Efficient User Incentives in Extreme Edge Sensing: A New Learning-Based Scheme

by

Omar Naserallah

A thesis submitted to the
Graduate Program in Department of Electrical and Computer Engineering
in conformity with the requirements for
the degree of Degree of Master of Applied Science

Queen's University
Kingston, Ontario, Canada
May 2024

Dedication

For the sake of Allah,

to my family,

and to my people in Palestine.

Abstract

Extreme Edge Sensing (EES) systems utilize the built-in sensors of users' smart devices to collect data from the surrounding environment and employ their processors to carry out edge computing tasks. Emerging as a solution to remote sensing challenges, EES systems are noted for their efficient time and cost management, scalability, and the ability to gather real-time data. Efforts to enhance these systems have focused on improving quality of data (QoD) and coverage, as well as on developing incentive schemes to optimize performance. In this thesis, we assess the impact of users' mobility and availability on the spatiotemporal coverage and QoD of EES systems, considering the heterogeneity of users. We propose a distribution-aware and learning-based dynamic incentive scheme. Specifically, we consider the randomness of users' mobility and velocity using a 2-dimensional random waypoint (RWP) model and support the learning-based incentive scheme with a long short-term memory (LSTM) model. The LSTM model utilizes the users' historical data to predict their availability to perform the sensing tasks. The proposed scheme is used to enhance system performance and effectively manage the trade-off between quality and cost, by recruiting users based on the required quality and cost constraints to meet the minimum quality requirement within a constrained budget. Our findings demonstrate that the proposed scheme enhances the spatiotemporal coverage and QoD in EES systems.

List of Publications

- **Conference Publications**

  O. Naserallah, S. B. Azmy, N. Zorba and H. S. Hassanein, "Impact of Users' Mobility on the Quality of Edge Sensing Systems," GLOBECOM 2022 - IEEE Global Communications Conference, Rio de Janeiro, Brazil, 2022.

  O. Naserallah, S. B. Azmy, N. Zorba and H. S. Hassanein, "Task Assignment in Extreme Edge Sensing: Balancing Response Time and Incentives," ICC 2024 - IEEE International Conference on Communications, Denver, USA, 2024. (accepted)

- **Journal Publications**

  O. Naserallah, S. B. Azmy, N. Zorba and H. S. Hassanein, "Novel Distribution-Aware and Learning-Based Dynamic Scheme for Efficient User Incentivization in Edge Sensing Systems," in IEEE Open Journal of the Communications Society. (submitted)

Acknowledgments

I would like to express my sincere gratitude to Prof. Nizar Zorba and Prof. Hossam Hassanein for their invaluable support and guidance throughout the research and writing of this thesis.

I am profoundly grateful to my family for their unwavering support. They are the wind beneath my wings, pushing me forward with their love and encouragement. Their happiness is my greatest inspiration, driving me to achieve so I can always see their smiles of pride.

To the Miari family, your hospitality made me feel like I was surrounded by family, and I will forever cherish the warmth and comfort you provided during my time there.

A heartfelt appreciation goes to my dear friends Sherif Azmy and Mohamed Ads. Your companionship and unwavering presence have been a source of strength and joy. And to all the members of TRL, you have enriched my journey in ways I can't express.

List of Abbreviations

AI	Artificial Intelligence
AoI	Area of Interest
BIP	Binary Integer Programming
CNN	Convolutional Neural Network
CSI	Channel State Information
DL	Deep Learning
EC	Edge Computing
EES	Extreme Edge Sensing
GBMC	Greedy Budgeted Maximum Coverage
IoT	Internet of Things
LSTM	Long Short-Term Memory
MAD	Median absolute deviation
MAE	Mean Absolute Error

MEC	Mobile edge computing
ML	Machine Learning
MCS	Mobile Crowd Sensing
MSE	Mean Square Error
QMS	Quality Metric Satisfaction
QoD	Quality of Data
QoI	Quality of information
RMSE	Root Mean Square Error
RVRP	Random Variable Reward Program
RWP	Random Waypoint Model
WAA	Winner Auction Algorithm
WSN	Wireless Sensor Networks

List of Symbols

$Q^{\mathbf{t}}_{\mathbf{min}}$	Minimum required quality of each task t
$N_{\mathbf{total}}$	Total number of users in the EES system
N_m	Corrected user count
$N^{\mathbf{k}}_{\mathbf{n}}$	Available users from each participants class
T	Set of sensing tasks.
$X_{\mathbf{AoI}} \times Y_{\mathbf{AoI}}$	Area of interest borders
L	Number of subcells within the AoI
$f_X(x)$	RWP 1D PDF movement
p	Presence probability in a subcell
y°, $y^\circ + \bigtriangledown$	Borders of the subcells on y-axis
x°, $x^\circ + \bigtriangledown$	Borders of the subcells on x-axis
$D_{\mathbf{max}}$	Maximum possible travel distance within a subcell
$V_{\mathbf{max}}$	Maximum velocity of users

$V_{\mathbf{min}}$	Minimum velocity of users
$V_{\mathbf{th}}$	Velocity threshold for task completion
$P(N)$	Probability of N users being in a subcell
$N_{\mathbf{min}}$	Minimum number of users
q	Complementary probability $1 - p$
Ω	Necessity factor
x_1	Impact of probability of satisfying the minimum number of sensing users on the necessity factor
x_2	Impact of satisfying the QMS on the necessity factor
x_3	Impact of satisfying the deadline on the necessity factor
$Q_{t,\mathbf{ach}}$	Achievable quality for task t
$C(t)$	Total cost for each task
C_n^k	Cost of users from different classes
Q_n^k	Quality of users from different classes
x_n^k	Recruitment decision parameter
B_t	Task budget constraint

Contents

List of Tables

List of Figures

Chapter 1

Introduction

1.1 Overview and Motivation

Enabling urban infrastructures with some level of awareness is a critical component in constructing smart cities. Achieving this awareness efficiently and cost-effectively has been a long-term goal in smart city planning [1]. Over the years, efforts such as mobile crowd sensing (MCS) and edge computing (EC) have been critical in reaching this goal [2]. MCS leverages widespread smartphone use within populations to carry out sensing tasks, effectively turning users' devices into a network of sensors. However, MCS's capabilities are confined to collecting and sharing data. As the computational power of smartphones continues to evolve, there is an escalating demand for advanced technologies capable of leveraging the advancements made in smartphone technology to their fullest extent. Extreme edge sensing (EES) signifies a shift towards incorporating processing the sensed data on smartphones, facilitating applications such as traffic, environmental monitoring, and smart city initiatives in a more integrated manner [3].

The essence of EES is its innovative integration of EC with MCS, combining

the power of sensing and computational analysis while employing effective incentive mechanisms for a diverse range of participants [4]. Hence, EES emerges as a powerful solution for decentralized sensing challenges. By leveraging the potential of smartphones, it transforms these devices into dynamic sensors and computing units spread across various locations and times. This strategy effectively overcomes the limitations faced by traditional centralized sensing methods, such as high setup costs and constrained coverage areas.

1.2 Challenges

While groundbreaking, EES introduces its own complexities. One significant source of complexity arises from the diverse expertise and limited controllability of participants who contribute data [5]. This diversity, known as user heterogeneity, is a pivotal consideration since EES systems rely on user-centric methodologies, with participants' smartphones performing sensing and computing tasks. Users exhibit heterogeneity in aspects such as their devices' capabilities, availability patterns, and the quality of data (QoD) they can provide, among other factors [5]. Addressing the heterogeneity of participants is crucial due to its impact on various aspects of EES systems, including task allocation and QoD. The varying capabilities and contributions of users introduce significant challenges that must be included in the design of EES systems making user heterogeneity a critical factor to consider when ensuring the effectiveness and reliability of these systems.

In EES systems, the responsibility for assigning tasks to the participants, commonly known as the sensing crowd, falls upon the sensing campaign administrator.

This process, referred to as task allocation, is complicated by the heterogeneous nature of the participants and the diverse requirements of the tasks, thereby presenting a significant challenge in the allocation process. Effective task allocation is crucial as it directly impacts the efficiency and QoD collected by the EES system [6]. Properly matching tasks with participants optimizes resource utilization and enhances participant engagement, ensuring the system's operational success.

The flexibility of EES systems has led to their widespread application, introducing an additional layer of complexity. Sensing tasks vary significantly, influencing users' willingness to participate based on the specific requirements of each task [7]. For instance, emergency tasks demand quicker response times compared to environmental monitoring. Recognizing and adapting to these task-specific requirements is essential for the effective operation of EES systems.

EES leverages user mobility to achieve broad sensing coverage [8], setting it apart from other sensing techniques, such as Wireless Sensor Networks (WSN) that rely on (mostly) stationary sensors. Instead, EES utilizes the smartphones of mobile users for sensing tasks, enabling a more accurate representation of the area of interest (AoI). This mobility aspect makes EES highly flexible and suitable for various applications. Nonetheless, the mobility factor introduces complexities in ensuring QoD, managing task allocation and maintaining system performance. Additionally, user movement incurs certain costs, such as transportation and the consumption of mobile resources including battery life. Addressing these costs is essential for sustaining optimal system functionality.

In the framework of EES systems, users or participants play a pivotal role. It is

essential to ensure the motivation of these participants through incentives [9]. Nevertheless, the operation of EES systems is subject to financial limitations, necessitating the careful optimization of incentive schemes to ensure system performance is maintained within a constrained budget. Incentives are broadly classified into monetary rewards and non-monetary benefits, such as additional user services. Incentives are also differentiated into fixed and dynamic incentives, allowing for adaptation to the specific needs and dynamics of the system.

1.3 Contributions and Objectives

In this thesis, our primary objective is to provide an insight on the dynamics of EES systems particularly focusing on the influence of mobility and availability patterns of the sensing crowd. We aim to assess how these factors impact EES systems' performance, efficiency, and effectiveness in diverse settings. Furthermore, we introduce a distribution-aware and learning-based dynamic approach for optimizing user recruitment in EES systems. This approach is designed to adaptively respond to the changing distribution patterns of potential participants, thereby enhancing the system's ability to efficiently utilize available resources and improve data collection outcomes.

We aim to provide solutions to address the inherent challenges in deploying and managing EES systems in real-world scenarios. Specifically, we utilize the random waypoint (RWP) model to investigate the impact of users' mobility on the QoD in EES systems. Leveraging insights gained from mobility patterns, we employ long short-term memory (LSTM) model predictions to optimize task allocation, seeking to strike

a balance between cost and QoD. Additionally, we introduce a novel, distribution-aware, and learning-based dynamic incentive scheme to mitigate the effects of users' mobility and availability on QoD. By interlinking these approaches, we aim to develop a comprehensive framework that enhances the efficiency and reliability of EES systems in capturing high-quality data while adapting to the dynamic nature of user behavior and environmental conditions.

1.4 Thesis Outline

This thesis is organized as follows: Chapter 2 presents a comprehensive background and literature review on EES systems, including the architecture, quality concerns, user mobility, and the use of machine learning (ML) to improve EES systems. Chapter 3 discusses the impact of users' mobility on the quality of EES systems, analyzing how mobility models can influence the QoD and system performance. Chapter 4 presents a novel incentive scheme for EES. Chapter 5 reports the simulation results of the proposed system. Finally, Chapter 6 concludes with a summary of findings and discusses potential avenues for future research.

Chapter 2

Background and Literature Review

This chapter explores the architecture of EES systems and examines relevant literature that looks into different challenges related to quality, mobility, and incentives from various perspectives. Additionally, we examine the integration of ML models within crowd-sensing systems to address these challenges effectively. By examining insights from existing research, we aim to provide a comprehensive understanding of the current approaches in EES architecture and their application in overcoming key challenges in data quality, user mobility, and incentive mechanisms.

2.1 Extreme Edge Sensing Architecture

EES provides a robust foundation for modern sensing campaigns, yet it introduces complexities due to its decentralized nature and diverse ownership. This section outlines the architecture and operational details of an EES system.

To understand the distinctive characteristics of sensing in EES, it is important to differentiate it from conventional sensing methodologies. We examine EES to understand what catalyzed its emergence. Influences stem from various technological frameworks, including MCS, WSNs, crowd sourcing, the IoT, distributed cloud, and

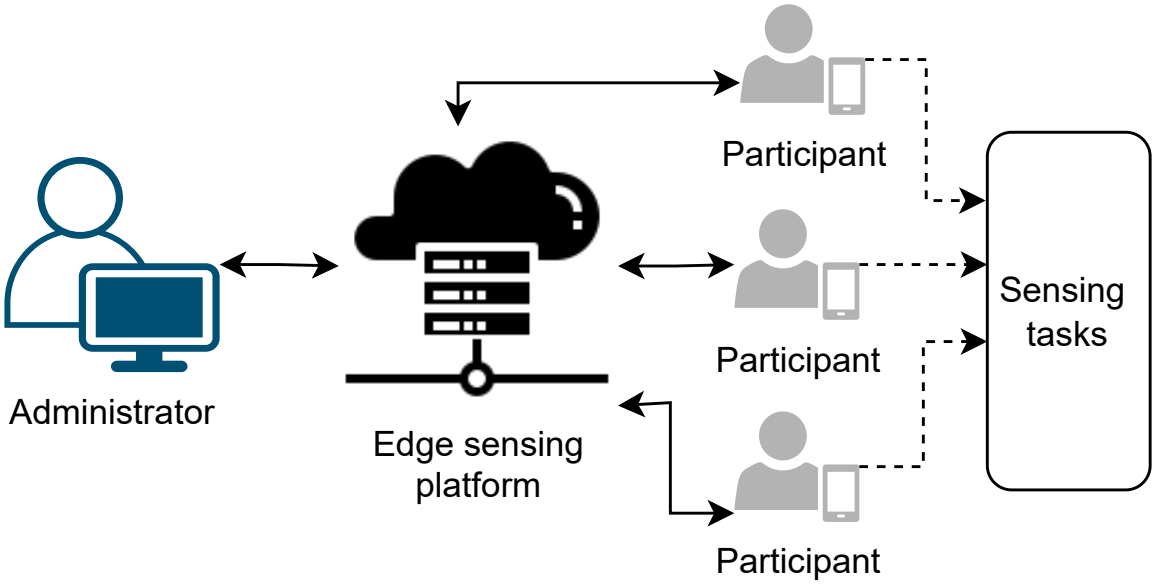

Figure 2.1: EES Architecture

edge computing paradigms. Further catalyzing EES's evolution have been significant advancements in hardware technology, particularly the rise and spread of smartphones and wearable devices over the past two decades. These elements collectively have redefined the data collection, processing, and analysis, marking a departure from traditional sensing models and establishing a new paradigm in EES. In EES, *sensing* transcends the traditional boundaries of merely capturing physical phenomena or relying on virtual sensors for data interpretation. It encompasses the integration of intelligent processing, the dynamic nature of sensor deployment (mobility), and reduced cost since the sensing infrastructure is the participants' smartphones. This paradigm shift has made EES an invaluable tool for public safety, emergency, and crisis response, as well as unlocking many potential applications ranging from environmental monitoring to recognizing incidents.

