Task Assignment in Extreme Edge Sensing: Balancing Response Time and Incentives

Omar Naserallah[1], Sherif B. Azmy[1], Nizar Zorba[2], and Hossam S. Hassanein[3]

[1]*Department of Electrical and Computer Engineering, Queen's University, Kingston, ON, Canada*
[2]*Department of Electrical Engineering, Qatar University, Doha, Qatar*
[3]*School of Computing, Queen's University, Kingston, ON, Canada*
Emails: [omar.naserallah, sherif.azmy]@queensu.ca, nizarz@qu.edu.qa, hossam@cs.queensu.ca

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***Abstract*—Extreme Edge Sensing (EES) offers an enhanced approach to efficient remote sensing by utilizing the computational capabilities of user devices for immediate data processing. In contrast to traditional Mobile Crowd Sensing (MCS), EES provides both data collection and local data processing to accelerate decision-making. However, due to the variability in participant capabilities and task requirements, the complexity of task assignments becomes challenging. This complexity necessitates a mechanism that balances incentives and response time, ensuring tasks are completed within predefined budget and time limits. This paper presents a new task assignment strategy that categorizes participants based on their capabilities and task needs. Using the Hungarian algorithm, our methodology optimizes task assignments with an objective function aiming to minimize both monetary and time costs. We then evaluate the minimum budget needed for successful task completion and its dependency on objective function parameters. A comparison of our method's performance against a standard greedy approach demonstrates its effectiveness. The results suggest that our method enhances the efficiency and reliability of task assignment in EES systems, with potential applications in smart cities, environmental monitoring, and other areas requiring efficient remote sensing.**

***Index Terms*—Edge sensing, Mobile Crowd Sensing, Extreme Edge Sensing, Response Time, Incentive, Assignment.**

I. Introduction

In the pursuit of creating smart cities, an essential component is endowing urban infrastructures with some form of awareness. Achieving this awareness efficiently and cost-effectively has been a long-standing goal in smart city design [1]. Over the years, efforts such as Mobile Crowd Sensing (MCS) and Edge Sensing have been pivotal in reaching this objective [2]. Each of these methods, however, has its limitations.

Edge sensing involves computation at low latency, applicable in scenarios like Internet of Things (IoT), industrial IoT, and remote sensing [3]. The challenge with Edge Sensing lies in its inherent limitations regarding cost and spatial reach since sensors must be deliberately deployed across specific areas. On the other hand, MCS, capitalizing on the pervasiveness of participant devices like smartphones, overcomes these spatial limitations [4]. However, MCS overlooked the computation aspect, focusing more on data collection.

Herein lies the significance of Extreme Edge Sensing (EES). EES represents a harmonious blend of Edge Sensing and MCS by integrating sensing and computation, along with robust incentive schemes to cater a heterogeneous participant pool, EES provides a formidable approach to decentralized sensing. Through EES, the capabilities of smartphones are harnessed, transforming them into mobile sensing and computing nodes operating over diverse locations and time frames. Doing so addresses many remote sensing challenges previously associated with centralized methods, including high deployment costs and limited coverage.

Nevertheless, EES has a new set of complexities, as with any innovative paradigm. The diverse nature of participants, coupled with the multifaceted task requirements, amplifies the challenge of task assignment [5]. In this context, the importance of meeting deadlines emerges as a critical factor. Timely completion of tasks is paramount, especially when delays can significantly impact the overall efficiency and effectiveness of the system. Furthermore, the development of suitable incentive schemes becomes a focal point. These schemes must be carefully designed to address the varying motivations of participants while ensuring alignment with performance metrics such as response times [6]. The challenge lies in balancing the effectiveness of these incentives with the practicalities of implementation, reflecting the evolving nature of the state of the art in this field.

