EFFICIENT INCENTIVE MANAGEMENT IN REPUTATION-AWARE MOBILE CROWD SENSING

By

SEHRISH KHAN

NATIONAL UNIVERSITY OF MODERN LANGUAGES ISLAMABAD

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By

SEHRISH KHAN

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Thesis Title: Efficient Incentive Management in Reputation-Aware Mobile Crowd Sensing

Submitted By: Sehrish Khan **Registration #:** 44MS/CS/F20

Master of Science in Computer Science (MSCS)
Title of the Degree

Computer Science
Name of Discipline

Dr. Sajjad Haider
Name of Research Supervisor

Signature of Research Supervisor

Dr. Basit Shahzad
Name of Dean (FE&CS)

Signature of Dean (FE&CS)

Name of Pro-Rector Academics

Signature of Pro-Rector Academics

July 16, 2022

AUTHOR'S DECLARATION

I Sehrish khan

Daughter of Karamdad khan

Registration # 44 MS/CS/F20

Discipline Computer Science

Candidate of **Master of Science in Computer Science (MSCS)** at the National University of Modern Languages do hereby declare that the thesis **Efficient Incentive Management in Reputation-Aware Mobile Crowd Sensing** submitted by me in partial fulfillment of MSCS degree, is my original work, and has not been submitted or published earlier. I also solemnly declare that it shall not, in future, be submitted by me for obtaining any other degree from this or any other university or institution. I also understand that if evidence of plagiarism is found in my thesis/dissertation at any stage, even after the award of a degree, the work may be cancelled and the degree revoked.

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Sehrish khan

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Date

ABSTRACT

Title: Efficient Incentive Management in Reputation-Aware Mobile Crowd Sensing

The revolution in internet of things (IOT) technology have made possible crowdsourcing-based content sharing such as mobile crowd sensing (MCS), which aims to collect content from mass users and share it with participants. The content sharing is especially attractive because, users act as both content provider and user while shared content help in service providing or gaining. In previous researches, the main problem identified is that MWs may give false reporting by sharing low-quality reported data to reduce the effort required and gain reputation. Task related false reporting improved by hiring enough MWs for a task to evaluate the truth worthiness and acceptance of information but there are budget constraints on it. The monetary rewards are used to motivate the data collectors and to encourage the participants to take part in the network activities. As mobile workers are, the main entity to provide services so rewards are given based on reputation system also made mobile workers work efficiency more important in Mobile crowd sensing (MCS). The incentives given to mobile workers (MW) based on reputation play a dramatic increase in service usage and provide a motivation to mobile workers, and build a trust to use the service. In the underlying research, we identified that they have not considered the difficulty level of a task that result in to good reputation on performing a number of easy tasks. While a person, performing difficult task may gain less score for reputation. For this, we proposed four difficulty levels of tasks (DLT) for reputation evaluation on a crowd-sensing network, on which the MW reputation will be evaluated.

Keywords: Mobile crowd sensing (MCS); Reputation; incentive; Mobile worker (MW); Difficulty level of Task (DLT).

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LIST OF ABBREVIATIONS

AES	Advance encryption technique
CNS	Crowd sensing network
DLT	Difficulty level of task
DRL	Dynamic incentive mechanism
GPS	Global positioning system
IOT	Internet of things
MCS	Mobile crowd sensing
MW	Mobile worker
MU	Mobile user
PACE	Privacy preserving data quality aware incentive scheme
PQRP	Reputation quality aware recruitment for platform
SIM	Staged incentive mechanism
SP	Service provider
ZD	Zero Determinant

LIST OF SYMBOLS

R_{S_c}		Reputation score of mobile worker
D_{LT}		Difficulty level of task
Sr		Sensing report of task
h(li) L		History of location li from set of locations L
Q , Q_Score, E(Q)		E(Q)Expected quality of task, Q desired quality of task , Q_Score after completion quality score of task
T , ti		Task and sub tasks
dt , Dt		dt submitted task completion , Dt dead line of task completion
Rq[ti]		Reported quality of any task
α	-	Threshold parameter
β	-	Beta store value for future use
$\in$	-	Belong to
$\notin$	-	Not belongs to

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DEDICATION

This thesis work is dedicated to my parents and my teachers throughout my education career who have not only loved me unconditionally but whose good examples have taught me to work **hard** *for the things that I aspire to achieve.*

CHAPTER 1

INTRODUCTION

1.1 Overview

With the changing paradigms of technology in the present era, the present section give overview of the Mobile crowd sensing. Different dimensions of it to achieve the goal of the study. Internet of things is an interconnection of different sensing and computation use for different purposes. The detail study of mobile crowd sensing and its usage is explained in this chapter.

1.2 Introduction to mobile Crowd Sensing

The revolutionary expansion in technology and IOT devices have increased the importance of mobile crowd sensing. Internet of things (IOT) devices almost 50 billion are vastly, used over recent years like sensors smartwatches, smart phones and wearable devices. In[1], all these have embedded sensors. The increase in IoT usage have also changed opportunities and challenges. Mobile crowd sourcing is a service in which mobile user collectively make a mobile cloud and share different services such as data collection, computing and processing of data and sell it on internet. The main components involved are service consumers who use online services to outsource their task, mobile users use computing services for task completion. Centralized servers are the platform related to tasks, users and consumers and provide services for task request, allocation-computing data related to task and manage feedback of consumer and mobile user. Local servers provide services to local cloud services related to task, they also collect information of other mobile users within a locality and collect reports of users [2].

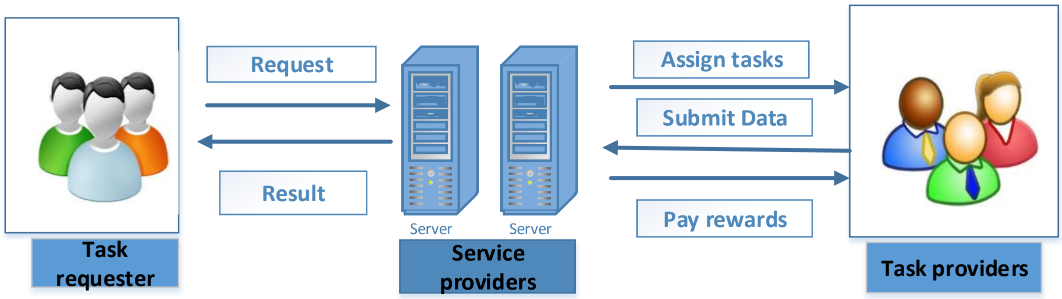


Figure 1.1: The mobile crowd-sensing network

Mobile crowd sensing outsource tasks related to data collection, processing to users, by using sensor devices they sense data compute on cloud computing and provide services. Crowd sensing provide cost effect services by motivating users to participate. In Crowd sensing mobile users are involved in service provision of task, it depends on human intelligence so mobile users' social attributes also have impact on task computation activities so mechanism have developed to handle the social activities. The Trust factor also expected from services that are being provided, because billions of devices and human work in collaboration. In all this paradigm mobile phone is an essential entity. In mobile crowd, sensing MCS and cloud computing Mobile phone is the entity, which is exploited most. The existence of wireless sensors has made portability of computation and sensing of MCS, this lead to exploitation of mobile phone technologies. The worldwide presence of mobiles provides wireless services to general public [2].