Similar to MCS, 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. 2.1. The EES system is initiated by the administrator, who sets the objectives, defines data collection parameters and sensing tasks, and selects the phenomena to be monitored. This role is critical for smart city management to meet operational needs efficiently.

EES participants are individuals from the community who engage with EES by performing tasks specified by the system's administrator. These tasks are undertaken in exchange for rewards, which may be services or monetary incentives. Participation by these individuals can occur in two distinct manners: firstly, through participatory involvement, where participants actively engage in and complete the tasks; and secondly, through opportunistic involvement, where the presence of participants at specific locations and times enables the automatic execution of tasks, often through sensors in devices they carry. This approach allows for a flexible and efficient method of data collection and processing, leveraging the crowd's potential for a broad spectrum of information gathering.

The EES platform is the critical infrastructure enabling interaction between EES administrators and participants. It automates the deployment of EES campaigns by providing a central platform for administrators to recruit participants, assign tasks, and evaluate their performance, reliability, and QoD. This platform is used for task distribution and serves as the main center for data aggregation, processing, and analysis, establishing itself as a centralized hub for most of EES activities. It provides an efficient and effective mechanism for managing the dynamic workflow of EES campaigns, from task assignment to data utilization, streamlining the collaborative efforts of administrators and participants to achieve the campaign's goals.

The term "sensing tasks" encompasses many activities, particularly in the context of technologies akin to EES, which boasts diverse applications. In essence, a sensing task refers to the directive issued by the administrator to participants via the platform, outlining specific data collection objectives. Given the diverse nature of these tasks, the requirements associated with each can significantly differ, introducing a layer of complexity to EES systems. These systems are thus tasked with adapting to accommodate the varied demands of each sensing task. This challenge that underscores the need for flexible and robust system design to ensure seamless operation across various applications.

2.2 Literature Review

2.2.1 Quality in EES

Evaluating the effectiveness of EES systems involves a multi-faceted analysis, where quality is perceived through various lenses, leading to diverse interpretations. This variability stems from the broad spectrum of EES applications, each with distinct objectives and, unique benchmarks for quality and performance. For example, EES systems deployed in emergency scenarios prioritize swift task execution within tight deadlines as critical quality indicators. In contrast, applications less urgent by nature may afford to deprioritize speed in favor of other quality metrics, showcasing the adaptability of quality standards across different EES implementations.

At the heart of this challenge is the heterogeneity in user expertise and device capabilities, which introduces a non-trivial risk of data inaccuracies. Such variability, inherent in the user-centric architecture of EES systems, potentially compromises QoD, a cornerstone of system reliability. The ultimate goal of EES systems is to

accurately reflect users' environments, necessitating high QoD and extensive system coverage. This dual requirement aims to ensure that tasks are not only completed but are done so with a level of quality that leaves no room for system blind spots.

This section reviews previous literature on the quality of EES systems, emphasizing the different perspectives and challenges associated with evaluating effectiveness in various application scenarios. It explores how different benchmarks for quality and performance are shaped by the specific objectives of EES implementations, from critical emergency response to less urgent applications.

Amidst these challenges, [10] introduces an approach to improving IoT data quality in MCS through a cross-validation technique. The method capitalizes on the power of crowds by employing a validating crowd to assess and improve the data quality provided by a contributing crowd. This strategy utilizes a weighted random oversampling and a privacy-aware, trust-oriented probabilistic push algorithm to enhance the credibility of data without requiring extensive redesign of existing systems. While this approach allows for significant improvements in data quality by integrating crowdsourced validation effectively, it relies heavily on the availability of a cooperative and diverse validating crowd and the sophistication of its probabilistic models, which may pose challenges in terms of scalability and practical implementation in highly dynamic environments.

Building on the theme of leveraging community dynamics for quality assurance in MCS, [11] explores a strategy that leverages social network interactions. The authors propose a crowd sensing approach using social network-aided collaborative trust scores to guarantee data quality in MCS systems. This method harnesses the connections within social networks to evaluate the trustworthiness of data collected

from users, integrating statistical and social trust metrics. The work uses the social network theory, which allows participants connected through common tasks to vote on each other's reputation, thereby enhancing the credibility and reliability of the data. Similar to the approach by [10], this method seeks to harness the collective power of groups, focusing more directly on the relational dynamics among participants. It also presents its own set of challenges in maintaining consistent data quality across diverse and large-scale deployments.

Further leveraging social networks for quality assurance, [12] propose a methodology that intensifies the focus on collaborative trust within social networks to enhance data quality in MCS systems. The approach employs a dual mechanism that not assesses direct feedback from task outcomes and capitalizes on indirect social endorsements within the user community. This multi-layered evaluation strategy utilizes the interrelations of social networks to derive more accurate trust scores for users, effectively predicting and enhancing the quality of data submissions. However, the reliance on the structure and strength of social connections, which may vary across different communities and demographics, could pose challenges to the system, echoing the complexities observed in the strategy presented in [11].

Addressing data quality challenges in scenarios marked by data scarcity [13] presents an approach to estimating data quality in MCS systems, particularly under scarce data. The study introduces two quality metrics designed to assess and ensure the reliability of data collected from sparse scenarios. These metrics leverage statistical techniques to evaluate data quality dynamically, accounting for the small scale and potential errors inherent in MCS data collection. The methodology focuses on the practical application of these metrics within smart city frameworks, aiming to

enhance the decision-making processes by providing reliable data despite the limited availability of sensor readings. However, the effectiveness of these metrics heavily relies on their precision in statistical estimation and the assumptions about data distribution, which might not always hold in highly dynamic urban environments.

Similarly, [14] introduces a quality metric tailored for MCS systems with limited data availability due to sparse participant engagement. Through the analytical comparison between trimmed mean and median absolute deviation (MAD) filtered mean, this metric facilitates effective outlier detection and quality estimation under constrained sample conditions. Introducing a sensitivity parameter within this metric allows system administrators to fine-tune accuracy and manage accepted value ranges, directly addressing the heterogeneity and potential inaccuracies inherent in participant-contributed sensor data. This metric complements the earlier work [13], extending the utility of quality assessments to environments characterized by data scarcity and variable participant activity.

Designing incentive schemes to maintain proper quality is another common approach, [15] addresses data quality challenges in MCS systems by developing a reputation-based incentive mechanism for credible caching device selection. This approach leverages the quality of data users provide as a key metric for determining their reliability as caching candidates, enhancing service efficiency and data credibility. Specifically, the system employs a quality-aware user reputation model that uses previous data submissions to predict future data reliability, thereby guiding the selection of caching candidates. This evaluation is performed through a reputation algorithm that updates user scores based on the accuracy and utility of their data submissions compared to established quality benchmarks. While this method ties data quality directly to user

incentivization, enhancing data reliability and system performance, it depends on the continuous accuracy of behavior predictions, which may vary with user compliance and environmental factors.

Building upon the principle of tying incentives directly to data quality, [16] introduces the Thanos incentive mechanism, which enhances data quality in MCS systems by considering the quality of information (QoI) alongside traditional incentive models. The Thanos mechanism utilizes a reverse combinatorial auction approach where data buyers reward participants for their participation and the quality of the data they provide. This approach is particularly significant as it aligns participant incentives with the quality rather than quantity of data, addressing the critical data reliability in crowd-sensed information. The framework is designed to be efficient and to ensure that participants are truthful in revealing their data quality, using game-theoretic approaches to maintain a close-to-optimal social welfare outcome. Unlike the approach by [15] , which emphasizes a predictive model based on past user behavior, the Thanos mechanism integrates a more dynamic and market-driven approach that actively engages buyers and sellers in setting the value of data, potentially offering more immediate adaptability to changing data quality scenarios. However, the reliance on participants' honest data quality reporting and the complexity of implementing a reverse auction could pose practical challenges in deploying such a system on a large scale.

The work in [17] addresses the quality of sensing service in MCS networks through a trust-driven contract incentive scheme. The scheme in [17] addresses data reliability by integrating a trust evaluation mechanism that assesses the credibility of mobile users and platforms based on their past interactions. The system effectively excludes

unreliable or malicious participants by setting a trust threshold. Furthermore, the framework incorporates privacy preferences into the incentive contracts, optimizing users' and platforms' engagement and utility. This dual approach ensures the quality and reliability of the collected data and addresses the challenges of participant incentive compatibility and individual rationality within MCS environments. However, the model's dependency on accurate historical interaction data and the complexity of managing continuous trust assessments could pose implementation challenges.

From a different perspective, [18] proposes a data collection mechanism to enhance the quality of MCS systems by integrating a predictive model that forecasts the quality of data a participant can contribute. This mechanism employs the Binomial-Poisson distribution to estimate the likelihood of high-quality data submission before actually receiving the data, a method that contrasts sharply with traditional approaches that only assess data quality post-submission. Specifically, this model predicts the amount of high-quality data each participant will likely generate by applying an expectation maximization algorithm to optimize the distribution parameters. Although this approach potentially improves data quality and efficiency by filtering participants based on predicted data quality contributions, it depends on the accuracy of the predictive model, which can be significantly affected by the variability in participant behavior and environmental factors.

Lastly, [19] tackles the challenges of maintaining high data quality in MCS systems enhanced by mobile edge computing (MEC). The paper introduces a quality-aware sparse data collection algorithm that optimizes data collection by reducing redundancy and ensuring comprehensive spatiotemporal coverage. The approach leverages the implicit correlation among data points and uses compressive sensing techniques to

efficiently reconstruct high-quality data from sparse inputs. This method addresses the issue of users' unpredictable mobility by predicting data quality in real time, enabling dynamic task allocation to users based on their predicted data contribution quality and location. However, the dependency on precise real time data analytics and the complexities involved in managing the computational aspects of CS and implicit correlation analysis could pose challenges, particularly in scaling this approach in highly dynamic environments.

Exploring the quality domain within EES systems reveals a diverse landscape of application-specific demands and challenges in maintaining data integrity. The literature reviewed here presents a spectrum of innovative solutions, from robust data validation frameworks to dynamic incentive schemes, each contributing uniquely to the advancement of EES systems. As the domain evolves, ensuring high-quality data collection and fostering participant engagement remain paramount for researchers and practitioners. Through continued collaboration and innovation, we can address these challenges and propel the field of EES forward.

2.2.2 Users' Mobility in EES

Building upon our examination of EES systems' quality, we now focus on another aspect: user mobility. The unique mobility patterns of users play a pivotal role in shaping the effectiveness of EES systems, influencing factors such as QoD, task allocation, and overall system performance. Recognizing the impact of user mobility, it becomes imperative to look into how this dynamic factor shapes the operational dynamics of EES systems. In the following discussion, we will explore the existing literature on

this subject, highlighting studies that contribute to enhancing spatiotemporal coverage and addressing the challenges posed by user mobility within EES systems. The aim is to gain a deeper understanding of the relationship between user mobility and the operational efficiency of EES systems.

In their analytical work, [20] leverage detailed human mobility patterns from the ParticipAct data set to refine MCS strategies, emphasizing the importance of understanding spatial and temporal user behaviors for task allocation and scheduling. By analyzing metrics like the radius of gyration and location entropy, this method refines MCS task deployment, ensuring tasks are issued to users within the correct context, although it relies on the accuracy and completeness of mobility data.

To address the influence of mobility on task assignment, [21] presents a utility-based subcontracting method for optimizing task allocation in MCS by addressing the dynamic and unpredictable nature of user mobility. This approach employs a Markov chain-based mobility model to predict the movement patterns of participants, allowing for strategic task distribution among nodes (users) expected to be in key locations at future times. By integrating these predictions with a utility function that evaluates each node's potential data collection capacity, the system can subcontract tasks to those most likely to fulfill them effectively. This method enhances the quality and coverage of collected data. However, the reliance on accurate mobility predictions and the complexity of calculating utility functions introduce challenges, particularly in scenarios with rapid changes in participant movement patterns.

Further enhancing task allocation efficiency, [22] addresses the challenge of unpredictable user mobility in MCS with IncentMe, employing a game-theoretical reverse

auction for task allocation. The framework dynamically aligns tasks with participants based on bids, reflecting their mobility and willingness to perform tasks, thus optimizing task distribution for improved data collection reliability. However, its dependency on complex computational models and the assumption of participant honesty in bidding introduces potential limitations.

Building upon the understanding that user mobility complicates traditional sensing paradigms, [23] introduces the iLOCuS strategy. This approach optimizes sensing distribution in vehicular crowd sensing systems, encouraging vehicle mobility towards less-sensed areas to counteract the natural congregation in busy areas. Formulated as a non-linear multiple-choice knapsack problem, iLOCuS employs a tailored incentive mechanism, blending monetary rewards with task-specific requests, thereby aligning vehicle agents' motivations with the overarching goals of crowd sensing. This strategy reconciles divergent objectives and significantly enhances data collection coverage and quality, marking a critical advancement in the field.

Expanding on dynamic task allocation in vehicular contexts, [24] optimizes participant recruitment by harnessing predictable mobility. This work introduces a strategy that considers future vehicle trajectories, enhancing spatiotemporal data collection coverage. By utilizing a semi-Markov process based on historical data, this predictive recruitment framework effectively addresses the limitations of static methods in dynamic urban environments. However, it also introduces computational complexities due to its dependency on accurate trajectory predictions and real-time data analysis.