The current literature explores optimizing task assignment scheme designs, by addressing the challenges associated with them. Authors in [7] developed a multi-objective task assignment to maximize social welfare. However, they did not consider the deadline for tasks and the participants' availability. In [8], a multi-task allocation scheme was designed, but the authors did not account for time restrictions and the heterogeneous capabilities of participants. Similarly, in [9], an efficient task allocation system was proposed, yet it overlooked the diversity in participants' capabilities. In [10], a deadline sensitive task assignment was presented, by considering budget and deadline constraints, as well as the heterogeneity of participants. However, aspects like response time and the availability of participants were not addressed. Existing work primarily focuses on optimizing task assignment schemes. However, there is only marginal attention given to simultaneously considering participant heterogeneity, availability, response time, and the constraints of budget and time.

In light of these considerations, the contributions of this paper are as follows:

- Introduction of an innovative, incentive-based approach to response time, aimed at minimizing the cost of completing EES tasks within their deadlines.
- Comprehensive analysis of EES system performance, providing insights into the necessary budget for successful task completion, as well as identifying potential budget savings for system administrators.

Realizing these contributions holds the potential to shape more efficient and effective EES system deployments, optimizing both resources and participant engagement.

The paper is structured as follows: Section II offers a detailed exposition of EES and the underlying system model. The proposed model and its nuances are discussed in Section III. Section IV presents simulation results and performance evaluations. Conclusions and key takeaways are summarized in Section V.

II. System Architecture and Model

EES provides a robust foundation for modern sensing campaigns, yet it introduces complexities due to its decentralized nature. This section outlines the architecture and operational details of an EES system, where administrators recruit participants to execute edge-sensing tasks. We also present a mathematical representation of the system that underpins the discussions in subsequent sections.

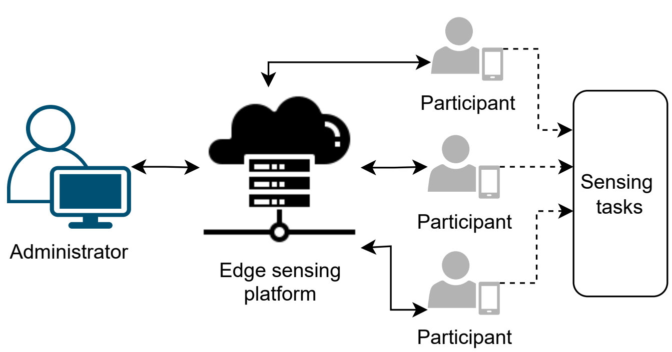

Fig. 1. EES architecture

A. System Description

The architecture of the EES system revolves around four main components: the administrator, participants, the EES platform, and the sensing tasks, as illustrated in Fig. 1.

The system is initiated by the administrator, who sets the objectives, defines data collection parameters and sensing tasks, and selects the phenomena to be monitored. The formalized tasks are then shared via the EES platform, bridging the gap between the administrators and a diverse group of potential participants. The platform plays a vital role in matching tasks to participants based on expertise and availability [11]. During the data collection phase, participant devices, or edge sensing nodes, process the gathered data, converting raw input into actionable results. The results are then communicated to the administrator to use in the next step, which might involve a form of decision-making or actuation in the context of a smart city [12].

Task initiation is primarily the responsibility of the administrator. With information on expected participant availability, the administrator ensures efficient task deployment. These tasks are then made available to participants through the EES platform. Task assignment within the system prioritizes cost and time considerations alongside the availability of participants to ensure that tasks are completed successfully. In particular, the administrator carefully recruits candidate participants in a manner that guarantees that the tasks are completed during the required deadline and within the assigned budget limitations.

B. System Model

In our model, each sensing task t is divided into N_t sub-tasks, each assigned to a unique participant, resulting in a requirement for N_t participants in total. The division of a task into sub-tasks is inherently determined by the task's nature and its associated deadline.

In an EES platform, the administrator operates under a maximum allowable budget threshold, denoted as $B_{\max,t}$, for each task t. From which, an active budget, B_t, is allocated and subsequently utilized to recruit participants in exchange for an incentive payment, $X_t^{(i,j)}$. Subscripts i and j correspond to the sub-task index and participant index, respectively. The total number of participants eligible to be selected from the participants' pool for task t is denoted by the variable P_t.