Many people with devices sense information and perform tasks in efficient manner. Such as environment monitoring, traffic, indoor localization etc. Task with the relevant participant matching is an important issue in crowd sensing because quality and effectiveness of task depends on it. In[3], proposed the frame work for matching task and participant .participants model consist of three characters ,attribute requirement and supplement. Task description given on publishing task. The participant attribute such as reputation, mobility should match task uploads. MCS server is responsible for task and participant attribute publication. The requirements from participants are sent to server this shows interest for task selection in matching process. The supplement of participant are the social behavior and social tags. Task model is further categorize in to task model such as basic spatial weighted coverage and area quality and point task related to task location and participant arrive at location to finish task. The completion rate maximization CRM complete as many as tasks possible where participant task utilities optimization (PTUO) completes tasks according to global participant task.

Human actively involved in crowd sourcing paradigm, especially the task that are easier for human and computer. In[4], task completion at specified location and time spatial crowd sourcing is a popular category in crowd sourcing. Spatial crowd sourcing increases the industrial success that includes economy sharing for services such as Uber and gig walk, and spatiotemporal data collection e.g. open street map. In this survey, four issues addressed. 1) Task assignment 2), quality control, 3) incentive mechanism, 4) privacy protection. In task assignment e.g. large amount of data of rides, data receive everyday on spatial platform. The platform arranges the tasks to suitable workers with maximizing total number of task and minimizing travel cost of workers. Quality control ensures high quality task completion by using quality model and aggregation techniques. Incentive mechanism designed to relation between supply and demand to attract workers. Privacy protection in terms of task, workers and result needs to be, transformed properly for privacy protection.

Data collecting approaches distribute large amount of sample .one individual sample may not provide sufficient information; aggregate of many individuals can provide high quality measurement. In[5] large number of incentive techniques are reviewed, that motivate people to participate in crowd sensing. They designed requirements that incentive mechanism must have. In the survey they considered following characteristics of design.1) economy feasibility, that include activities related to budget issue and non-monetary incentive techniques. These techniques provide social rewards such as fun and games. 2) Data quality should be high so that it should be high so that it is use in reputation schemes. Taxonomy based on level of user participation in system. Monetary static incentives are fixed incentive amount in advance according to some criteria’s. Monetary dynamic incentives depends on real time scenarios, and for each task, there is a variable budget value. Social interaction incentive uses technology that includes social media services such as SMS, blogs, emails etc. These services are provided free of cost and advantages are given on using these services.

Mobile devices and receiver platform in mobile crowd sensing paradigms collaborate with social sensors in mobile devices such as GPS. That are used to act on human activities and relationships. Human not only sense data but also compute data with objective needs. Now sensors are also smart enough to participate in sensing and computing task. The survey based on three categories:1)public security related applications used to detect events such as fire, earth quake ,emergency event management, crime detection and public health care. 2) Smart city applications using mobile crowd sensing, manage administration, environment protection and smart transportation. 3) Location based applications provide framework for people to urban movement pattern across several global cities[6]. That effect on their digital behavior changes. These computations are then provided for research projects and psychology of human and other social computational fields.

Learning based mobile crowd sensing comparing different schemes for learning assistant. The studies in mobile crowd sensing execute learning techniques for gaining information, such as participant behavior and sensing data pattern. This survey give overview of learning assisted approaches from participant and task viewpoint. Where task is divided into set of frameworks to accomplish. In human centric, the two entities are task participant and task organizer. Participant collect data through mobile devices and report the sensing data. Tasks organizers overall control and manage the task process. mobile crowd sensing is further divided in to; i) task creation, ii) assignment of task, iii) execution of task and iv) aggregation of data. The main characteristics of MCS are Mobility relevant Features, that worker complete task at certain location and result depend on the location status. Sensing relevant feature is urban sensing, execute and control the sensor having high-energy consumption. Important aspect to take control of sensing devices and control their energy consumption. On the other hand, MCS execute the phone-embedded sensors having variety of models. In data sensing the trained data quality, build a relation between participant motion and sensing quality for estimation of data quality in mobile crowd sensing. For reputation and ability estimation Gompertz function for scoring of reputation and crowd noise monitoring. For sensing result aggregation Expectation Maximization (EM) algorithm for reliability estimation. That results further use weight of truthfulness of sensing data. In Small-scale evaluation recruited within 4 week to complete task.in open dataset evaluation using algorithm use to trace large number of task participant[7].

In mobile crowd, sensing network MCS mobile workers (MW) are hired to sense data. On contrary the approach in [8], has advantages as well as limitations in lacking sensing quality. This is participatory sensing. Crowd contributors provide services and in result expect rewards. Incentive mechanism that keeps network participant motivated to contribute in remarkable sensing. Due to selfish behavior of mw, Considerable mechanisms for incentives are developed. In CSN, the unreliable participants' contribution is questionable. For the solution, several approaches came up in literature by different researchers. Solutions for various aspects considered (e.g. Received data truthfulness, latency and report). Effective reputation based approaches were considered in different aspects, that is a breakthrough high quality data sensing. author proposed concentric and vote based approaches [8]. In contrast, we considered Literature as helping to achieve reputation quality. Reputation quality aware recruitment for platform (PQRP)[9], and in [10], decentralized approach based on block chain both provided reputation score on the basis of reviews from users. To fill the gap of reputation based on task difficulty we proposed this system.

In this research, we present a reputation-based scheme based on difficulty or level of task (DLT). For reputation score measurement, we presented four task difficulty levels. Incentives for task based on its reputation. Difficulty level of task effect reputation of a mobile worker. Task according to difficulty will be categorized by Service provider so mobile worker have clear picture in mind for incentives. This builds trust for system.

1.2 Motivation

As in IOT technology, mobile crowd sensing is an emerging field, which plays an important role in providing services to users. The main entities are requester (user), service provider and Mobile workers that are recruited by service organizations to provide services. The incentives are given to mobile workers based on reputation. There are different mechanisms for reputation scoring but they have some challenges so there is a need of a new technique of reputation that based on task difficulty level for fair and up to the mark scoring.

1.3 Architecture of mobile crowd sensing

The entities that interact with each other in a typical crowd sensing network[11], are as follows as shown in fig 2.

- **Mobile crowd sensing(MCS) platform**

A centralized mobile crows sensing platform sense data request from client and after analyzing forward the task request to service provider.

- **Client**

Clients or requesters are individuals or groups of organizations that request for task or services from platform. They upload their specification to get their work done.

- **Provider**

The providers are the mobile users who participate in mobile crowd sensing to provide services based on sensing data requested by clients. The return the data to central platform. MCS forward this data to requester.