Similarly, [25] explores the dynamic management of mobile crowds to achieve uniform spatialtemporal coverage, especially within vehicular crowd sensing. The authors propose a probabilistic control mechanism that dynamically adjusts incentives

for participants, without requiring prior knowledge about their mobility patterns. This model leverages real-time data on participant density and vehicle movements to probabilistically allocate tasks, aiming to maintain a balanced distribution of tasks across different areas and times. This approach adapts to the varying density of vehicles and ensures broad coverage, it introduces computational complexity due to the need for ongoing real-time data analysis and the probabilistic nature of task allocation.

Mobility prediction is a commonly used approach in addressing mobility challenges, [26] explores user mobility prediction within the "Buy4Me" delivery system, utilizing a probability-based model that considers historical trajectory data. The system predicts future movements by analyzing past location patterns, to forecast likely user encounters at specific venues. This prediction is essential for determining the feasibility of friends completing delivery tasks without significant detours. Despite this strategic approach, the model's accuracy depends on the availability and quality of historical data, which may not consistently capture the complex variables influencing human mobility.

Further exploring predictive models, [27] presents PURE, a strategy for enhancing MCS efficiency by focusing on user mobility through a semi-Markov process to forecast mobility trajectories. This model categorizes users into distinct pricing plans, aiming to reduce data uploading costs by dynamically optimizing the recruitment of participants based on real-time data on users' locations and movements, which minimizes unnecessary data transmission costs.

An online scheduling framework is proposed in [28] to address the complexities of

managing the spatiotemporal aspects of data collection in urban sensing. By utilizing real-time updates on participants' locations and their devices' sensing capabilities, the framework selectively activates sensors where and when they are most needed, adapting to the ever-changing urban landscape. This activation aims to maximize data coverage and utility while minimizing redundancy, addressing the inherent challenges of participant mobility and urban dynamics. However, the methodology's real time dependence introduces a layer of computational complexity, requiring continuous processing of variable data streams to make immediate scheduling decisions. The framework's reliance on precise, up-to-the-minute data and the calculations involved highlight potential challenges in scalability and efficiency.

The exploration of user mobility within EES systems reveals a dynamic landscape characterized by challenges and innovation opportunities. The literature provides diverse strategies and solutions, from optimizing sensing distributions to leveraging mobility patterns for enhanced coverage and data quality. As EES systems evolve, these insights will play a crucial role in shaping future developments, ensuring systems remain effective and adaptable to the dynamic interplay of user mobility and environmental demands. Moreover, the identified gap in understanding the impacts of mobility patterns across different urban contexts suggests a promising avenue for further research. Future studies may yield more refined and scalable EES solutions tailored to specific urban environmentsby addressing this gap.

2.2.3 Incentive Schemes in EES

Continuing our work on EES systems, we now pivot towards incentive schemes. Incentive schemes serve as a cornerstone in the operational success of EES systems,

addressing the pivotal challenge of motivating user participation under varying constraints. This subsection delves into how research navigates the delicate balance between incentivization and resource optimization, shedding light on strategies and approaches aimed at fostering user engagement and maximizing system efficiency. By examining the evolving landscape of incentive schemes within EES systems, we aim to gain insights into the mechanisms that drive user participation and contribute to the overall effectiveness of these systems.

A location-based incentive mechanism for participatory sensing systems is presented in [29]. This mechanism utilizes a reverse auction format where users submit their data collection bids, and the system selects the most cost-effective bids while ensuring broad geographic coverage. The mechanism considers the lowest bids by integrating a greedy budgeted maximum coverage (GBMC) algorithm. It prioritizes the geographic distribution of the data collectors to maximize area coverage within the constrained budget. This dual focus on cost and coverage enhances the utility and efficiency of data collection efforts. However, users' reliance on strategic bid placement and the system's ability to accurately assess geographic coverage can pose challenges, particularly in environments with highly dynamic user distributions or irregular geographic data collection needs.

Expanding on similar principles of adaptive and spatially aware incentive design, [30] introduces a dynamic, demand-driven incentive mechanism for MCS systems, specifically tailored to address the unique challenges posed by location-dependent tasks. This mechanism dynamically adjusts the rewards for tasks based on real-time demand, which is calculated using a demand indicator that considers factors such as task deadline, completion progress, and the number of potential participants. By

doing so, it aims to balance the popularity of tasks, ensuring that even those in less favorable locations are completed timely. The approach differs from fixed-reward systems that do not account for tasks' fluctuating demand and popularity due to their spatial distribution. The authors use an analytic hierarchy process for reward calculation, allowing for precise adjustments that are responsive to the evolving needs of the system. However, the complexity of dynamically adjusting incentives and the dependence on accurate real-time data could introduce challenges in scalability and execution.

Similarly, [31] introduces a budget constraint incentive mechanism for spatial-temporal MCS, aiming to efficiently allocate tasks within a limited budget while ensuring broad geographic coverage. The mechanism applies a sub-module approximation algorithm for participant recruitment, designed to solve this NP-hard problem by selecting the most cost-effective user bids that satisfy spatial and temporal task requirements. Additionally, it employs a winner auction algorithm (WAA) based on the reverse auction concept, which allocates critical payments and ensures that the system maintains truthfulness, individual rationality, and high computational efficiency. Using logistic regression to analyze user preferences from historical data further refines task matching, making the system dynamically responsive to changing conditions and user availability, thereby enhancing the overall effectiveness of the crowd sensing effort. However, the reliance on precise logistic modeling and the challenges of coordinating such a complex system in real time could present operational challenges.

In a different approach to enhancing user engagement, the research in [32] presents a task-bundling-based incentive mechanism for location-dependent MCS systems,

which strategically bundles tasks with varying popularity to address the participation unbalance problem. This mechanism dynamically bundles high-popularity (hot) tasks with low-popularity (cold) tasks, encouraging workers to undertake a mix of tasks to receive rewards, thus ensuring a more equitable distribution of task participation across the system. The bundling process analyzes real-time data on task popularity from previous rounds to adjust task groupings continually, aiming to balance the workload among participants and maximize task completion rates. Additionally, the system considers the geographic proximity of tasks within each bundle to minimize travel requirements, thereby enhancing the feasibility of task completion based on users' locations. However, the effectiveness of this strategy relies on the accurate categorization of tasks into hot and cold, and the dynamic nature of task popularity might introduce complexities in maintaining consistent incentive structures, potentially affecting long-term participant engagement.

Another highlighted incentive mechanism is shown in their study [33], which introduces a two-stage task-bundling-based incentive mechanism for mobile crowd sensing that effectively enhances participation by combining smaller tasks into bundles. This method allows aggregating of budgets from several smaller tasks, making it financially viable for users to participate and complete the bundled tasks. By leveraging the group buying concept, the mechanism ensures that even tasks with smaller individual budgets become attractive through cumulative financial incentives. The system utilizes an algorithm that assesses the compatibility of tasks within a bundle based on their location and required completion time to maximize efficiency and attractiveness to potential participants. The system operates by having agents represent bundles of tasks, who then engage in a double auction to match these bundled tasks with

suitable users. This approach, similar to [32] in its use of task bundling to increase incentive attractiveness, differs by integrating a more sophisticated auction-based matching system that enhances budget efficiency and aligns participant capabilities more closely with task requirements. This method increases the probability of task completion and maintains budget efficiency and participant fairness. However, the complexity of managing multiple task bundles and ensuring truthful participation from all stakeholders poses significant challenges.

Utilizing incentives for quality enhancement is a commonly used approach in the literature. The authors in [34] introduce an incentive mechanism for MCS systems, focusing on the integrating levels and data quality to ensure high-quality data collection. The work presents a data quality and bid-based incentive mechanism, which selects winners based on a reverse auction that considers the data quality submitted by users and their bid amounts. This dual-focus approach not only maximizes the benefit of the platform by choosing users who offer high-quality data at lower bids but also ensures that data quality is dynamically updated based on the actual quality of data submitted. The mechanism is designed to be truthful and computationally efficient, encouraging user participation by providing monetary incentives reflecting their effort in data collection and quality . However, the dependency on users' honest data quality reporting and the complexity of implementing such a comprehensive auction system could pose challenges in real-world applications.

Similarly, [35] introduces an incentive mechanism based on reputation and trust to mitigate the adverse effects of selfish behavior in MCS networks. The mechanism, named RTM, integrates reputation and trust assessments to influence node behavior. It calculates service quality, link reliability, and time heat factors to determine

comprehensive pricing for rewarding service providers. This approach uses real-time performance metrics to dynamically adjust incentives, ensuring higher rewards go to nodes demonstrating reliable and quality service delivery.

Moreover, the study in [36] introduces QUOIN, an incentive mechanism for crowd sensing networks that ensures binformation quality and usability. This mechanism employs a market-based approach underpinned by a Stackelberg game model [37], which balances the interests of data collectors, service providers, and consumers. QUOIN sets prices based on the quality and quantity of data submitted, using dynamic pricing to encourage higher-quality data submissions and optimal resource allocation. Specifically, it utilizes variable pricing that adjusts based on real-time data quality assessments, incentivizing participants to continuously improve the quality of their submissions to maximize their rewards. This system also ensures that the data collected is not only of high quality but also usable for the intended applications, addressing key challenges in crowd sensing such as the participation of volunteers and the effectiveness of data collection. The incentive model optimizes interactions among stakeholders to maintain a satisfactory level of profits and active participation. However, it depends on the correct setting of game parameters and the alignment of incentives with real-world data demands and user behaviors.

Moreover, when considering incentivization, [38] presents the utility-maximization incentive mechanism (UMIM), which is designed to optimize incentives in MCS systems by maximizing the utility of data collected through a reinforcement learning approach. This mechanism leverages the influence propagation within social networks, where the utility derived from shared data acts as a non-monetary incentive, reducing the need for direct payments and effectively lowering overall incentive costs.

Specifically, the UMIM approach utilizes a deep reinforcement learning model using the proximal policy optimization algorithm enhanced with a priority experience replay mechanism, which adjusts incentive strategies dynamically based on evolving participant engagement and data utility. This dynamic adjustment allows for more efficient resource allocation and ensures higher quality data collection by incentivizing only the most valuable contributions. The approach contrasts with traditional incentive mechanisms that do not account for the changing scale of participant numbers and their associated costs, which can lead to unsustainable incentive strategies in large-scale MCS deployments.

Additionally, the work presented in [39] is a pricing-based incentive mechanism for edge-cloud collaboration in MCS systems, which optimally integrates EC to enhance data efficiency and social welfare. The two-stage game design involves a bargaining game between users and edge-cloud servers and a data trading game among regional edge-cloud servers. A dynamic bargaining algorithm based on the Stackelberg and Rubinstein models is utilized in the first stage, allowing for strategic price negotiation that benefits users and servers. The second stage employs a quasi-Newton iterative pricing algorithm to optimize data trading prices across servers, ensuring optimal distribution of resources and maximizing overall system utility. However, this complex game-theoretical framework relies heavily on accurate data trading and bargaining dynamics, which may introduce significant challenges in scenarios with less predictable user behavior and fluctuating data needs.

Furthermore, the work in [40] presents an incentive mechanism that focuses on dynamic pricing and historical participation to optimize user engagement in MCS. This system uses a reverse auction with dynamic pricing influenced by a virtual

participation credit (RADP-VPC), which encourages continuous user participation by accounting for past bidding behavior and frequency of participation. This historical data is used to adjust incentives, rewarding consistent participants with better chances in future bids, thereby maintaining an active user base and preventing incentive cost explosions, such as situations where few participants drive up the bid prices due to reduced competition.

Exploring the literature reveals the pivotal role of incentive schemes in EES systems, crucial for aligning user participation with system efficiency and data quality. The methodologies discussed herein signify substantial advancements in the field, from harnessing geographical positioning to navigating budget constraints and integrating social dynamics and trust evaluations. As EES systems continue their evolution, these insights serve as a foundational framework for future research endeavors. Further refinement of incentive schemes is key to ensuring their adaptability and effectiveness in the face of evolving user behaviors and technological advancements. Moreover, effective incentive mechanisms not only enhance the operational efficiency of EES systems but also carry profound implications for their scalability and long-term sustainability in diverse application contexts.

2.2.4 Machine Learning in EES

Concluding our exploration beyond incentive schemes in EES systems, our attention now shifts to the integration of ML, marking the final section of this chapter. Integrating of ML into EES and crowd sensing represents a pivotal advancement in addressing the myriad of challenges these systems face. This subsection explores the innovative applications of ML models within the literature, highlighting how they

enhance system efficiency, data quality, and user engagement. By exploring the intersection of ML and EES, we aim to uncover the transformative potential of these technologies in overcoming obstacles and driving advancements in the field.

Addressing the pivotal challenge of data trustworthiness in MCS systems, an approach presented in [41] named EndorTrust. EndorTrust blends crowdsourcing with a reputation-based system that leverages worker endorsements to evaluate and predict the quality of contributions. By employing ML to account for the diversity in tasks and participant skills, EndorTrust enhances the trustworthiness of crowdsourced data. This system's dynamic adjustment of endorsement strengths, predicated on actual performance, ensures the accurate prediction of contributors' reliability. This method addresses critical issues such as the investment of effort into low-quality contributions, encouraging the provision of high-quality data.

Meanwhile, another approach presented in [42] introduces a federated learning-based methodology to elevate data quality in MCS. This approach utilizes a lightweight neural network model deployed on mobile devices that dynamically recruits users for tasks based on contextual factors such as time and location. Outperforming established algorithms like RAGUR and CATA, this strategy underscores the impact of contextual elements on data quality. The fusion of advanced AI techniques with privacy-preserving mechanisms presents a direction for optimizing user recruitment in MCS, showcasing enhancements in data quality.

Furthermore, [43]'s false sequential data (FSD) framework employs deep learning techniques to address vulnerabilities to malicious inputs and sensor inaccuracies. FSD, through a combination of LSTMs and conventional ML classifiers, authenticates data against various attack scenarios. This framework highlights the potential

of DL to enhance MCS data integrity. FSD's approach, without presupposing data source trustworthiness, promises enhanced security and reliability for IoT-driven data collection in smart applications.

Moreover, authors in [44] propose integrating federated learning with MCS to navigate the complexities of privacy and data reliability. By enabling collaborative learning among mobile devices without the need to share raw data, F-Sense preserves user privacy while fostering a cooperative learning environment. Accompanied by an incentive mechanism that rewards participants based on the qualitt of their contributions' , F-Sense specifically addresses MCS challenges, enhancing task efficiency and participant motivation.