Recruitment of participants requires careful consideration of their expected response times, $R_t^{(i,j)}$, to ensure compliance with the task deadline, $R_t^{\max}$. This necessitates that $\max\{R_t^{(i,j)} | i, j \in \{1, \ldots, N_t\}\} < R_t^{\max}$. Response times are estimated based on historical participant performance, with tools such as machine learning (ML) models being capable of classifying participants into response time categories [13]. It is assumed in this work that such classification has already been conducted.

Notably, the system operates under two interconnected perspectives: the macro-economic perspective of the administrator and the micro-economic perspective of the participants. These perspectives will be further explored and connected through the cost function definition in the subsequent section, aiming to optimize sub-task allocation efficiency and effectiveness.

III. Refined Task Allocation Strategies

EES is central to modern sensing campaigns where a primary challenge in this domain is optimally assigning tasks to participants, balancing costs, and task-specific constraints. This section, details our proposed system, addressing the task assignment challenge, the costs involved, and the optimization techniques we use to ensure effective task allocation.

A. Matching problem

The task assignment phase begins by identifying the pool of available participants. As mentioned earlier, participants are categorized into classes based on their average $R_t^{(i,j)}$. The ML model's predictive capabilities offer administrators insights into participants' expected availability during specific time intervals. The main goal is to assign tasks to a variety of participants, optimizing the allocation to meet the task's requirements and minimizing incentivization costs. This balance ensures efficient task execution while controlling expenses.

Our system assumes that each participant can execute only one sub-task at a time. As a result, each sub-task is dedicated to a participant, leading to a bipartite matching problem. The intention is to optimize sub-task allocation to participants. Participant recruitment is captured in a matching $\mathcal{M}_t \in [0,1]^{N_t \times P_t}$ $\forall t$. The matchings are selected by optimizing over a cost-weighted graph represented by matrix $\mathbf{C} \in \mathbb{R}^{N_t \times P_t}$.

As Fig. 2 shows the system matches each sub-task to a participant, completing the task when all sub-tasks are complete. We assume a higher number of participants than sub-tasks, so $P_t > N_t$. In general, the aim is to minimize the cost of completing the task within the deadline, as promptly and cost-effectively as possible, without exceeding the budget.

The incentive for each participant depends on their response time. Faster responders are expected to receive higher incentives. The incentive amount is determined using Eqn. (1).

$$X_t^{(i,j)} = \beta - \alpha R_t^{(i,j)}, \tag{1}$$

where $\alpha \in \left[0, \frac{\beta}{R_t^{(i,j)}}\right]$ is a penalty rate determined by the administrator, varying based on the assigned sub-task's nature and its delay tolerance. More pressing tasks require a higher α value. The initial incentive, β, represents the maximum incentive a participant can attain, which we express as

$$\beta = \frac{B_t}{N_t} \tag{2}$$

This structure ensures fairness among participants according to their response time, by establishing a consistent starting incentive for everyone but adjusts the final amount based on their response time as shown by Eqn. (1) and Eqn. (2).

To better represent the cost of assigning a subtask to a user, our system adopts a comprehensive approach, factoring in all task requirements, including delay and incentive amounts. These factors are combined based on the task's nature, resulting in a new cost parameter aiding in task assignment optimization.

This new assignment cost parameter, $C^{(i,j)}$, combines delay and cost factors as

$$C^{(i,j)} = \omega R_t^{(i,j)} + (1-\omega) X_t^{(i,j)} \tag{3}$$

where, ω represents the weight for response time from assigning sub-task i to participant j, showing the relative importance between the normalized response time $R_t^{(i,j)}$ and the normalized incentive amount $X_t^{(i,j)}$. Its consideration of all possible cases is presented in the following matrix

$$\mathbf{C} = \begin{bmatrix} C^{(1,1)} & C^{(1,2)} & \dots & C^{(1,P_t)} \\ C^{(2,1)} & C^{(2,2)} & \dots & C^{(2,P_t)} \\ \vdots & \vdots & \ddots & \vdots \\ C^{(N_t,1)} & C^{(N_t,2)} & \dots & C^{(N_t,P_t)} \end{bmatrix} \tag{4}$$