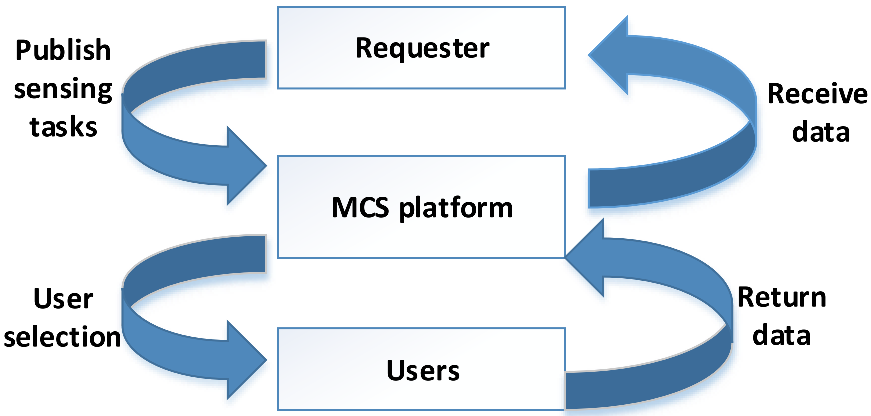


Figure 1.2: Architecture of mobile crowd sensing

The platform of mobile crowd sensing act as an interface between different entities such as clients that send request and providers that are workers. Mobile devices that sense data and forwarding sensing data to main server /platform. The sensing data can be of different types and forward it to clients. The sensors are able to monitor data from different application and from outdoor, buildings and public places etc. Apart from data collection platform act as client interface manager that allow that obtain values from real time sensors and then provide visual interaction such as graphs and maps.in client user interface configure different parameters and sent to server[12]. The client data management is also responsibility of the server and stores it[13],[14].

The client is the requester that send task request along with its specification to server. Client directly interact with server then its query is forwarded to service provider.in some systems client gives reviews about the service provided by worker[15].

The provider is the mobile worker that provide their services; these are the large number of participants that contribute in a system. They are recruited by the organizations or platform. The recruitment process consists of different investigations and after completion of tasks incentives are given according task parameters[16].

1.4 Applications of mobile crowd sensing

The crowd sensing is applicable in different fields as follows:

1.4.1 Health care monitoring

In health, care sensors are used to monitor patient vital signs locally and remotely. These sensors provide early detection of patient adverse health conditions. Biosensor monitors and reads specific measurements such as blood pressure, heart rate and body temperature. The data collected from biosensors then forward to medical specialists for analysis and diagnosis. Smartphones are designed in a specific way with embedded sensor to facilitate these services[17]. MCS is used to transfer large amount of health care data to centralized cloud. Then, data cloud computing and analytics used to study population health status and take appropriate measure[18].

1.4.2 Environment

In recent years' world is shifting towards large number of sensors technologies. The environment is sensed and monitored to deliver variation in its condition such as humidity, temperature, pollution and air quality etc. Increased industrialization and agriculture activities due to expanding population needs, led to degradation of air quality due to omission of toxicants in air, these effects not only limited to air but also effecting water quality. A mixture of sensors and smart phones provide monitoring. The demand on sensors technologies have increased in recent years. These sensors could be categories in to three categories: physical sensors monitor physical quantities such as temperature, light etc. Chemical sensors measure gas, ions carbon dioxide. Biological sensors measure bacteria tissues, viruses, and immunity. MCS by using these sensors provide accurate estimate these variabilities and effect on human[18]. This information can be used for preventing pollution and environmental effects on human[16].

1.4.3 Tourism

Tourism can be significantly, promoted by using technology such as crowd management, context and location aware services. The techniques allow tracking tourist location for safety and providing directions about: Nearest shopping centers, coffee shops restaurants etc. the information received from sensors can provide prospect about popular locations and services could be planned and provided for that. For example, iot sensor detect location of visitor in museum stand in front of item and by using appropriate technology the relevant information is forwarded to visitor smart phone[18]. This information is also transferred to central server for processing which lead to determine popular item in the museum. The information received from iot sensors can be used to promote tourism by providing incentives and collecting more points to visit the most tourist attraction region and sites [19] .

1.4.4 Social services

Social can be categories into social networking and sensing information. In social network user share information to complex problems on different systems such as Facebook, twitter and LinkedIn. In contrast, social sensing applications collect data about personal activities and further sends it to remote server for processing. User can also make freelancing account and create social network. these social links help him find customer or service provider for online services[17]. The data collected on daily basis and analyzed to publish reports or journals for the true picture of social networks.

1.4.5 Traffic flow management

Crowd sensing contribute an important aspect by collecting information about traffic to improve public and private social decision related to traffic.

- **Traffic related info collection**

Real time road monitoring crowd sensing is drawn much consideration. Different researches propose real time system that provide aid in monitoring. Platform for data collection using cellular networks to upload data related tasks. The information related to cars, buses pedestrians and taxi from city are collected and examine the traffic status. This information use in controlling unexpected traffic trends with, predicted patterns. All these show the changing economy status and development structure of a city.by using smart cards, which measure latitude, longitude and id company measure features. These are used to improve quality of life of citizens[16].

- **Traffic service improvement**

The crowd sensing data is used to optimize the transport quality. Applications are used to monitor the routes of buses and taxi routes. The mobility pattern of traffic to determine the dense traffic spots and splitting and guiding regarding other routes. These applications used to fix traffic problems and improve the living standards.

1.4.6 Location based services

Sensors equipped devices, mobile crowd sensing vastly use in providing location services. The location aware services use in mobile applications such as searching location, advertisement based on location indoor localization to find object and locations[16].

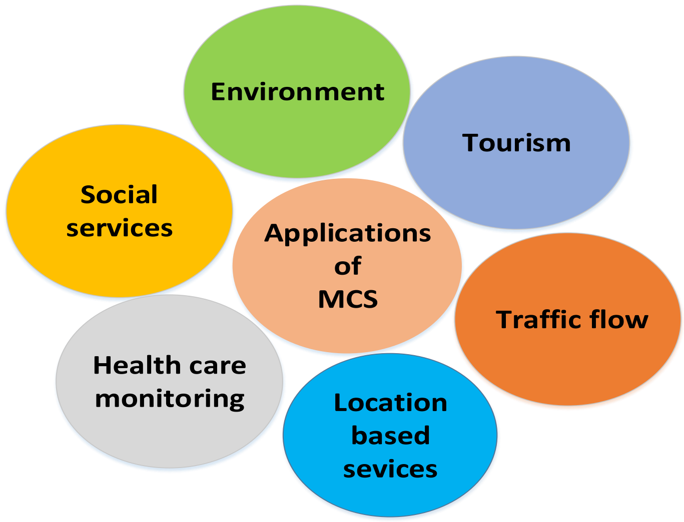


Figure 1.3: Application of Mobile crowd sensing

1.5 Problem Background

The emergence of smart devices and technologies such as mobile phones, tablets and different hand held devices equipped with various sensing and computational capabilities have given rise to Mobile crowd sensing (MCS). Large number of approaches proposed for the sensing of quality of data, that mobile workers are recruited and monetary incentives are given based on quantity, quantity and truthfulness of the task submitted. The problem here is that by little effort to gain maximum benefits mobile workers share low quality data and perform false reporting.