The literature explores the role of ML models in improving task assignment strategies. In this context, a task allocation in MCS is described in [6] by presenting a method that employs fuzzy logic to predict participants' movements accurately. This approach surpasses traditional probabilistic models by accounting for daily movement variabilities among workers, thus facilitating precise task allocation across spatial and temporal dimensions. Validated by real-world datasets, this methodology significantly boosts task completion rates and establishes fuzzy logic as a groundbreaking tool in MCS, opening new avenues for research and system optimization.

Similarly, [45]'s ESTA scheme applies federated learning to MCS task allocation, ensuring data privacy and operational efficiency. ESTA adeptly navigates the intricacies of privacy risks and task allocation inefficiency by predicting user distribution and selecting high-quality data based on trust evaluations. This scheme's integration of user distribution forecasts and trust assessments not only secures quality data collection but also exemplifies the strategic management of MCS challenges through

ML.

Moreover, an MCS framework is proposed in [46] for ensuring reliable service delivery on the network's edge and cost-efficient operations in MCS systems. They introduced key components such as an RVRP auction-based recruitment scheme and a CNN-based data detection scheme. A case study on smart transportation demonstrated the framework's effectiveness. However, there are clear challenges, such as the computational overhead of deep learning, particularly in dynamic environments where training data requirements are non-static. Tackling this challenge of dynamic environments, researchers in [47] present CountMeIn, an adaptive machine learning system for crowd estimation in smart cities using Wi-Fi and street cameras. CountMeIn improves accuracy by transferring calibration tasks from cameras to machine learning. Results from a pilot study show significant error reductions compared to other known methods. However, it is noted that the system measures estimated numbers rather than exact numbers, which may not be suitable for certain applications like airport security.

Similarly, a new crowd density observation system is tackled in [48], measuring cellular signal strength to estimate crowd density. Deep neural networks are employed for analysis, achieving an accuracy of about 78% in distinguishing crowd density stages. This approach offers a privacy-friendly alternative to camera-based systems, but does not eliminate the issue of reliability due to inaccuracies. The work in [49] also uses Wi-Fi and introduces Wi-CaL, a system utilizing WiFi channel state information for simultaneous crowd counting and localization. The evaluation shows a 91.4% localization accuracy with five people in a small room. Comparisons with existing metrics demonstrate improved performance. In addition to highlighting the potential

of WiFi CSI for crowd estimation and comparing conventional machine learning and deep learning approaches, the authors assert that while their system shows promise in estimating larger crowd sizes, further practical evidence is needed to extend its applicability to estimating massive crowds.

The exploration of ML applications within EES and crowd sensing systems reveals a dynamic landscape of technological innovations to overcome existing challenges. From reputation-based systems and federated learning to applying fuzzy logic and DL techniques, the contributions discussed significantly advance the fields of EES and crowd sensing. These advancements not only enhance data quality, system efficiency, and user engagement but also pave the way for future research, underscoring the transformative potential of ML in shaping the future of crowd sensing and edge computing technologies.

2.2.5 Summary

While most works are interesting, our research adopts a comprehensive methodology designed to optimize the performance of EES systems. Our approach considers the inherent challenges of user heterogeneity, mobility, and availability, integrating advanced ML techniques to enhance incentive mechanisms dynamically. We deploy a multi-faceted strategy that addresses the QoD and ensures efficient system scalability and user engagement under varying operational conditions. Table 2.1 shows the literature reviewed by research objectives and associated references.

Objective Description	References
Enhancing data quality through crowdsourcing	[10], [11]
Leveraging social networks for quality assurance	[12]
Quality metrics in sparse data environments	[13], [14]
Incentive schemes to enhance data quality	[15], [16], [17]
Predictive models for data quality assessment	[18], [19]
Enhancing spatiotemporal coverage based on users' mobility	[23], [24], [25]
Predictive mobility models for improved data management	[26], [27]
Task allocation efficiency through mobility insights	[20], [21], [22], [28]
Enhancing data trustworthiness and quality using ML	[41], [42], [44]
Improving system security and data integrity using ML	[43]
Optimizing task allocation and efficiency using ML	[6], [45]
Advancing urban crowd estimation and localization using ML	[46], [47], [48], [49]
Incentives for spatiotemporal coverage	[29], [30], [31]
Task participation and data quality incentives	[32], [33], [34], [35], [36]
Incentive optimization	[38], [39], [40]

Table 2.1: Literature summary

Chapter 3

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

We utilize the RWP model to simulate participant mobility. The RWP model, randomly assigns destinations and speeds within a specified area, integrating pauses to reflect real-life movement. Its primary advantage for EES research lies in abstracting complex human movements into manageable forms, making them suitable across various environments. The RWP model strikes an essential balance, understanding mobility's impact on EES systems without the details of specific behaviors or geography. This methodology ensures that our EES framework is flexible and realistic, providing a solid foundation for enhancing system design and performance analysis.

3.1 System Model

The proposed system takes into account the heterogeneity of available users by categorizing them into classes according to the QoD they provide and the associated incentive costs for each class. This classification allows the system to optimize the incentive scheme and user recruitment based on the cost/quality trade-off, aiming to

meet the minimum required quality $Q^{\mathtt{t}}_{\min}$ of each task t at the lowest possible cost. The EES system being considered consists of N_{total} users distributed across the AoI. However, users' ability to complete the sensing task can be influenced by their mobility [50]. To address this, we propose a corrected user count N_{m} that considers their movement speeds. This corrected user count is crucial because users with high velocities may face difficulties in ensuring the successfully completing the sensing task.

The existence of users within the system does not necessarily imply their availability or willingness to perform the sensing task; we denote the set of available users as $N^{\mathtt{k}}_{\text{n}} = \{[u^1_1, u^1_2, ..., u^1_{\text{n}}], [u^2_1, u^2_2, ..., u^2_{\text{n}}], ..., [u^{\mathtt{k}}_1, u^{\mathtt{k}}_2, ..., u^{\mathtt{k}}_{\text{n}}]\}$, which shows the count of users n in different classes k who are available to perform the sensing tasks, and the summation over all n and k is always less or equal to N_{m}. The set of sensing tasks is defined as $T = \{t_1, t_2, t_3, ..., t_t\}$, where each task $t \in T$ has a different sensing duration based on its nature. Available users are expected to complete the entire sensing duration of the task before sharing the collected data. Furthermore, the minimum required quality $Q^{\mathtt{t}}_{\min}$ varies for each task, reflecting the varying levels of importance among different sensing tasks.

The AoI is $X_{\text{AoI}} \times Y_{\text{AoI}}$ dimensions, and it is divided into L subcells to study the distribution of users over the entire AoI. Users are considered to follow the widely known 2-dimensional RWP model to assess the mobility effects [50].

3.2 Analyzing User Mobility's Impact on Extreme Edge Sensing System Quality

For a user executing RWP movement along a line $[0, X_{\text{AoI}}]$, their location (x) can be depicted by the probability density function (PDF)[51]

$$f_X(x) = -\frac{6}{X_{\text{AoI}}^3}x^2 + \frac{6}{X_{\text{AoI}}^2}x \tag{3.1}$$

The 1D PDF needs to be transformed into 2D to accommodate square-shaped subcells. This transformation considers two separate 1D movements: one along the x-axis and another along the y-axis, as Eqn. (3.2) shows.

$$p = \int_{y^\circ}^{y^\circ+\bigtriangledown} \int_{x^\circ}^{x^\circ+\bigtriangledown} \left(\frac{-6x^2}{{X_{\text{AoI}}}^3} + \frac{6x}{{X_{\text{AoI}}}^2}\right) \times \left(\frac{-6y^2}{{Y_{\text{AoI}}}^3} + \frac{6y}{{Y_{\text{AoI}}}^2}\right) dxdy \tag{3.2}$$

By solving Eqn.(3.2), the probability p that a user is present in the subcell is formulated, with y°, $y^\circ + \bigtriangledown$, x° and $x^\circ + \bigtriangledown$ representing the borders of the subcells. The probability is obtained in Eqn.(3.3).

$$\begin{aligned} p = &\left(\frac{-2((y^\circ+\bigtriangledown)^3 - (y^\circ)^3)}{{Y_{\text{AoI}}}^3} + \frac{3((y^\circ+\bigtriangledown)^2 - (y^\circ)^2)}{{Y_{\text{AoI}}}^2}\right) \\ &\times \left(\frac{-2((x^\circ+\bigtriangledown)^3 - (x^\circ)^3)}{{X_{\text{AoI}}}^3} + \frac{3((x^\circ+\bigtriangledown)^2 - (x^\circ)^2)}{X_{\text{AoI}}^2}\right) \end{aligned} \tag{3.3}$$

The system's reliability needs to be ensured by addressing users' mobility. Task completion becomes constrained by space and time when users are in motion. Therefore, it is necessary to employ an appropriate approach that accounts for the impact of mobility on Eqn. (3.3). Since users may not always be able to complete tasks due to their mobility, it is important to quantify this impact. N_m provides a more precise estimation of the number of users considered suitable for allocation to the sensing tasks, as it takes into account the impact of mobility on users' spatial positioning.

Assuming that within a subcell, the distance a user travels is uniformly distributed, ranging from $D_{\min}$ to $D_{\max}$, where $D_{\max}$ represents the maximum possible travel

distance within a subcell. With users moving at a fixed speed, the time spent in the subcell is inversely proportional to this speed. Based on the application of the EES system, a time threshold to guarantee task completion should be specified. For instance, emergency applications have strict time constraints on sensing compared to environmental monitoring. The velocity threshold can be created from the time threshold.

To improve the system's performance by giving tasks to users who will take the appropriate time to finish them, it is, therefore, necessary to consider a threshold for user velocity. The quality metric's performance will be enhanced considering of the corrected number of users, as it will provide a more accurate user number after removing users with higher velocities and lower task completion rates. The corrected number of users N_m is then formulated as

$$N_{\mathrm{m}} = N_{\mathrm{total}} \left(1 - \frac{V_{\max} - V_{\mathrm{th}}}{V_{\max} - V_{\min}}\right) \tag{3.4}$$

where $V_{\max}$ and $V_{\min}$ are the maximum and minimum velocities of users, respectively, and V_{th} is the velocity threshold. Driving the system to extreme values of $V_{\mathrm{th}} = V_{\max}$ or $V_{\mathrm{th}} = V_{\min}$ will result in logical results.

To further enhance the estimation of the number of users, the LSTM model is utilized to predict the number of users $N_{\mathrm{n}}^{\mathtt{k}}$ based on their historical data and availability pattern. The prediction of $N_{\mathrm{n}}^{\mathtt{k}}$ will enable the system to estimate the achievable quality and satisfy the quality requirement.

Among typical time-series forecasting techniques, LSTM has been selected due to its ability to comprehend long-term sequences of observations. Compared to traditional recurrent neural networks (RNNs), LSTM is an enhanced RNN architecture

created to simulate temporal sequences and their long-range dependencies more accurately [52]. The LSTM model will help cut expenses and save unneeded incentives by predicting $N_{\mathrm{n}}^{\mathtt{k}}$ to complete the sensing tasks at a certain time. The LSTM model uses the users' historical data to predict their availability to perform the sensing tasks. Then, the system uses the prediction data to check the satisfaction of the quality metric; this will enable the system to optimize the incentivization process as it will only incentivize the users to perform the sensing in specific spatiotemporal subcells based on the need.

By substituting the subcell's coordinates (x, y) into Eqn. (3.3), determines the probability p that a user is present in the subcell. This step is crucial for computing the probability $P(N)$, which represents the likelihood of N users being in a specific subcell, as

$$P(N) = \begin{pmatrix} N_{\mathrm{n}}^{\mathtt{k}} \\ N \end{pmatrix} p^N q^{N_{\mathrm{n}}^{\mathtt{k}}-N} = \frac{N_{\mathrm{n}}^{\mathtt{k}}!}{(N_{\mathrm{n}}^{\mathtt{k}}-N)!N!} p^N q^{N_{\mathrm{n}}^{\mathtt{k}}-N} \tag{3.5}$$

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

The probability that the quality metric fails to be met for any specified minimum number of users $N_{\min}$ can be articulated as

$$P\left(N < N_{\min}\right) = \sum_{N=0}^{N_{\min}} \begin{pmatrix} N_{\mathrm{n}}^{\mathtt{k}} \\ N \end{pmatrix} p^N q^{N_{\mathrm{n}}^{\mathtt{k}}-N} \tag{3.6}$$

The distribution of users within the system's subcells, as shown in Fig. 3.1, demonstrates a non-uniform spread due to the RWP mobility model, illustrating that users are dispersed unevenly across the subcells.

