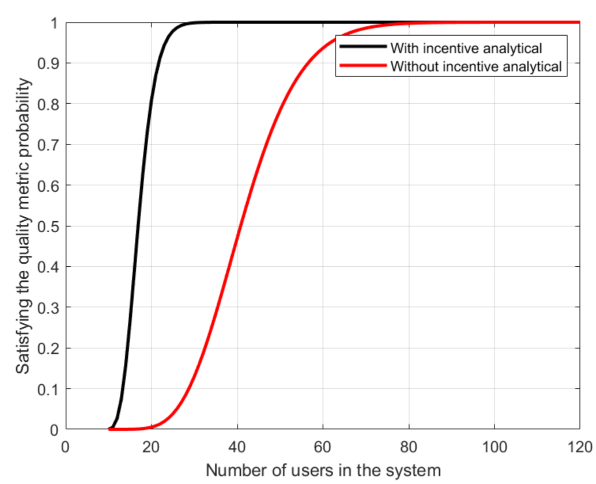

Fig. 6. Number of users effect on the quality metric

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