In literature the approach [9] ,mobile workers are hired on the basis of reputation and data quality reporting for maximizing profit of the platform . It has two phases selection of suitable worker and verification of quality of the task submitted. The reputation is based on skill, also considering the quality platform utility. Incentive mechanism is based on the rewards that are provided based on the quality of work and task completion constraints are involved.

Decentralized approach in [10], the time and cost of data collection through mobile devices and advance sensors for performing different tasks and assignment in mobile crowd sensing can be reduced through participation of members. The participants are service provider; data collector and service consumers.to motivate data collectors to participate in activities related to network monetary rewards are given. Privacy issue is dealt with Advance encryption standards. The reputation system for data integrity and fake reviews are tackled with registered reviews. Through registration the data provided is compatible and reliable. Smart contract used for conflict management. Reputation system mainly depend on the reviews provided by the service consumer on which incentives are given to service provider and data collectors.

From literature we observe the reputation mechanism mainly depend on reviews from the service consumers and also depend on the maximum task completion of task for reputation to gain maximum reward. Our proposed system tackles this issue by updating reputation through difficulty level of task so that difficult tasks can also be accomplished ensuring an efficient system.

1.6 Problem Statement

During the reputation calculation for the MW, difficulty level of a task is not considered in schemes[20] and [21]. It results into misconception of a good reputation for a MW who is doing a large number of easy tasks with good quality to obtain a high reputation. On the contrary, a person performing difficult task may gain less score for reputation. The MW performing difficult tasks may get some lower score while missing the quality level of that difficult task. It also results into lesser reputation score.

1.7 Research Questions

1. What are the factors that affect the reputation score?
2. How the incentives are affected by reputation score?
3. How a task difficulty level effect the reputation of a mobile worker?

1.8 Aim of the Research

In the era of emerging technologies in Mobile crowd sensing, mobile devices play an important role. The mobile workers’ reputation is an important factor, which can effect user, worker and platform. Based on reputation incentives are distributed among participants. We aim to improve the overall reputation mechanism so that related entities gain maximum benefits out of it. Difficulty level of task will measure the reputation of worker, which ultimately effect incentives of workers and platform will get a clear vision for their future recruitment of most reputed individuals.

1.9 Research Objectives

1. Identify the factor for Reputation score measurement
2. To evaluate the incentives for a task based on its reputation
3. To identify the effect of difficulty level of a task on reputation of a mobile worker

1.10 Scope of Research Work

In mobile crowd, sensing service provider or worker is an important entity that is a driving force in a system .in this research we considered reputation of mobile worker as an important aspect for reward and incentive mechanism. For reputation score measurement we consider different factor e.g. reviews from requester, task quality as well as difficulty level of task. Task is categories in to different difficulty levels and reputation score is measured in those levels. In literature, different factors are considered for reputation score measurement but task difficulty level was ignored result in higher reputation by completing less difficult task in abundance.

1.11 Thesis Organization

The remaining part of the thesis is organized; section chapter 2 gives literature study, in section 2.1 mobile crowd sensing paradigms discussed, in section 2.3 in literature study about incentive mechanism in MCS, is discussed in section 2.4 reputation of mobile worker detailed discussed, section 2.5 different incentive and reputation mechanism advantages and limitations presented. Section 2.6 consist of research gap and direction and section 2.7 consist of summary of chapter. Chapter 3 consists of methodology that is collection of data from literature to identify the problem from specific area. The framework gives the idea of the research direction followed to do the work. Chapter 4 offers detail of proposed algorithm and details of it. The data flow diagrams explain the direction of data flow in proposed system. The architecture of system diagram explain from task sensing to selection of worker and reputation updation and store it in database for further use.

Chapter 5 will provide performance evaluation in the form of graphs. The different categories of graphs such as platform utility, quality versus quantity, mobile worker utilization and time computation. These all shows the system performance. Chapter 6 will give summary of contributions, simulation results and future direction etc.

CHAPTER 2

LITERATURE REVIEW

2.1 Overview

Crowd sensing is an emerging field in recent years with the advancement of technology. Advancement of technology brings potential applications in different fields. This sensing process of different devices also raised different issues related to user recruitment and incentives given to them based on reputation. In this chapter, we review different existing research efforts on workers' recruitment and reputation in mobile crowd sensing.

2.2 Mobile crowd sensing paradigm

Mobile crowd sensing can be categories in to two paradigms according to user active involvement in the sensing process. These are participatory and opportunistic paradigms.

2.2.1 Participatory sensing

Participatory paradigm requires active involvement of device user. Based on real world mobility traces[22]. They will collect data e.g. take pictures, record videos and audio samples. Apart from this, they make interactive and quick decision with different entities of MCS.

More and more participants are involved in task allocation and appropriate task will be assigned to each participant and the basis of availability of participant. This Paradigm highly depends on user, willingness to participate and dedicate their resources.

2.2.2 Opportunistic Sensing

In opportunistic based sensing it creates ease for the participant by automatically collecting and computing data from the devices[23]. Users are not possibly aware that applications are gathering data on their sensors. That is, devices made automatic decision regarding sensing data. This system is technically difficult to build. Due to complexity of this paradigm, this is limited to few mobile crowd-sensing applications.

2.3 Incentives mechanism in MCS

The incentive-based schemes discussed to get solutions of the problem identified. The approaches use different mechanism for their computations. Their advantages and limitation are identified by other schemes. The details if schemes discussed as follows.

In [20], the author have proposed reputation quality aware recruitment (RQRP) for platform to provide high quality reporting in mobile crowd sensing. The scheme is divided into pre and post quality measures. Based on mobile quality reporting provides incentives to mobile workers (MW) and maximize profit in iot. A recruitment mechanism to hire skilled MWs while mainly considering feasible budget, quality, platform utility, and individual rationality. In the similar a selection algorithm and reputation-updating system that considers the weight and score for both reporters and requesters.

In macro tasking crowd sensing system Google help outs and elance provide human intelligent to solve tasks. Requesters post task and worker solve it to gain reward. Malicious workers exhibit their selfish behavior to gain maximum benefit by decreasing efficiency of platform. In [24]the author proposed zero- determinant (ZD) strategy which provide incentive to competitive selfish workers and provide high quality. First, they formulated crowd sourcing as multi players iterated game having incomplete information. The information own by each worker and actions are hidden from other workers. Decision are made bottom up way for cooperation enforcement of selfish workers to provide quality solution. Competitive workers take tasks with incomplete information and repeated interactions among them. Payment schemes ex-ante and ex-post somehow prevent free riding. Restricts requester on false reporting, in order to refuse for payment given to workers. Focused worker choose ZD strategy. In iterated game starting outcome initialized and player profile determine a stochastic process, player restrict their moves on the basis of previous outcome .this this process using characteristics of makov chain in which probabilities calculated from players strategies .one worker do not know the actions of other worker but maintain social welfare ,that is observed by the system. Free riding problem taking incentive without submitting desired quality work still exist.