After demonstrating the influence of user mobility on the EES systems in this

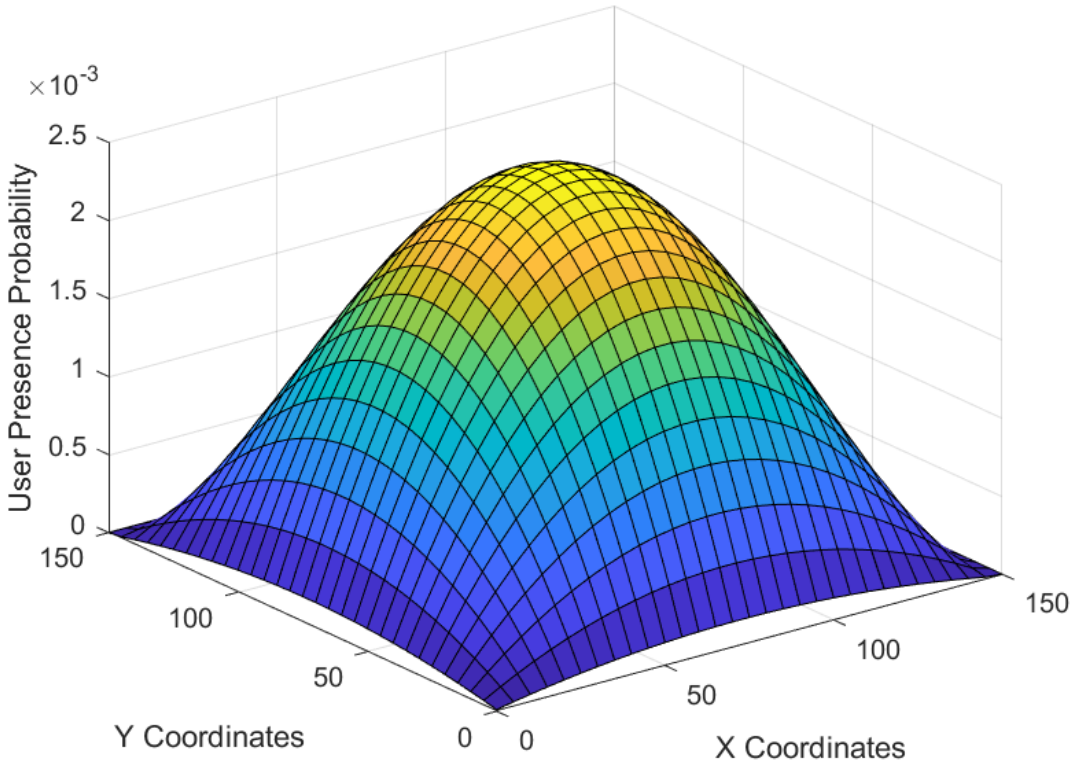

Figure 3.1: Users' distribution over the AoI

chapter, we proceed to address these challenges in the following chapter. In Chapter 4, we introduce the predictive tool to forecast user availability. Leveraging these predictions, we propose a learning-based incentive scheme designed to optimize the recruitment and incentivization within EES systems.

Chapter 4

Learning-Based Incentive Scheme for Extreme Edge Sensing

To design a realistic model, we consider the heterogeneity of users participating in the sensing task, as they have varying abilities and use different devices with different capabilities.

4.1 LSTM Model

As aforementioned, users are categorized into three k classes based on the QoD they provide and associatied with specific incentivization costs. Furthermore, we recognize that users' presence within the AoI does not guarantee they are available to participate. To tackle this challenge, we have integrated an LSTM model to predict the availability patterns of users in different classes.

A dataset that emulates users and their availability pattern is created to train the LSTM model. Since the users are assumed to be heterogeneous, the dataset shows the available number of users from each class. The dataset provides the number of available users in each location every 10 minutes for 8 hours daily, more granularity in

the time domain can be achieved if needed. The focus of the dataset is on the central subcell to study the temporal coverage of the system, as analyzing the central subcell would account for interactions from all adjacent subcells. A degree of randomness is introduced to evaluate the model in real-life situations where the user's availability pattern varies. This stochastic behavior is induced by employing a uniform distribution to select a subset of users for pattern alteration. In our system, we used a 70/30 data split for training and testing the LSTM model, allowing for effective learning and robust evaluation.

Table 4.1: Example of users' availability pattern

Time	12:00	12:10	12:20	12:30	...
Class 1	2	4	3	3	...
Class 2	4	3	5	4	...
Class 3	10	8	8	9	...

Table 4.1 provides an example of the dataset used in the study. The availability patterns of different user classes (k=3) are used to train the LSTM model. Utilizing the LSTM model prediction for the recruitment of users will enable the system to ensure the quality metric satisfaction (QMS).

In order to evaluate the LSTM model performance under ideal conditions, we run the system without injected randomness. Fig. 4.1 shows the LSTM model performance. It is clear that the model can to learn the users' availability pattern and succeeds in predicting the number of available users from each class for doing tasks at certain hours of the day. The test root means square error (RMSE) is equal to 0.097, the mean square error (MSE) equals 0.009, and the mean absolute error (MAE) is equal to 0.069 in the zero randomness scenario. The LSTM model performs well

under no randomness conditions, which is the bottom line for performance in realistic systems. In Chapter 5, we test the model behavior by considering randomness in realistic conditions.

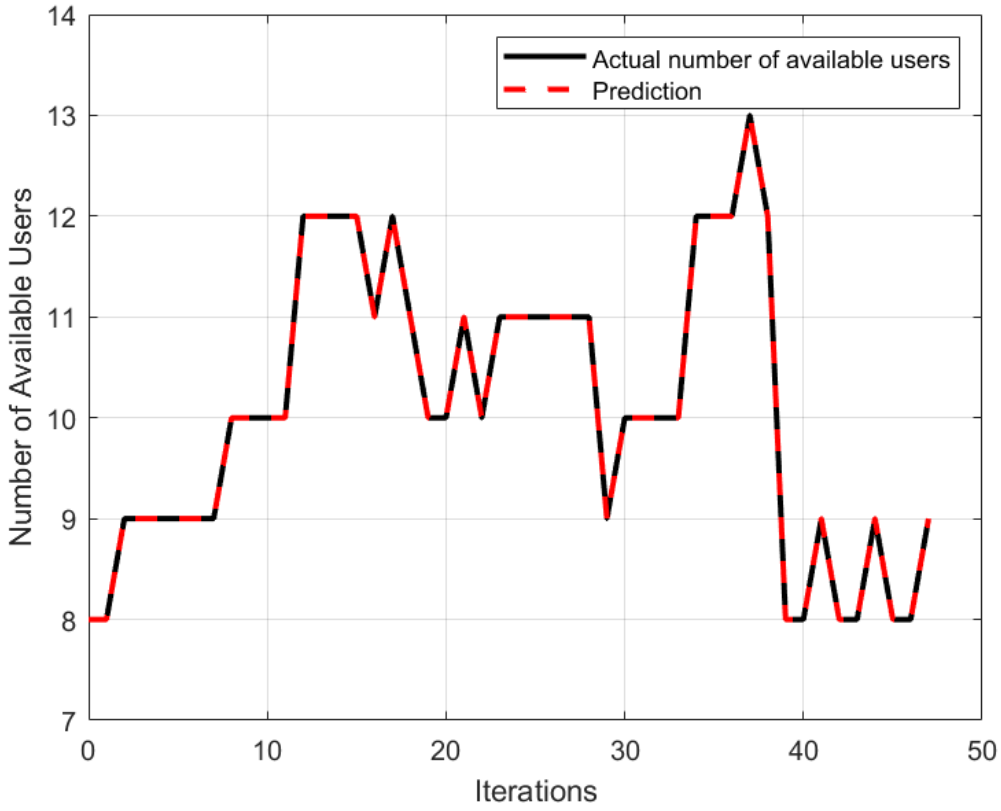

Figure 4.1: LSTM model performance

4.2 Optimization of Task Allocation and Incentivization

To address the impact of users' mobility in the previous chapter, we now propose a distribution-aware and learning-based dynamic-incentive scheme which looks into multiple aspects: necessity factor, attraction area, and recruitment optimization.

4.2.1 Necessity factor

To guarantee the completion of tasks with an acceptable QoD, we now propose a necessity factor (Ω), where the demand for incentive to complete the task is indicated by the necessity factor. Normalized from various parameters, Ω indicates the degree of incentivization required to ensure task completion. For instance, $\Omega = 0$ if there are sufficient users and the QoD is met. The optimal necessity factor may be determined by considering a variety of scenario parameters. By designing attraction regions inside the targeted subcells, this factor is determines a dynamic incentive for each scenario, shifting the distribution of users across subcells. Our formulated Ω is proposed as

$$\Omega = w_1 x_1 + w_2 x_2 + w_3 x_3 \tag{4.1}$$

where x_1, x_2, and x_3 reflect the impact of three scenario parameters, the probability of satisfying the minimum number of sensing users, QMS, and deadline on the necessity factor, respectively. Based on how important each parameter is to achieve the task goal, the administrator can set each parameter weight (w_1, w_2, and w_3), while the summation of the weights is unity. Each of these weights ensures guaranteed unitless summation within Ω.

Each subcell has a different number of available users. This distinction should be considered in the incentive system to ensure that all tasks, regardless of location, adhere to the minimum number of sensing users.

$$x_1 = \ln(2 - P\left(N \geq N_{\min}\right)) \tag{4.2}$$

where $P(N_{\min})$ is the probability of satisfying the minimum required number of sensing users $N_{\min}$, obtained from Eqn. (3.5). This parameter is essential in establishing the necessity factor because, as a consequence of the mobility model, central subcells are more likely to satisfy the minimum required number of sensing users than subcells on the border. It is important to note that $P(N_{\min})$ is inversely related to the need for incentives, where a decrease in $P(N_{\min})$ will drive a larger x_1 value.

The required QMS should be met in order to reach a satisfactory QoD. As a result, the need for incentives is influenced by the number of measurements,

$$x_2 = \ln\left(2 - \frac{Q^{\mathtt{t}}_{\text{ach}}}{Q^{\mathtt{t}}_{\min}}\right) \tag{4.3}$$

where $Q^{\mathtt{t}}_{\text{ach}}$ represents the estimated achievable quality based on the LSTM prediction and $Q^{\mathtt{t}}_{\min}$ is the minimum required quality for each task. With higher achievable quality, it is clear that incentives are less necessary.

To ensure that the tasks are completed within the given time frame, the deadline is a crucial factor that should be considered. The need for incentives to ensure the accomplishment of the sensing task increases as the deadline approaches.

$$x_3 = \ln\left(1 + \frac{1}{j - i - 1}\right) \tag{4.4}$$

where j is the task deadline, we can see that as the sensing duration i gets larger, the value of x_3 increases, and the need for an incentive is higher.

4.2.2 Attraction area

Based on the information from the preceding subsection, with $0 \leq x_1 \leq \ln(2)$, $0 \leq x_2 \leq \ln(2)$, and $0 \leq x_3 \leq \ln(2)$, along with the condition that $w_1 + w_2 + w_3 = 1$, it

follows that $0 \leq \Omega \leq \ln(2)$. Consequently, the calculation of the normalized necessity factor proceeds as follows,

$$\overline{\Omega} = \frac{\Omega}{\ln(2)} \tag{4.5}$$

The calculation of the necessity factor facilitates the creation of an attraction zone within the specified subcell, which can be implemented as follows,

$$g(x, y) = \left(1 - \overline{\Omega}\right) A_t + \left(\frac{\overline{\Omega}}{p}\right) A_c \tag{4.6}$$

with p obtained from Eqn. (3.3) as mentioned earlier, to represent the users' presence probability within the targeted subcell, and where A_t represents all the points within the AoI as,

$$A_t = \left(u\left(x_d + X_{\text{AoI}}\right) - u\left(x_d - X_{\text{AoI}}\right)\right) \cdot \left(u\left(y_d + Y_{\text{AoI}}\right) - u\left(y_d - Y_{\text{AoI}}\right)\right) \tag{4.7}$$

while A_c corresponds to all the points within the targeted subcell as,

$$A_c = \left(u\left(x_d - (x^\circ + \bigtriangledown)\right) - u\left(x_d - x^\circ\right)\right) \cdot \left(u\left(y_d - (y^\circ + \bigtriangledown)\right) - u\left(y_d - y^\circ\right)\right) \tag{4.8}$$

The coordinates of each point are evaluated using Heaviside unit step functions [53]. Using the Heaviside unit step function, it is possible to distinguish between points inside and outside the targeted subcell.

Eqn. (4.6) is used to scale the distribution of users' locations by creating an attraction area in the subcell $[x^\circ, x^\circ + \bigtriangledown][y^\circ, y^\circ + \bigtriangledown]$, while $\overline{\Omega}$ is the normalized necessity factor between 0 and 1. A higher $\overline{\Omega}$ will result in more users attracted to the targeted subcell. Eqn. (4.6) and Eqn. (3.3) can be multiplied to obtain the distribution of the new users, which is thought to be a response to the demand for further users within the targeted subcell to complete the sensing task successfully.

4.2.3 Recruitment optimization

The total cost for each task $C(t)$ is the incentivization amount of the recruited users to perform the task $C(t) = \sum_{k=1}^{K} \sum_{n=1}^{N} C_n^k$. To overcome the task assignment challenges associated with users' heterogeneity, the following binary integer programming (BIP) optimization is formulated

$$\min_{x_n^k} \quad C(t) \tag{4.9a}$$

$$\text{s.t.} \quad \sum_{k=1}^{K} \sum_{n=1}^{N} x_n^k C_n^k \leq B_t \tag{4.9b}$$

$$\sum_{k=1}^{K} \sum_{n=1}^{N} x_n^k Q_n^k \geq Q_{\min}^{\mathtt{t}} \tag{4.9c}$$

$$x_n^k \in \{0, 1\}, \quad \forall n \in [N_n^k], \quad \forall k \in [K] \tag{4.9d}$$

The system optimization aims to minimize incentivization costs while ensuring QMS. The variables C_n^k, and Q_n^k represents the cost and quality of users from different classes. The decision parameter x_n^k determines which users are selected for the sensing task. The system operates within the task budget constraints B_t and a minimum

quality threshold $Q^{\mathfrak{t}}_{\min}$ to guide users' recruitment and incentivization process.

The assignment of tasks is conducted through the optimization process over a cost-weighted graph, represented by the matrix $\mathbf{W} \in R^{N_n^k \times T}$. This process begins with formulating the cost matrix $\mathbf{W}$, incorporating all costs associated with participant recruitment. The Hungarian algorithm is utilized to optimize task assignments, as indicated in Algorithm 1, specifically from lines 9 to 19. Participant allocation is denoted by the binary matrix $\mathbf{A} \in 0, 1^{N_n^k \times T}$. Recognized for its efficiency in computation, the Hungarian method plays a pivotal role in facilitating rapid task assignments, a critical aspect of real-time systems. Additionally, it reliably delivers optimal solutions for one-to-one matching scenarios, which aligns with the objectives of the ES system. This method is simple and versatile, making it easy to adapt to different cost and objective functions. Additionally, it can address real-life limitations such as participant availability and task deadlines. These features ensure that the assignments adhere to the system's operational requirements.

Algorithm 1 illustrates the comprehensive operation of the proposed method, factoring in variable elements like user mobility and availability. It offers a dynamic solution to address prevailing challenges, leveraging the RWP and LSTM models. This method adeptly balances the cost-quality trade-off, optimizing the approach based on each task's requirements.