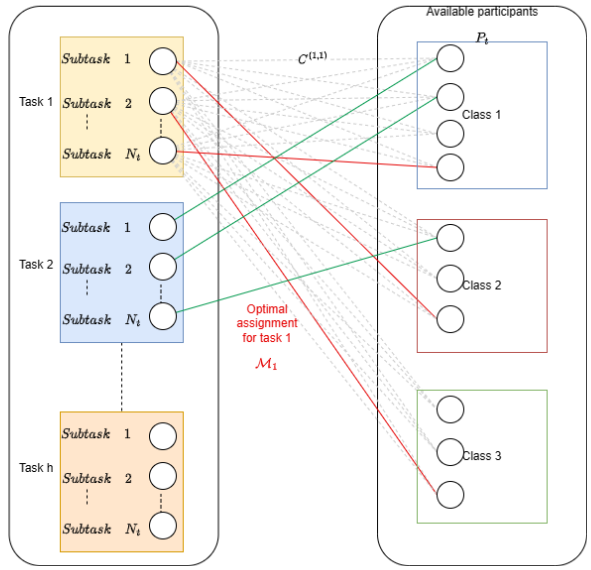

Fig. 2. Matching problem

B. Optimization problem

The system prioritizes optimizing each task assignment based on task requirements and participant recruitment costs as

$$\min_{r^{(i,j)}} \quad \mathbf{C}^T \mathbf{A} \tag{5a}$$

$$\text{subject to} \quad \sum_{i=1}^{N_t} \sum_{j=1}^{N_p} r^{(i,j)} X_t^{(i,j)} \leq B_t \tag{5b}$$

$$r^{(i,j)} R_t^{(i,j)} < R_t^{\max} \quad \forall i,j \tag{5c}$$

to ensure task assignments remain within the budget B_t and response time constraint $R_t^{\max}$. Here, $r^{(i,j)}$ indicates if the sub-task is assigned to the participant. The assignment of participants is represented using the binary matrix $\mathbf{A} \in \{0,1\}^{N_t \times P_t}$. Due to the variabilities associated with EES systems, the matching and optimization are performed on a per-task basis.

After creating the cost matrix $\mathbf{C}$ with all participant recruitment costs, the Hungarian algorithm is employed for task assignment optimization [14]. This approach is illustrated in Algorithm 1. Renowned for its computational efficiency, the Hungarian method ensures rapid task assignment, essential for real-time systems. It also guarantees optimal solutions in one-to-one matching, aligning with the EES system's objective. The method's simplicity and its adaptability to various cost and objective functions allow the integration of system-specific metrics. More importantly, it can handle real-world constraints like participant availability and task deadlines, ensuring assignments comply with the system's requirements. In essence, the Hungarian algorithm refines task assignments, boosting the edge sensing system's performance and responsiveness.

Algorithm 1 Assignment Optimization

Require: T, N_t, ω, P_t, and k
for each task t in T **do**
  Initialize cost matrix $\mathbf{C}$
  for $i \leftarrow 1$ to P_t **do**
    for $j \leftarrow 1$ to N_t **do**
      Compute $C^{(i,j)}$
    end for
  end for

  Input: Cost matrix $\mathbf{C}$
  Initialize necessary variables and data structures for the algorithm
  while not all sub-tasks of task t are assigned **do**
    Perform row and column reductions on $\mathbf{C}$
    Cover the matrix $\mathbf{C}$ with the minimum number of lines
    if all sub-tasks of task t are assigned **then**
      return binary assignment matrix A for task t
    else
      Find the smallest uncovered element in $\mathbf{C}$
      Modify the matrix to improve the assignment for task t
    end if
  end while
end for

IV. Results and Discussion

The performance evaluation of our model is pivotal for understanding its potential applicability in real-world scenarios. This section focuses on the behavior of our model under various conditions, ensuring its robustness and efficacy.