In [25], designed participation and rewarding as two stage game . In CSP Crowd Sensing Service Provider, analyze participation level of mobile users and motivated users to contribute information in the social network and optical reward given using backward induction. Optimal incentives as discriminatory rewards and uniform rewards are given based on information shared. For Interaction between mobile user and CSP, shackle berg game used. Stage I Reward aiming the highest revenue and stage II participation level to maximize individual utility.

In [26] ,the author proposed dynamic incentive mechanism (DIM) that is based on the deep reinforce learning (DRL) without accessing mobile user private information. Incentive mechanism by taking mobile user (MU) own resource demand. The incentive mechanism based on two-stage stackelberg game users are classified in to two groups' leaders and followers. Stackelberg equilibrium provided feasibility to cope with MU's demand and limited resources. Greedy and random pricing strategy is also performed in DIM. DRL enable the service platform (SP) to learn the pricing strategy directly from experience without knowledge of MU's private information. Service provider need private information to complete the task that is not possible in some situations. Economical model to handle uncertain situations. This SE is authentic process to manage demand uncertainty and resource limitation. MU,s can be promoted to participate in the mobile crowd sensing game and private information is protected. DIM approach for dynamic game, without any data about private information learn pricing directly from game. Computational results show this approach is effective in both dynamic and static game, significant impact on uncertain demands.

In emerging era of mobile crowd sensing embedded mobile phone technologies becoming important for task sensing on much larger scale. With trial of task participant selection from a large number of users. In[27], caching sensing data for partial sensing data to lower the size of set of participants. The crowd sensing applications sense information that is generated by task participant and save it. The selected participant sense task from application assigned to them. In centralized as well as decentralized approaches, the data cashes that is uploaded by the participant, which are selected by system. The crowd-sensing platform create data storage components and make task participant selection. The work flow this system as follow: application generate sensing task and send it to participant selection appliance. Based on historical values of a participant selection is made and coverage of particular task in the past. If the location of selected task participant occur at some places then send it to relevant applications for storage of data. The participants have their unique pattern for visiting a task participation. This system assume that participant update system through piggyback. When a selected participant at a specific location make call, the data sensing application upload and store to data storage. Algorithm use for Estimation of participant coverage for a particular task. Poisson distribution for prediction of task by participant in the future. Caching use less participant in completing the same task in the previous coverage than the without caching.

For monetary incentive mechanism, it is a challenge to prevent malicious participant and non-reliable task requester. Quality aware incentive schemes are unable to preserve the privacy of participants and data quality is not measured. In [28], introduced privacy preserving and data quality aware incentive scheme (PACE). It consists of task requester, service provider and task participant. Service provider hires task participant and also responsible to prevent task requester to give unreliable data, task participant in charge of reliable data provision and in return earns reward. The main difference between PACE and other mechanism that it provides data to those who task provider who provide reliable data and receive incentive so that PACE can protect the identity and sensing data. The pace consists of requester, estimation, incentives on the basis of reliable data provision by the task provider, on reliable data submission the reliability is analysed and after confirmation payment is made to task requester by service provider otherwise does not pay any reward. Threat model observe the potential attacks on data such as data pollution attack, inference attack, Sybil attacks are considered. When two entities of model collide, application not be stable so assume that no collision occur. The security goals of this scheme consider there should be data privacy; no entity can access the data except paid owners can. Security gaol to prevent Privacy of task participant. The goal to achieve are completeness of data, zero knowledge mean service provider do not know anything about the data, it should only meet the requirement, zero knowledge model is used and assessment of reliability is made. This data technique is privacy encrypted so do not create any privacy leakage issue they also proposed zero knowledge model for data reliability estimation to protect data privacy [29], real world data set were used. The monetary rewards are same as the quality of data is same.

Modern crowd sensing plate form use piecewise reward approach, workers are paid for each task if their work quality is considered by the platform. Otherwise, there is a risk of their work rejected without any reward. In Crowd CO-OP [30], reward mechanism adds participating workers that share risk and individual worker paid is paid on the basis of amount of time completing HIT. the co-op group earnings are redistributed among the member on the basis of time they spend to complete task.co-op scheme is compared with piecework aiming to quickly complete HIT to increase personal wages of worker .co-op reward produces accurate labels for requester without worry about reward of single HIT. The loss of rewards that are missed due to rejection is shared among group without putting impact on the individual whose work is rejected. Loss of less experienced worker is covered in-group reward. five reward distribution schemes presented are: i) piecework with visible incentive ii) piecework with Hidden incentive iii) Co-operative with visible incentive iv) Co-operative with Hidden incentive v) Co-operative with hidden incentive and social comparison. All these schemes are evaluated on the API provided by MTurk crowd sourcing platform. Slow workers and free riders did not harm cooperative groups but this may create trust issues among workers result in monetary loss for group. The disadvantage of this approach is the low quality worker can increase rejection rate of task.

In [31] hierarchical incentive mechanism using a backward induction first solve contract formulation, and then solves the coalitional game with merge and split algorithm. They also proposed federated learning based privacy-preserving approach to collaborate with machine learning. This system allow collaboration among machine learning without danger of data privacy by sharing model parameters instead of raw data to exchange with the federation. The two challenges are incentive mismatch between model owner and user. As incentive mechanism is hierarchal, so in upper level the incentive received by the model owner is effected by the decision of other owner that in result, effect model owner. Contract represent maximization of contribution while minimizing incentive paid to its users. The owners take decision to join the federation that give them more profit. The workers collect data from published tasks by the model owner in crowd sensing to exchange contract rewards. The model owner selects the federation that by collaborating with other model owners that fulfil their profit margin. The models are train on locally data and the sent to trusted server for aggregation as shown in fig 2.1.