Algorithm 1 User Recruitment and Task Allocation in EES Systems

Require: N_{total}, T, User dataset, LSTM model, $Q^{\mathfrak{t}}_{\min}$, B_t

for each task t in T **do**
    Utilize RWP model to estimate the spatial distribution of available users
    Calculate the corrected number of users N_m
    Obtain the more corrected number N_n^k using LSTM prediction
    Compute quality metric satisfaction (QMS) for task t
    Calculate necessity factor (Ω) for task t and start the assignment starting by the most necessary task
    for each user in N_n^k **do**
        Initialize cost matrix $\mathbf{W}$, and necessary variables
        Apply Hungarian method to cost matrix $\mathbf{W}$

        while QMS not met **do**
            Perform row and column reductions on $\mathbf{W}$
            Cover the matrix $\mathbf{W}$ with the minimum number of lines
            if QMS met **then**
                return binary assignment matrix $\mathbf{A}$ for t
            else
                Update Ω
                Find the smallest uncovered element in $\mathbf{C}$
                Modify the matrix to improve the assignment for task t
            end if
        end while
    end for
end for
Output: Task assignments for all tasks in T with optimized quality and cost

Chapter 5

Simulation and Results

Simulations of an EES system under various situations are performed to test the mathematical expressions derived in this paper, and the obtained results are discussed in this chapter. The system is composed of nine square subcells. Users move within the AoI of the system, is considered $[0, X_{\text{AoI}}][0, Y_{\text{AoI}}]$. Users' velocity is uniformly distributed with $1 \leq v \leq 20$.

A one-step univariate LSTM model is developed, which uses 70% of the data for training and 30% for testing. The model's hyper-parameters are 3000 epochs, 100 neurons, and a batch size of 1. These numbers are selected through trial and error to prevent the model from over-fitting and under-fitting.

As shown in Fig. 3.1, the center subcell has a higher user density, which can significantly impact the system. The quality metric's probability of not being satisfied in border subcells is anticipated to be considerably higher than in center subcells. As a result, the AoI edges may turn into blind spots, preventing the complete system's coverage. Fig. 5.1 shows these probabilities, where it is clear that simulation results align with analytical results for both edge and center subcells.

Fig. 5.2 illustrates the relationship between V_{th} and the corrected user's number,

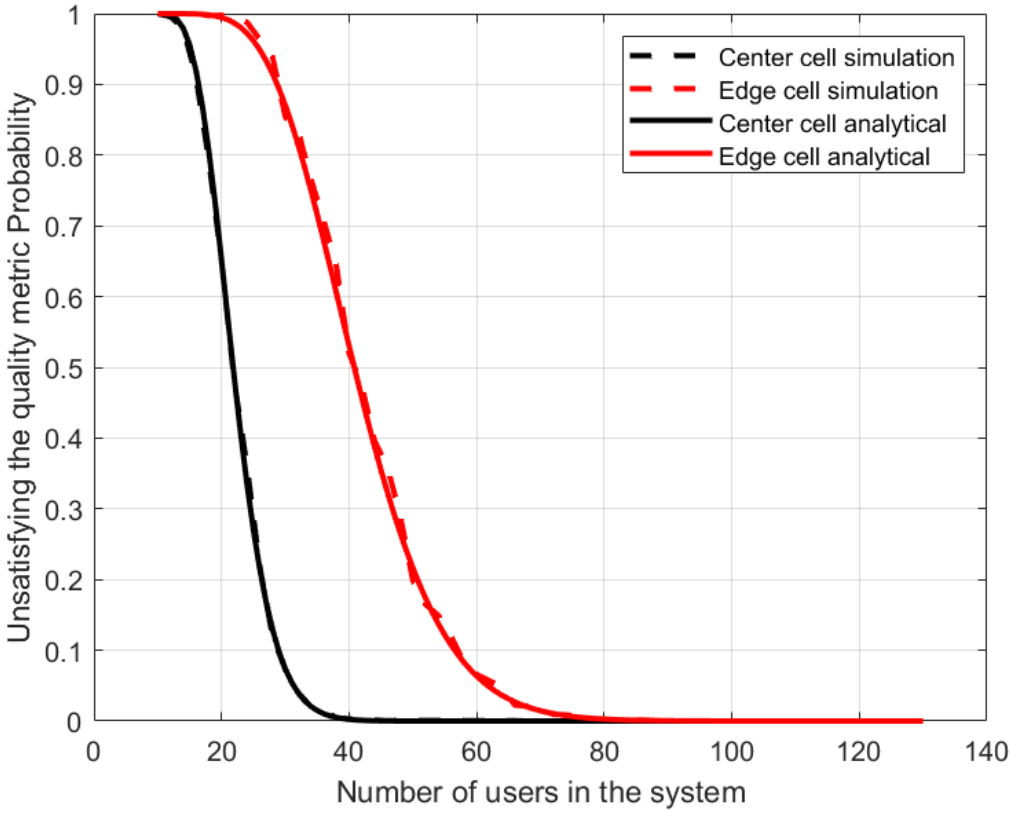

Figure 5.1: Subcell location effect on the quality metric

proving that although velocity may not impact user distribution, it does impact the number of users qualified to perform the sensing task. It is noticeable that the relationship is linear, as having a higher V_{th} will enable the system to include users at higher velocities, subsequently increasing the corrected number of users by including more users in the sensing tasks.

The ability of the incentive scheme to create an attraction area within a particular subcell is evaluated using Fig. 5.3 and Fig. 5.4. Users' attraction area was created in an edge subcell, as shown in Fig. 5.3, increasing the likelihood that users will be present in the targeted subcell.

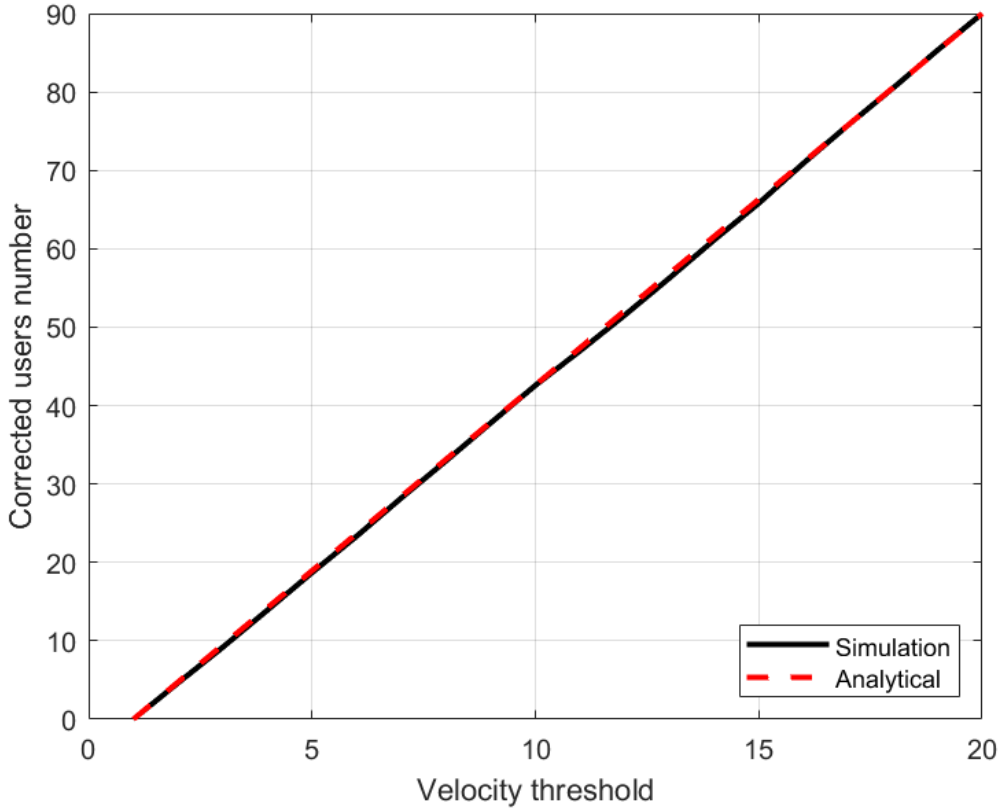

Figure 5.2: Velocity threshold effect on the corrected number of users

The formed attraction area can resolve various problems that ES systems encounter as it improves system coverage by increasing the likelihood of users' presence in desired locations, which increases the likelihood of quality metric satisfaction, as shown in Fig. 5.4. Additionally, it demonstrates that the incentive scheme improved the system's coverage without the necessity to add more users, making it a suitable incentive scheme for scenarios with a constrained budget.

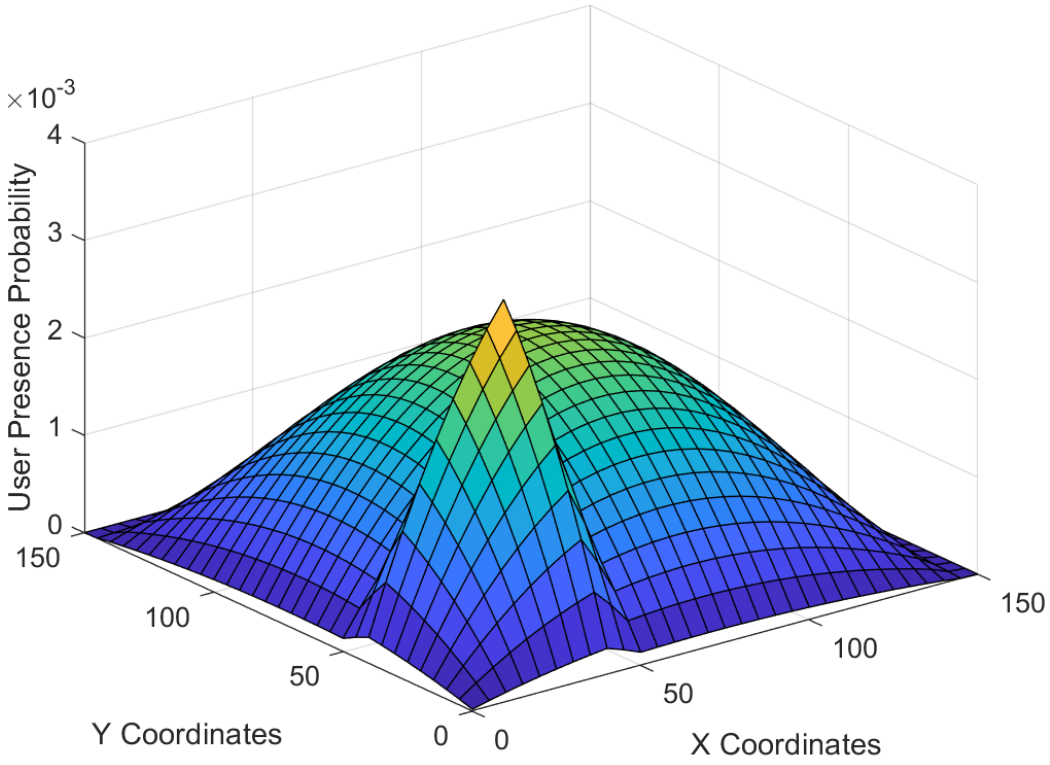

Figure 5.3: Attraction area

5.0.1 Effect of learning-based model

In this subsection we will evaluate the impact of integrating the LSTM model within the EES system.

Fig. 5.5 demonstrates how learning-based incentives exploit the LSTM model predictions to improve the system performance. We compare the distribution-aware incentive scheme and the LSTM learning-based incentive scheme. The non-incentive scheme is also included as a baseline for comparison. It is noticeable that the

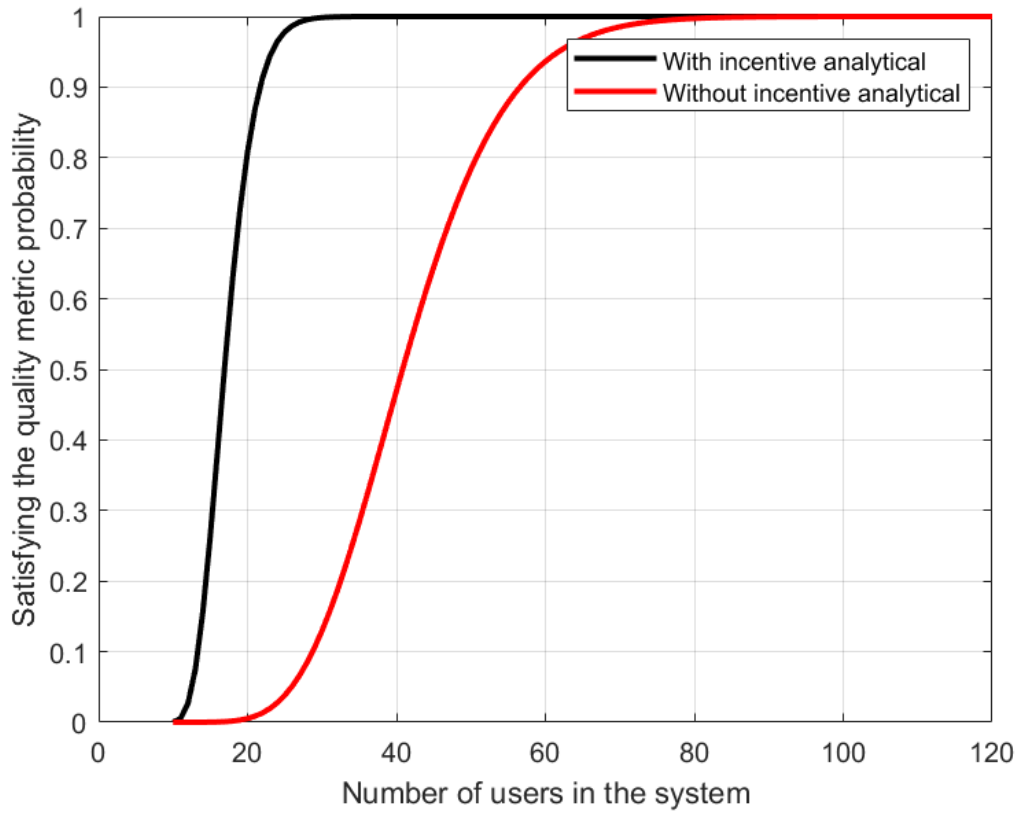

Figure 5.4: Number of users effect on the quality metric

learning-based incentive scheme helped the system maintain quality metric satisfaction. Although both incentive schemes improved the QMS, the learning-based incentive scheme outperformed the distribution-aware incentive scheme under a budget-constrained scenario due to its previous knowledge of the users' availability patterns. The proposed model utilizes this knowledge to assign tasks based on the users' availability. Moreover, this knowledge enables the system to estimate the achievable QMS. Therefore, this knowledge prevented any drop in the QMS, which enabled the ES system to maintain full spatiotemporal coverage.