We conducted simulations across a broad spectrum of conditions to comprehensively evaluate our proposed model. The performance metrics we focus on are the Successful Assignment Percentage (SAP) and profit. SAP quantifies the percentage of successful task assignments, where all sub-tasks are adequately assigned to participants, respecting the pre-set budget and response time constraints. Conversely, profit captures the net gain by subtracting paid incentives from the available budget. We structure our participants into k unique classes, represented by the total participant number, N_p. Tasks are further split into N_t sub-tasks. This section discusses how system performance is influenced by the parameters ω and α.

Fig. 3 illustrates the relative performance of our optimized algorithm against a traditional greedy approach. The superiority of our algorithm is evident as it achieves task assignments at a more economical rate while still adhering to delay restrictions, emphasizing the cost-effectiveness of our proposal.

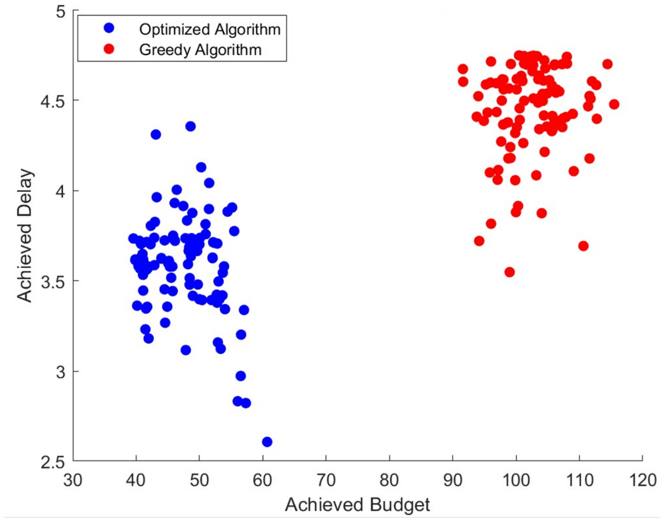

Fig. 3. Comparison between optimized and greedy algorithms

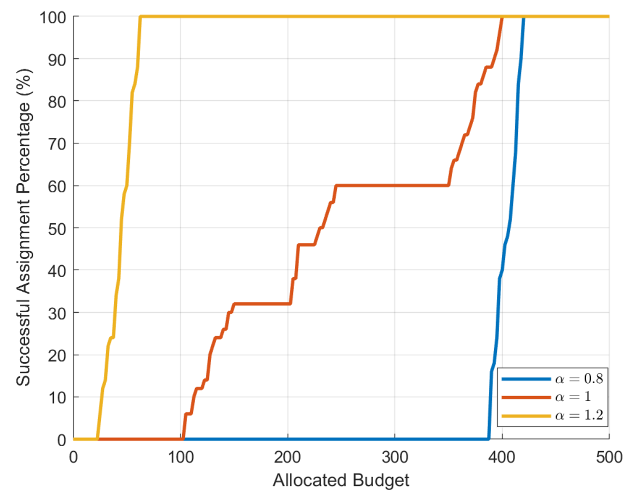

Fig. 4. SAP across varying α values

In order to understand the algorithm's behavior for different α and ω values, parameters pivotal for administrators, Figs. 4 and 5 are introduced. As depicted in Fig. 4, escalating the penalty rate facilitates task assignments at a reduced cost. Administrators must approach penalty rate settings judiciously, as extreme rates could deter participant engagement. Additionally, Figure 4 illustrates a step-like progression instead of a continuous curve, indicating that the success rate improves at specific budget increments. These increments align with the successful assignment of a sub-task within the respective budgetary increases.

Moreover, Fig. 5 demonstrates the variances in the SAP metric for assorted ω values. Alterations in ω values directly correlate with system efficacy. A setting with $\omega = 0$ is adept for non-urgent scenarios, whereas a setting with $\omega = 1$ is tailored for more pressing situations, even if it might incur a steeper