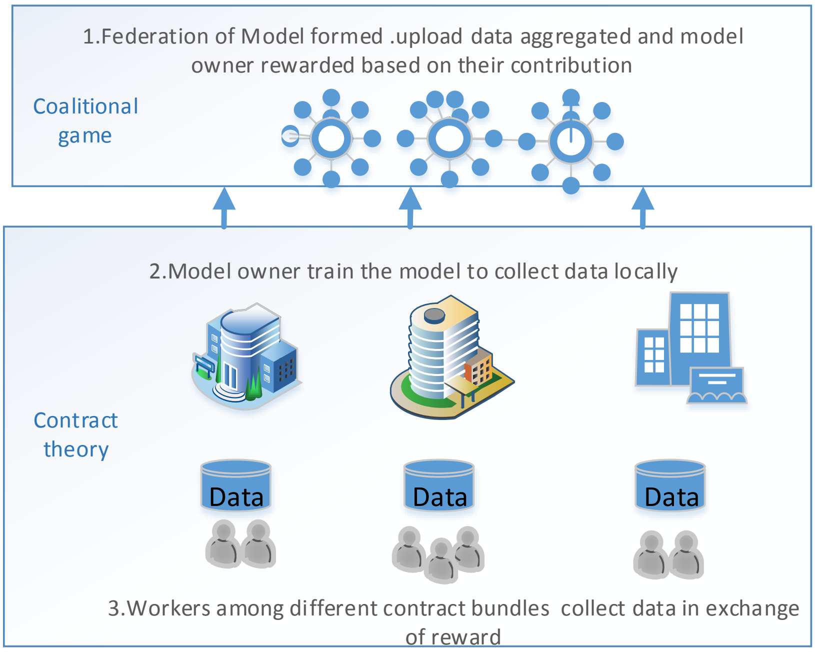


Figure 2.1: Hierarchical incentive model

Sensors for mobile applications are gathering data and Saving Cost and time inefficient manner in crowd sensing network. Data is collected from all devices and members e.g. Consumer, service provider and data collecting devices. Centralised methods are used to deal with all the CNS members that is a big security threat and susceptible to attack for privacy. The technique used is decentralised in [21]and [32], based on block chain. The rewards are used to motivate mobile workers and data users to take active part in network usage. For privacy leakage issue they used advanced encryption standard AES (28) technique. Repetition system also introduced to false data review and to solve other conflicts as shown in fig 2.2. Reputation is measured in gas consumption and string length being used. There is no proper standard Incentive distribution mechanism for mobile workers and network users. Existing content sharing strategies are not effective in personalised data sharing.

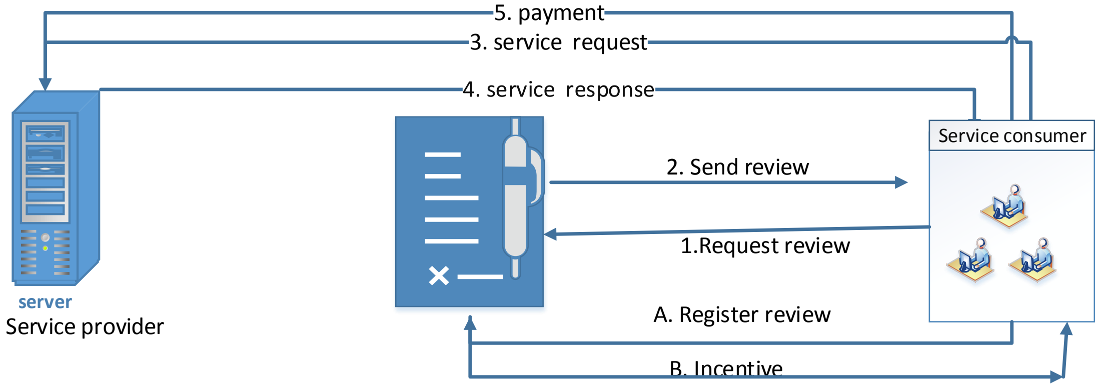


Figure 2.2: Reputation system for crowd sensing network

In the underlying research introduced social aware personalised content sharing strategy on mobile crowd sensing. It consists of two parts service provider and service user. The four main stages of their work are request formation in which they select contributor for their users. In second stage social structure created to tie the user within social relation and their social relation can also be find out to build trust. Cooperation scheduling help to evaluate content of the platform to maximize the profit and social wellbeing. In fourth value aided service offloading the content share through iot sensor. After filtering a selected according to one's specification data in provided to participants. The basic initiative in [33], was to introduce two stage pricing policy between by user and service provider. Solved subgame perfect Nash equilibrium NE [32]and [34], of proposed game effective pricing strategy developed. Two algorithms used Pareto optimal NE and Nash equilibrium are designed to perfect scheduling scheme and optimum pricing strategy can be achieved. They use stochastic network model and real world data set. The disadvantage of this approach is that third party involved with personal content uploading.

In [35], Cross-Space multi interaction based incentive called CSII, use history and sensing scenario for value of task estimation. To make workers group of suitable people task requester and worker have multiple sessions of meetings on budget to provide suggestions. After submission of task requester, pay the incentive. Incentives based on reverse auction bids and reputation score. The task value have influence of both online and offline data, user quality for specific task for task estimation. In mobile crowd, sensing stakeholders interact to improve quality of sensing task. The quality of user contributed data and incentive distribution can be improved through interaction on different phases of task performing. The entities that interact with each other are task requester, task publisher, management platform and worker, which perform task. A requester publish the task. The platform estimate the value based on location based social networking and then assign it to suitable workers. Divide the tasks according to districts and grid, the cell within grid is called square region. In task publishing, stage the interaction between platform and requester. Task is submitted on the platform, which estimate the financial plan and send to requester. The in selection stage the platform assign task, select worker based on Spatio Temporal. The worker accept or reject task. The platform search for worker until number of suitable workers met. To prevent the workers interest who lose bid also pay some incentive for participation, along with the winner workers. There are some limitations also applied to set of worker as 5, sensing tasks published 10. The worker can also complete a specific number of task at a time. The results show the feasibility by selecting number of worker within budget.

In[36], auction frame work for crowd empowered privacy preserving is developed. The platform act as an auctioneer in recruiting workers for task sensing. This scheme make it convenient for worker to provide their data as well as protection against their privacy preservation. The selection made on worker sensing expertise which directly encounter the drawbacks of game theory in which due to presence of numerous Nash Equilibrium cannot ensure accuracy of data or results. The workers privacy data depends on his own data presentation and some external factors, which act on his privacy factor. To get the level of accuracy we categories the anomalies which cause privacy preservation breach and count the impact of noise added by worker in evaluation of result. Also highlighted any hidden problem factors and accurate bid by worker to achieve truthfulness, rationality and efficiency in computation in incentive management. In the incentive mechanism when platform receive bids from workers, the platform evaluate the privacy deficit of each worker, which bid for a particular task. Platform after evaluation select the winner and according to incentive mechanism, incentives given to winner worker who fulfil the task requirements. The platform help worker to send their data according to requirements as well as their data’s privacy preservation.tn the last step the results of data aggregation are shown to the task requester. Workers by using system get a positive utility for their work. The results calculated in polynomial.

In[37], staged incentive mechanism (SIM) incentive and punishment mechanism examine for mobile crowd sensing. Incentive mechanism is divided in to two phase's recruitment and sensing of task. The recruitment stage contains payment incentive coefficient and stackelberg game. The recruitment process take place through game interaction. At data sensing level, data utility algorithm used for interaction. Winners selected and filtered by using data utility feature that is direct affected by time space association. Reputation of participant is based on data utility.to reduce the payment cost and waste punishment mechanism is presented. Compared with existing positive auction incentive mechanism (PAIM). Reverse auction mechanism (RAIM) compared with (SIM). Reputation calculation on Punishment mechanism control the malicious users, and saves wastage of resources and incentives. Sensing platform, deliver the task to and select the participant. Potential participants are those who participate in the task sensing activity. At recruitment stage platform, sense the task by using location based social network (LBSN). The participants recruiting performed mainly on this stage. To motivate and attract participant the sensing platform define some monetary rewards in advance. Due to sensing time and changes made at completion of the sensing task LBSN used for data access and provide solution. Sensing task is a multi-period and multi task at a location. Participants allocated at different locations and different task creates an unnecessary distribution. Therefore, divide multi task at multi sensing location into series of subtask on location based sensing network having direct effect on level of activities.