Concerned with the incentive schemes' normalized costs to satisfy the quality metric, Fig. 5.6 tackles the normalized cost as the number of incentives the system

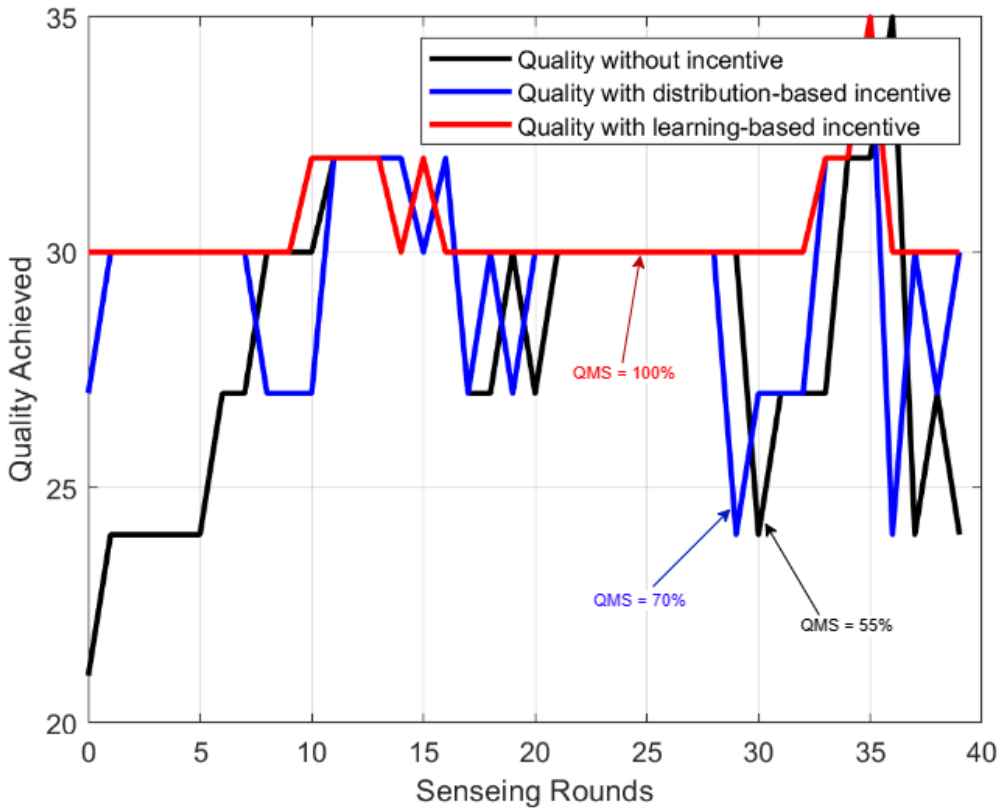

Figure 5.5: QMS Enhancement

needs to satisfy the quality metric. It is shown that the prediction-supported incentive scheme satisfies the quality metric at a reduced cost due to its previous knowledge of users' availability patterns. This knowledge enabled the learning-based incentive scheme to determine the minimum needed number of users to satisfy the quality metric and incentivize them. Thus, the learning-based incentive scheme succeeded in its objective as it was able to satisfy the QoD metric and minimize the cost, as shown in both Fig. 5.5 and Fig. 5.6.

Fig. 5.7 demonstrates the randomness's influence on the proposed scheme's performance. The results show the overall performance, taking into account all the system's

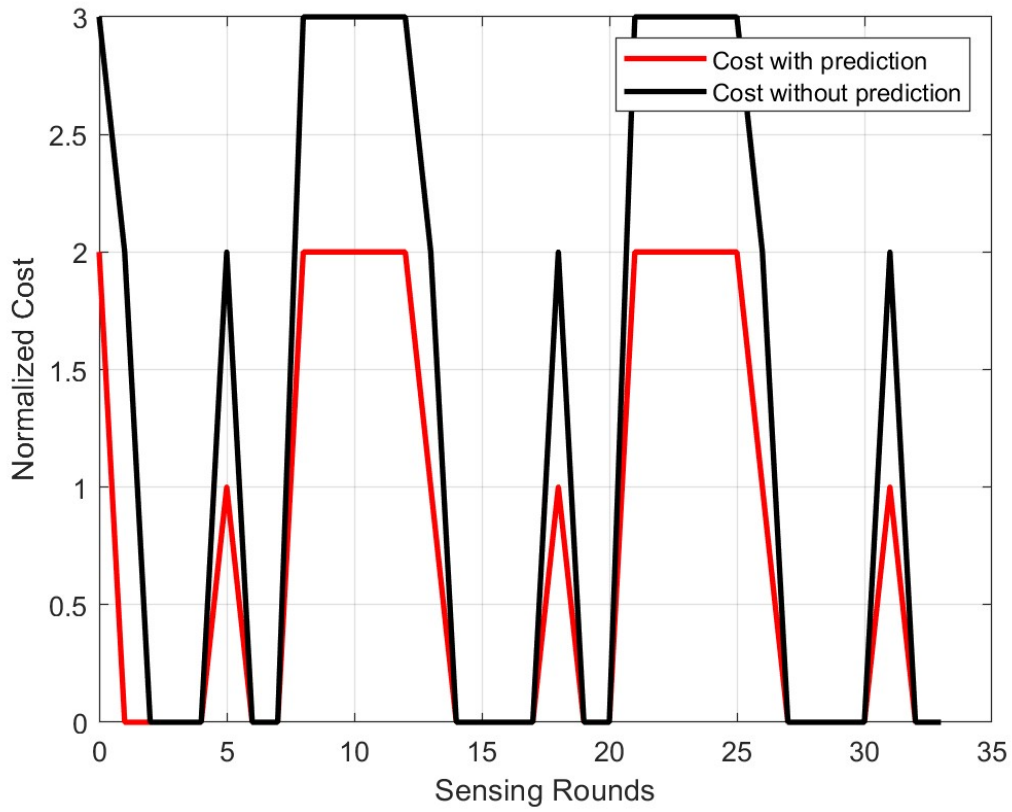

Figure 5.6: Cost comparison

parameters, such as user availability. Increasing the randomness in training and testing data results in increasing the percentage of error in the prediction, subsequently decreasing the QMS. However, as shown in Fig. 5.7, the randomness does not affect the QMS drastically, and the system was able to perform appropriately at a high randomness percentage.

Table 5.1 shows the LSTM model performance under various randomness percentages to test its ability to perform in real-life scenarios where users' availability patterns are not always fixed. As expected, as randomness increases, the percentage of error increases; however, the increment does not affect the system performance

drastically. The table clearly shows that the model is robust under randomization situations.

Table 5.1 shows the LSTM model performance under various randomness percentages to test its ability to perform in real-life scenarios where users' availability patterns are not always fixed. As expected, as randomness increases, the percentage of error increases; however, the increment does not affect the system performance drastically. For instance, at 10% randomness, the model maintains high prediction accuracy with only a slight increase in error, demonstrating resilience to minor perturbations in user behavior. The table clearly shows that the model is robust under randomization situations, capable of delivering dependable performance despite the increasing unpredictability of input data.

Table 5.1: LSTM model performance

Randomness	0%	2%	5%	10%
RMSE	0.097	0.19	2.24	2.79
Correct prediction	288	288	275	269
Incorrect prediction	0	0	13	19
Percentage of error	0	0	4.5%	6.6%

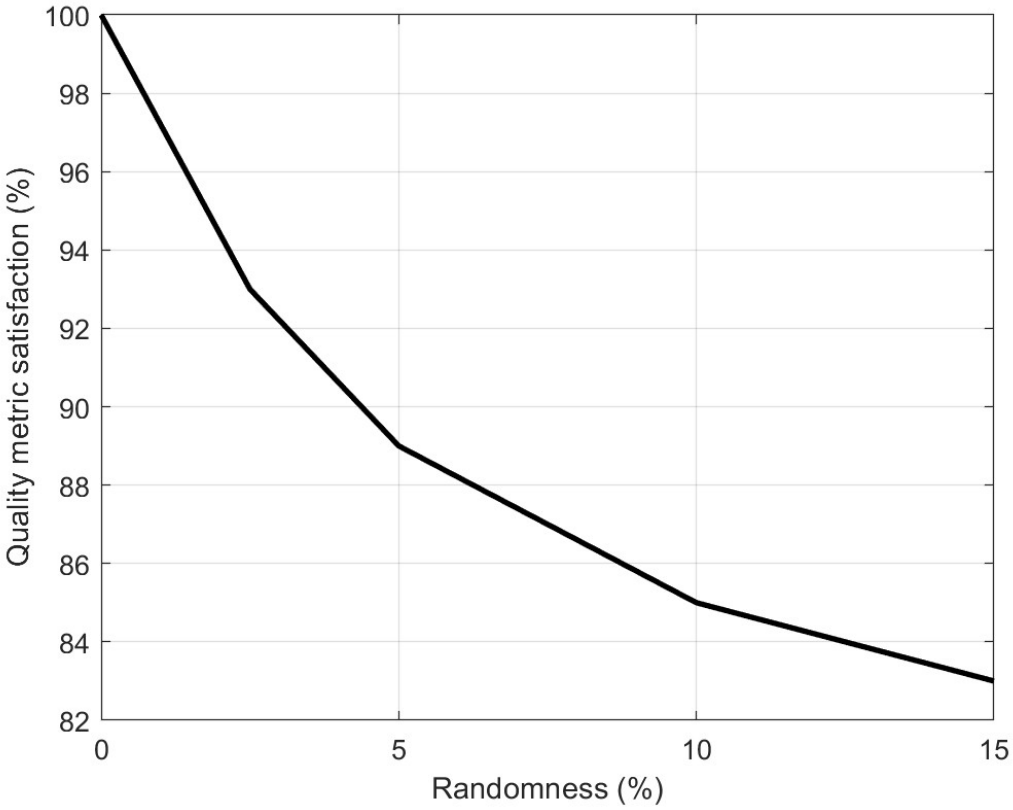

Figure 5.7: Randomness effect on QMS

Chapter 6

Conclusions

6.1 Summary and Conclusion

In this work, we develop and evaluate a novel distribution-aware and learning-based dynamic incentive scheme tailored for efficient user incentivization within EES systems. Recognizing the critical impact of user mobility and availability on both spatiotemporal coverage and QoD, our approach leverages a 2-dimensional RWP model alongside an LSTM model to predict users' availability for sensing tasks. This prediction not only addresses the challenges imposed by the inherent mobility of users but also efficiently manages the trade-off between quality and cost, thereby optimizing system performance within the constraints of a limited incentivization budget.

Our scheme introduces a corrected user count to accommodate users' mobility and a necessity factor that dynamically adjusts the incentive based on various scenario parameters, including the probability of satisfying the minimum required number of sensing users, QMS, and task deadlines. Furthermore, we employ the LSTM model to predict the number of available users, enhancing task allocation and enabling the system to meet the minimum quality requirement at the lowest possible cost. Through

comprehensive simulation, we demonstrated the effectiveness of our proposed scheme in improving QoD and system coverage, particularly by creating attraction areas within targeted subcells to optimize user participation.

Key to our approach is the integration of predictive analytics with dynamic incentive mechanisms, which not only mitigates the negative impacts of users' mobility and availability but also ensures the robustness and reliability of EES systems. Using LSTM for user availability prediction represents a significant advancement in addressing real-world challenges in EES, where user participation cannot be guaranteed. Our results affirm the scheme's capability to maintain QMS and enhance the system's performance under various conditions, including scenarios with budget constraints and varying user availability patterns.

In conclusion, our work significantly contributes to the field of EES by introducing a comprehensive framework that incorporates distribution-aware and learning-based dynamics for user incentivization. The proposed scheme addresses critical challenges in EES systems and sets a new benchmark for future research to optimize the interaction between user behavior and system performance.

6.2 Recommendations and Future Work

The presented work on a novel distribution-aware and learning-based dynamic incentive scheme opens several promising directions for future research within the domain of EES systems. In light of the findings and the challenges encountered, this section outlines key areas where future efforts could be concentrated to enhance EES systems', efficiency, and practicality.

Firstly, an immediate avenue for future work is the exploration of more sophisticated predictive models beyond the LSTM utilized in this study. Integrating of advanced deep learning techniques, such as convolutional neural networks (CNNs) for spatial data analysis and RNNs with more complex architectures, could offer insights into user mobility and behavior patterns. These models may enable a more dynamic and responsive incentivization mechanism, thus addressing the inherent variability in human behavior.

Secondly, the adaptation and fine-tuning of the incentive scheme to accommodate diverse user preferences and motivations stand as a critical area for further investigation. Personalized incentive models that consider individual user characteristics, such as their historical participation rate, preferred types of tasks, and sensitivity to different forms of incentives, could significantly improve user engagement and participation rates. This personalized approach could also extend to developing a more sophisticated segmentation of tasks based on their urgency and required data quality, optimizing resource allocation and enhancing the overall system efficiency.

Finally, the implementation and testing of the proposed scheme in real-world settings emerge as a crucial next step. Conducting pilot studies across different environments and user communities would provide valuable feedback on the model's practical challenges and user acceptance. These real-world implementations could highlight areas requiring adjustment or refinement in the incentive scheme, particularly in terms of scalability, user privacy concerns, and the adaptability of the system to varying operational contexts.

Making such considerations in future work can significantly enhance our approach.

Moreover, designing a more holistic model that addresses simultaneous multiple sensing tasks within EES systems should be explored. This development will consider the dynamics of user availability and the competitive nature of task incentives, especially crucial in scenarios with limited user resources. Investigating how incentives for multiple tasks may interact and influence each other's completion could lead to more effective strategies for task allocation and user engagement. Such improvements are expected to not only enhance data collection efficiency and quality but also ensure a robust and adaptive system capable of managing complexities introduced by competing tasks and limited user availability.