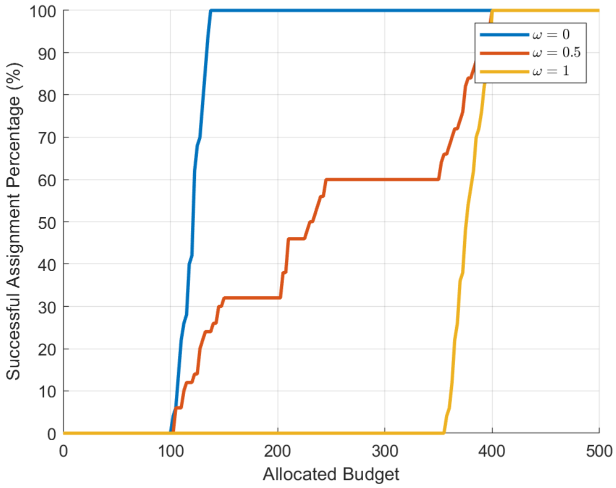

Fig. 5. Influence of ω values on SAP

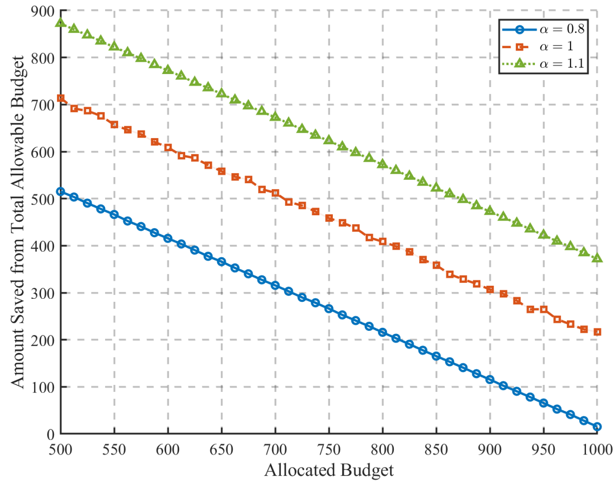

Fig. 7. Profit variations with different α values

cost.

Profit-based evaluations using varying ω and α values are presented in Figs. 6 and 7. In particular, Fig. 6 suggests that lower ω values yield higher profits, as the system leans towards longer response times but at reduced costs while still meeting delay thresholds.

Lastly, Fig. 7 demonstrates that a higher α leads to increased profits since participants incur penalties for longer response times. Tuning the penalty rate based on the EES application is of great importance for the system. High penalty rates can have a negative impact on participants' behaviours. Therefore, it is crucial for the administrator not to excessively raise the penalty rate in a greedy manner, as this could have adverse consequences.

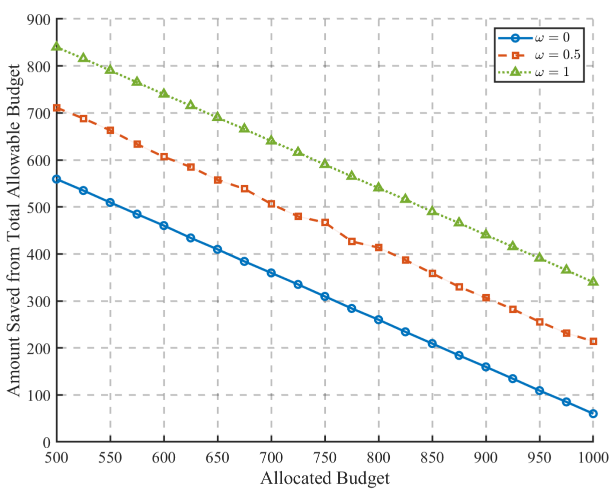

Fig. 6. Profit trends across different ω values

V. Conclusions

In this paper, we tackled the challenge of balancing cost and delay in an EES system involving heterogeneous participants. Our model takes into account the varying capabilities and availability of EES participants, ensuring the system is versatile enough to handle these differences. We incorporated weighting and penalty rate parameters, making the system flexible and able to meet different requirements, such as budget limitations and delay constraints. Our novel task assignment scheme addresses the assignment issue by solving the matching and optimization problems we put forth. We also utilized SAP and profit performance metrics, to evaluate the model's performance under different conditions. In conclusion, our proposed algorithm showcases promising results in terms of both SAP and profit, outperforming traditional greedy approaches and offering administrators flexibility in parameter settings. Future research could focus on more detailed participant behavior analytics and refined system adjustments, as well as exploring task prioritization strategies.

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