For monetary incentive mechanism, it is a challenge to prevent malicious participant and non-reliable task requester. Quality aware incentive schemes are unable to preserve the privacy of participants and data quality is not measured. In [28], introduced privacy preserving and data quality aware incentive scheme (PACE) .

It consists of task requester, service provider and task participant. Service provider hires task participant and responsible to prevent task requester to give unreliable data, task participant in charge of reliable data provision and in return earns reward. The main difference between PACE and other mechanism that it provides data to those who task provider who provide reliable data and receive incentive so that PACE can protect the identity and sensing data. The pace consists of requester, estimation, incentives based on reliable data provision by the task provider, on reliable data submission the reliability is analysed and after confirmation payment is made to task requester, by service provider otherwise does not pay any reward. Threat model observe the potential attacks on data such as data pollution attack, inference attack, Sybil attacks are considered. When two entities of model collide, application not be stable so assume that no collision occur. The security goals of this scheme consider there should be data privacy; no entity can access the data except paid owners can. Security gaol to prevent Privacy of task participant. The goal to achieve are completeness of data, zero knowledge mean service provider do not know anything about the data, it should only meet the requirement, zero knowledge model is used and assessment of reliability is made. This data technique is privacy encrypted so do not create any privacy leakage issue they also proposed zero knowledge model for data reliability estimation to protect data privacy [29], real world data set were used. The monetary rewards are same as the quality of data is same.

Mobile crowd sensing is widely used in collecting and analysing of data. The quality of data is not addressed properly in order to solve this problem in [38], authors proposed quality based truth estimation and a surplus sharing method. Unsupervised learning method [39], used to measure data quality, and reputation by filtering out anomalies that items. Consider surplus as sharing game and propose shapely value best method for payment of each user.

2.4 Reputation based approaches

This section contains reputation-based approaches, the schemes used for reputation computations. Explaining about their schemes working, and comparisons with other schemes. The usage and advantages as well as limitation highlight.

In [40], Fined grained ability reputation system two reputation systems introduced beta distribution and peer prediction ability reputation system. In Beta constructed a reputation system, which provide feedback and express rating updates workers ability based on history about worker and the current sensory data received. First, of all, it initializes the worker's reputation in system if history available it initializes according to it otherwise for new worker check white washing proof that it should not be existing worker entering with new identity. Then ability reputation is updated data provided by sensing, positive feedback added otherwise negative. In peer prediction reputation is executed by external raters, rewards are given on the basis of their feedback to prevent dishonesty ensures raters truthfulness. Fined grained ability reputation system is evaluated on the basis of min cost and ability max. In cost greedy approach used for all task and in ability also use greedy algorithm and payments are made on the basis of bids. the possible drawback of this system is that ability reputation is calculated in last, depending on the history. If few bad qualities appeared in history, it effects ability.

Workers are recruited to collect data and through mobile devices and provide it to platform. The data collected by workers varies in quality so developed a reliable crowd sensing system that ensures the quality of service. In [41], reputation based multi-Auditing algorithm (RMA)by integrating task based temporal (TTR)reputation based truth inference algorithm (RPM).Reinforcement learning and accuracy algorithm used to update request strategy and requester gradually adopt to their environment. Rational and irrational both workers used, as irrational workers prefer on individuality and rational worker adopt to changing strategies over time. For malicious collusion in PM, adaptive auditing is performed that allow rational requester to check result of workers and exact truth is known. Unsupervised voting algorithm is adopted to determine the truth. TTR mechanism is used to measure the reliability of each task. The requester identifies truth and a reputation score provided along with the data provided by the requester. Bonus payment mechanism allow worker to earn extra reward for correct result provision. Lyapunov theory provided assurance that due to stable state truth worthy behavior is observed. There is possibility of malicious collusion and reputation inflation.

In [42] , ER experience reputation the author proposed trust mechanism between device users in mobile crowd sensing plateform.in E-R model virtual interaction among device user and assessment of data quality considered. Trust indictors experience and reputation evaluated. Trust relationship was established and the then selecting the most trustworthy MCS user in data contribution task. The (QOD) quality of contributed data is assessed. Experience relationship between service requester and data contributor is calculated and trust relation is based on these two-trust indicators experience and reputation .user recruitment scheme based on the quality of service based on the QOD contributed. Predictive algorithm is used for comparison of trust schemes. Efficiency of QOS with high and low quality malicious users also provide trustworthy data and prevent contribution of falsified data.in MCS user can be a requester or service provider, they directly or indirectly interact with each other. In E-R Indirect Sensing model with participatory data acquiring method. Centralized cloud platform to operate all the processes task creation, execution recruitment and for incentives schemes. Trust component is integrated in centralized MCS platform, which manages virtual interaction between users. Indirect interaction is established, and their values are calculated based on the quality of data and feedback from consumers. Based on experience between two users the reputation is calculated and then trust value is calculated by the aggregated value of reputation and experience. For the trust evaluation, no data collected from malicious devices but malicious users can produce high score of QOD for recruit and after that produce low quality, which could possibly damage the service.so a trust score was set below that quality data was not acceptable. E-R model compared with polynomial regression model and average based scheme. Average based scheme can consider malicious users due to average QOD similar. Moreover, in regression model take more time to learn about malicious users. E-R model heavy penalize the low QOD scorers result in drop of trust relationship and reputation score.

In[43],quality of sensing data evaluated through mathematical model .the sensing data is submitted by crowd sensing mobile users. To ensure high quality sensing data with limited budget constraints generated a utility function for platform who recruit the task participants for sensing task. To solve the online scenario problem where users enter and exist task at any time, introduce a quality aware incentive mechanism. To motivate workers, the mechanism for chosen participants to provide extra incentives on their level of task completion and performance from history. Online quality aware is compared with online method “OMG” .and optimum gap reduce to 33.3% and budget B=1000. Truthfulness mean platform require truthful sensing data as already decided with participant. Rationality of individual is participant get incentive according to sensing cost. Budget feasibility rewarded cost should not more than total cost. Data quality mean, quality estimation is difficult before platform collect it. Malicious worker provide low quality sensing data and ultimately leave the crowd sensing. By proposing online incentive mechanism control these issues and maintains truthfulness, budget feasibility and computation efficiency. Simulation performed on real dataset and by comparing it with existing methods. The platform select the participant one by one by considering the sensing quality. The reputation value based on sensing quality of data. Data Quality measured by the hardware sensors. The more accurate sensor work the more data quality get better. The budget is divided in to upper and lower limits, while extra bonus reward depend on participant contribution. If basic budget is enough then more bonus is given.