While this thesis has laid the groundwork for employing learning-based dynamic incentive schemes in EES systems, the path forward calls for a multidisciplinary approach that embraces advances in machine learning, user-centric design, and ethical data management. By addressing these recommended areas, future research can significantly contribute to the evolution of ES systems, making them more efficient, user-friendly, and aligned with societal values.

Bibliography

[1] P. Emami-Naeini, J. Breda, W. Dai, T. Kohno, K. Laine, S. Patel, and F. Roesner, "Understanding people's concerns and attitudes toward smart cities," in *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*.

[2] M. Aboualola, K. Abualsaud, T. Khattab, N. Zorba, and H. S. Hassanein, "Edge technologies for disaster management: A survey of social media and artificial intelligence integration," *IEEE Access*, vol. 11, pp. 73 782–73 802, 2023.

[3] O. Naserallah, S. B. Azmy, N. Zorba, and H. S. Hassanein, "Impact of users' mobility on the quality of edge sensing systems," in *GLOBECOM IEEE Global Communications Conference*, 2022, pp. 4196–4201.

[4] M. Marjanović, A. Antonić, and I. P. Žarko, "Edge computing architecture for mobile crowdsensing," *IEEE Access*, vol. 6, pp. 10 662–10 674, 2018.

[5] Y. Liu, X. Liu, X. Li, M. Li, and Y. Li, "Participants recruitment for coverage maximization by mobility predicting in mobile crowd sensing," *China Communications*, vol. 20, no. 8, pp. 163–176, 2023.

[6] J. Zhang and X. Zhang, "Multi-task allocation in mobile crowd sensing with mobility prediction," *IEEE Transactions on Mobile Computing*, vol. 22, no. 2, pp. 1081–1094, 2023.

[7] Y. Zhen, Y. Wang, P. He, Y. Cui, R. Wang, and D. Wu, "Popularity balanced multi-task bundling for mobile crowd sensing," *IEEE Transactions on Knowledge and Data Engineering*, pp. 1–12, 2024.

[8] J. Wang, Y. Wang, D. Zhang, and S. Helal, "Energy saving techniques in mobile crowd sensing: Current state and future opportunities," *IEEE Communications Magazine*, vol. 56, no. 5, pp. 164–169, 2018.

[9] H. Jin, L. Su, B. Ding, K. Nahrstedt, and N. Borisov, "Enabling privacy-preserving incentives for mobile crowd sensing systems," in *IEEE 36th International Conference on Distributed Computing Systems (ICDCS)*, 2016, pp. 344–353.

[10] T. Luo, J. Huang, S. S. Kanhere, J. Zhang, and S. K. Das, "Improving iot data quality in mobile crowd sensing: A cross validation approach," *IEEE Internet of Things Journal*, vol. 6, no. 3, pp. 5651–5664, 2019.

[11] B. Kantarci, P. M. Glasser, and L. Foschini, "Crowdsensing with social network-aided collaborative trust scores," in *IEEE Global Communications Conference (GLOBECOM)*, 2015, pp. 1–6.

[12] H. Zou, H. Wang, Y. Cui, P. He, D. Wu, and R. Wang, "Worker selection towards high service quality in mobile crowd sensing," in *IEEE 96th Vehicular Technology Conference (VTC2022-Fall)*, 2022, pp. 1–5.

[13] S. B. Azmy, N. Zorba, and H. S. Hassanein, "Quality estimation for scarce scenarios within mobile crowdsensing systems," *IEEE Internet of Things Journal*, vol. 7, no. 11, pp. 10 955–10 968, 2020.

[14] ——, "Robust quality metric for scarce mobile crowd-sensing scenarios," in *IEEE International Conference on Communications Workshops (ICC Workshops)*, 2018, pp. 1–5.

[15] C. Zhao, S. Yang, P. Yan, Q. Yang, X. Yang, and J. McCann, "Data quality guarantee for credible caching device selection in mobile crowdsensing systems," *IEEE Wireless Communications*, vol. 25, no. 3, pp. 58–64, 2018.

[16] H. Jin, L. Su, D. Chen, H. Guo, K. Nahrstedt, and J. Xu, "Thanos: Incentive mechanism with quality awareness for mobile crowd sensing," *IEEE Transactions on Mobile Computing*, vol. 18, no. 8, pp. 1951–1964, 2019.

[17] M. Dai, Z. Su, Q. Xu, Y. Wang, and N. Lu, "A trust-driven contract incentive scheme for mobile crowd-sensing networks," *IEEE Transactions on Vehicular Technology*, vol. 71, no. 2, pp. 1794–1806, 2022.

[18] H. Gao, C. H. Liu, Y. Tian, T. Xi, and W. Wang, "Ensuring high-quality data collection for mobile crowd sensing," in *IEEE Wireless Communications and Networking Conference (WCNC)*, 2017, pp. 1–6.

[19] X. Xia, Y. Zhou, J. Li, and R. Yu, "Quality-aware sparse data collection in mec-enhanced mobile crowdsensing systems," *IEEE Transactions on Computational Social Systems*, vol. 6, no. 5, pp. 1051–1062, 2019.

[20] S. Chessa, L. Foschini, and M. Girolami, "Understanding human mobility for crowdsensing strategies with the participact data set," in *GLOBECOM IEEE Global Communications Conference*, 2020, pp. 1–6.

[21] Y. Wu, Y. Suo, F. Yu, and Y. Liu, "A utility-based subcontract method for sensing task in mobile crowd sensing," *IEEE Transactions on Industrial Informatics*, vol. 18, no. 2, pp. 1210–1219, 2022.

[22] F. Restuccia, P. Ferraro, S. Silvestri, S. K. Das, and G. L. Re, "Incentme: Effective mechanism design to stimulate crowdsensing participants with uncertain mobility," *IEEE Transactions on Mobile Computing*, vol. 18, no. 7, pp. 1571–1584, 2019.

[23] S. Xu, X. Chen, X. Pi, C. Joe-Wong, P. Zhang, and H. Y. Noh, "ilocus: Incentivizing vehicle mobility to optimize sensing distribution in crowd sensing," *IEEE Transactions on Mobile Computing*, vol. 19, no. 8, pp. 1831–1847, 2020.

[24] Z. He, J. Cao, and X. Liu, "High quality participant recruitment in vehicle-based crowdsourcing using predictable mobility," in *IEEE Conference on Computer Communications (INFOCOM)*, 2015, pp. 2542–2550.

[25] Y. Ogawa, G. Hasegawa, and M. Murata, "Probabilistic control of dynamic crowds toward uniform spatial-temporal coverage," *IEEE Transactions on Mobile Computing*, vol. 23, no. 2, pp. 1050–1065, 2024.

[26] Y. Qu, Z. Yu, and X. Zheng, "Buy4me: A delivery system via mobility prediction based on mobile crowd sensing," in *IEEE 12th Intl Conf on Ubiquitous Intelligence and Computing and 2015 IEEE 12th Intl Conf on Autonomic and*

Trusted Computing and 2015 IEEE 15th Intl Conf on Scalable Computing and Communications and Its Associated Workshops (UIC-ATC-ScalCom), 2015, pp. 1199–1203.

[27] E. Wang, Y. Yang, J. Wu, W. Liu, and X. Wang, "An efficient prediction-based user recruitment for mobile crowdsensing," *IEEE Transactions on Mobile Computing*, vol. 17, no. 1, pp. 16–28, 2018.

[28] Q. Zhu, M. Y. Sarwar Uddin, N. Venkatasubramanian, and C.-H. Hsu, "Spatiotemporal scheduling for crowd augmented urban sensing," in *IEEE INFOCOM 2018 - IEEE Conference on Computer Communications*, 2018, pp. 1997–2005.

[29] L. G. Jaimes, I. Vergara-Laurens, and M. A. Labrador, "A location-based incentive mechanism for participatory sensing systems with budget constraints," in *IEEE International Conference on Pervasive Computing and Communications*, 2012, pp. 103–108.

[30] J. Hu, Z. Wang, J. Wei, R. Lv, J. Zhao, Q. Wang, H. Chen, and D. Yang, "Towards demand-driven dynamic incentive for mobile crowdsensing systems," *IEEE Transactions on Wireless Communications*, vol. 19, no. 7, pp. 4907–4918, 2020.

[31] X. Kong, P. Li, T. Zhang, M. Tu, and Q. Liu, "A budget constraint incentive mechanism in spatial-temporal mobile crowdsensing," in *IEEE 21st International Conference on High Performance Computing and Communications; IEEE 17th International Conference on Smart City; IEEE 5th International Conference on Data Science and Systems (HPCC/SmartCity/DSS)*, 2019, pp. 1726–1731.

[32] Z. Wang, J. Hu, Q. Wang, R. Lv, J. Wei, H. Chen, and X. Niu, "Task-bundling-based incentive for location-dependent mobile crowdsourcing," *IEEE Communications Magazine*, vol. 57, no. 2, pp. 54–59, 2019.

[33] Y. Zhang and X. Zhang, "Bundlesense: A task-bundling-based incentive mechanism for mobile crowd sensings," in *29th International Conference on Computer Communications and Networks (ICCCN)*, 2020, pp. 1–9.

[34] W. Tan, J. Liu, Z. Liang, and K. Ding, "Based on bid and data quality incentive mechanisms for mobile crowd sensing systems," in *IEEE 25th International Conference on Computer Supported Cooperative Work in Design (CSCWD)*, 2022, pp. 89–94.

[35] H. Wang, C. Liu, Y. Wang, and D. Sun, "A novel incentive mechanism based on reputation and trust for mobile crowd sensing network," in *International Conference on Control, Automation and Information Sciences (ICCAIS)*, 2018, pp. 526–530.

[36] K. Ota, M. Dong, J. Gui, and A. Liu, "Quoin: Incentive mechanisms for crowd sensing networks," *IEEE Network*, vol. 32, no. 2, pp. 114–119, 2018.

[37] M. S. Allahham, A. Mohamed, A. Erbad, and M. Guizani, "Motivating learners in multiorchestrator mobile edge learning: A stackelberg game approach," *IEEE Canadian Journal of Electrical and Computer Engineering*, vol. 46, no. 1, pp. 69–76, 2023.

[38] X.-W. Yao, X.-T. Yang, Q. Li, C.-F. Qi, X.-J. Kong, and X.-Y. Li, "Umim: Utility-maximization incentive mechanism for mobile crowd sensing," *IEEE Transactions on Mobile Computing*, pp. 1–14, 2023.

[39] L. Zhang, Z. Li, and X. Chen, "Incentive mechanism design for edge-cloud collaboration in mobile crowd sensing," in *IEEE INFOCOM 2020 - IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS)*, 2020, pp. 1196–1201.

[40] J. Yangchin and N. Marchang, "Incentive mechanism for mobile crowd sensing using reverse auction dynamic pricing and recent history," in *3rd International Conference on Advances in Computing, Communication, Embedded and Secure Systems (ACCESS)*, 2023, pp. 6–11.

[41] C. Wu, T. Luo, F. Wu, and G. Chen, "Endortrust: An endorsement-based reputation system for trustworthy and heterogeneous crowdsourcing," in *IEEE Global Communications Conference (GLOBECOM)*, 2015, pp. 1–6.

[42] W. Zhang, Z. Li, and X. Chen, "Quality-aware user recruitment based on federated learning in mobile crowd sensing," *Tsinghua Science and Technology*, vol. 26, no. 6, pp. 869–877, 2021.

[43] S. Afzal-Houshmand, S. Homayoun, and T. Giannetsos, "A perfect match: Deep learning towards enhanced data trustworthiness in crowd-sensing systems," in *IEEE International Mediterranean Conference on Communications and Networking (MeditCom)*, 2021, pp. 258–264.

[44] Y. Jiang, R. Cong, C. Shu, A. Yang, Z. Zhao, and G. Min, "Federated learning based mobile crowd sensing with unreliable user data," in *IEEE 22nd International Conference on High Performance Computing and Communications; IEEE 18th International Conference on Smart City; IEEE 6th International Conference on Data Science and Systems (HPCC/SmartCity/DSS)*, 2020, pp. 320–327.

[45] Z. Li, S. Zhang, N. Xiong, and W. Liang, "Achieving efficient and secure task allocation scheme in mobile crowd sensing," in *IEEE 10th International Conference on Cyber Security and Cloud Computing (CSCloud)/2023 IEEE 9th International Conference on Edge Computing and Scalable Cloud (EdgeCom)*, 2023, pp. 78–84.

[46] Z. Zhou, H. Liao, B. Gu, K. M. S. Huq, S. Mumtaz, and J. Rodriguez, "Robust mobile crowd sensing: When deep learning meets edge computing," *IEEE Network*, vol. 32, no. 4, pp. 54–60, 2018.

[47] G. Solmaz, P. Baranwal, and F. Cirillo, "Countmein: Adaptive crowd estimation with wi-fi in smart cities," in *IEEE International Conference on Pervasive Computing and Communications (PerCom)*, 2022, pp. 187–196.

[48] K. Shibata and H. Yamamoto, "People crowd density estimation system using deep learning for radio wave sensing of cellular communication," in *International Conference on Artificial Intelligence in Information and Communication (ICAIIC)*, 2019, pp. 143–148.

[49] H. Choi, M. Fujimoto, T. Matsui, S. Misaki, and K. Yasumoto, "Wi-cal: Wifi sensing and machine learning based device-free crowd counting and localization," *IEEE Access*, vol. 10, pp. 24 395–24 410, 2022.

[50] M. Alzard, S. Althunibat, and N. Zorba, "On the performance of non-orthogonal multiple access considering random waypoint mobility model," in *ICC IEEE International Conference on Communications*, 2022, pp. 721–725.

[51] E. Hyytia, P. Lassila, and J. Virtamo, "Spatial node distribution of the random waypoint mobility model with applications," *IEEE Transactions on Mobile Computing*, vol. 5, no. 6, pp. 680–694, 2006.

[52] A. Joshi, P. K. Deshmukh, and J. Lohokare, "Comparative analysis of vanilla lstm and peephole lstm for stock market price prediction," in *International Conference on Computing, Communication, Security and Intelligent Systems (IC3SIS)*, 2022, pp. 1–6.

[53] C. Bettstetter and C. Wagner, "The spatial node distribution of the random waypoint mobility model." 01 2002, pp. 41–58.