In[44], trust based minimum cost quality aware (TMCQA), select trustworthy reporter for collection of data. The data collection process improve the data coverage range and adjust the optimize cost under the system budget. TMCQA has following prominent features: i) the trust evaluation of data reporter/provider is established according to machine learning. In peer-to-peer network data reporter is considered as entity for main data collection instead of sample, which is different from other schemes so TMCQA is more practical approach .ii) the selection of data reporter based on three key elements which help in improving data collection process. a) Consider the value of trust for reporter, the more trustworthy reporter result in to high quality of data. b) The sensing covering range c) the user data reporter having lower data collection cost selected for optimal selection. The trust value learned from history to ensure high quality of data so any false data quality prevented. The history trust value is learned with time decay. The expected rewards and incentives for collectors, distributors by considering trust value, make evaluations to select data collectors. The reporter sense and collect from a sensing location. The sensing location or city is divided in to different parts that are called grids. The applications collect data in a network. The application pay considerable amount to data reporters for collection of data. The report is consider valid if data collected is valid with minimum budget requirements.

Many sensor devices are connected in iot network; task scheduling is an important issue when sensor nodes have limited resources. The previous Q learning task scheduling schemes only consider angle which effect network performance. In[45], (QFTS-GV) Q learning based flexible task scheduling with global view proposed successful task scheduling, reduce delay in task and maximize usage of iot sensors. This framework consists of state set; action set and reward function according to global view, which is base of proposed scheme. The nodes having high power protected and relaxed nodes increase their transmission for beneficial network. This task scheduling adapt the environment. Q learning algorithm, help in choosing nodes the task, which is more beneficial, and save energy. This will reach local optimization goal and global is ignored. The IQ task scheduling consider all nodes equally hence, they consume more energy. This scheme increases the nodes with high-energy consumption node transmission distance, increase the task execution chances. High-energy consuming nodes try to complete complex task first to reduce risk. Because a failure occur in task execution, it reduce energy drain and maximizing iot sensors life. To refine task scheduling different strategies applied to different nodes to optimize global network. When task execute successfully it give positive feedback otherwise negative feedback receive. Power recovery action is scheduled for checking communication anomaly in the network is ended or not.

In[46], QnQ based on reputation model that divide users in to different classes such as honest ,selfish and malicious. The result score used to give incentives to the users. QnQ by combining quality and quantity make sure in different participants behavior. Rating feed mechanism to ensure the truthfulness, find probability mass for positive and discounted probability of mass for unreliable facts. For clarification of evidence truthfulness, liner model is used to convert it into quality of information. Quality of information events are used for reputation scoring. The reputation and incentive degradation is compared with Dempster Shafer model and QoI is compared with Josangs belief model. QoI score include total massive feedback to minimize the malicious rating about a task. By combining quality and quantity reputation scoring measures the contribution of each user. The two main advantages of this reputation system is that it (i) it separate the user types weather it is honest ,dishonest selfish.(ii) it form an incentive distribution system based on the user behaviors in performing tasks. This scheme based on evidences from feedback instead of taking scores from history .through reports calculate a reputation score by keeping record of that published task and the specific user contributed in them .the reputation score normalized by setting intervals. Later on, this reputation normalization score is used by combining with quality and quantity in incentive distribution.

In crowd, sensing Mobile workers are recruited to complete task assigned from requester and get profit for this. As workers are selfish in nature, they try to maximize their profit while minimizing cost. In [47], truthful incentive mechanism pays workers on the basis of task completed and their reputation from previous performance and future prediction. The pricing scheme is divided in to two parts, first is partial payment that depends on workers' reputation and other depends on completion of task. Workers with high reputation perform better and performance depend on different tasks. When final payment is made, it will be provided according to proposed scenario difference of actual performance of task and the reputation. Expected performance bound is set. Punishment is given if performance of worker is lower than the expected bound. If performance is higher than the reputation, reward will be given. Request is categories in to two factors data accuracy and response time.in real time response time of worker is important; workers are encouraged to upload their information as soon as possible. For data accuracy, TD algorithm is used to measure the data accuracy of each workers' data. If data value deviate from truth-value, then worker is assigned a low value. Contribution of workers' performance in-group is ignored.

In[48], reliability is considered as the trust factor and task completed within local and global context in eq (1). Wg denotes importance global views and Wl denotes local views. whereas Wg+Wl=1

$$\text{Re=Wg*}\ \frac{\text{Number of globally jobs completed}}{\text{Number of globally jobs accepted}} + \text{Wl} *\ \frac{\text{Number of locally jobs completed}}{\text{Number of locally jobs Accepted}} \qquad (2.1)$$

The reputation of individual user is the number of jobs accepted and completed over a period T, task submitted, data integrity preserved by resource over a period T, identity of resource over a period T and in the last capability of the cloud resources. Whereas W1+W2+W3+W4+W5 =1 as weight factors as shown in eq (2):

$$\text{Re=W1*}\ \frac{\text{accepted jobs}}{\text{submitted jobs}} + \text{W2*}\frac{\text{completed jobs}}{\textit{accepted jobs}} + \text{W3*}\frac{\text{data integrity}}{\text{jobs completed}} + \text{W4*identity} + \text{W5* capability.} \qquad (2.2)$$

Availability mean authorized entity such as platform made available or provide service or resources and data storage on demand. The services are also available when not all clouds nodes are available. Availability is the relation of time in which system functions can be completed. This is represented in directly proportional or percentage. This is represented in quantities that system is going to work when some of its components are down. The resource availability is calculated as shown in eq (3).

$$AV_{R_K} = \mathrm{W_g} \times \frac{A_{Kg}}{N_{Kg}} + W_l \times \frac{A_{Kl}}{N_{Kl}} \qquad (2.3)$$

R1, R2 …... Rm are the resources. For K= 1, 2 ….m, N_{Kg} represent number of jobs send to resource R_K over a time period T, A_{Kg}represent number of jobs accepted by cloud resource over time globally, N_{Kl} represent number of jobs submitted over the time period locally , W_l represents local views and $\mathrm{W_g}$ represents global views. Whereas Wg+Wl=1.

In [49], computation efficient reputation algorithm addresses the problem of workers' true label is addressed against the noisy labels. They consider the worker's reputation in broad sense that have no assumption on their labelling strategy. The proposed algorithm filters out the workers in crowd sensing network. Identifying the true labels in noisy inputs in online environment is challenging due to following reasons. (a) Worker can anonymous and can provide malicious label information (b) the workers reputation is unknown (c) majority labels are receive from a small subset of workers. This research provides the true label of adversarial worker strategies where no assumptions on their labeling. Deterministic labeling, where workers always give same labels. In addition, malicious workers can provide fake labeling and degrade the accuracy of labels. Workers are categories according to honest and adversarial. Honest workers use probabilistic model to provide labels. The adversarial workers are identifying through the computation score of reputation and trust of each worker. We assign penalties to workers the higher the penalties the worst will be reputation of workers.

High level of participation and large number of users requires for sensing and collecting data in MCS. In the underlying research paying certain monetary reward to service provider is the main purpose. Therefore platform have high intake of resourced due to high demand for data quality. In[50], Reverse Combinatorial Auction Based Endowment Effect (RCBEE) is inspired by the enterprises to share payments to motivate employees in daily life and show trustworthiness towards task. This research map a relation between it. To introduce endowment effect, design endowment assets, assign them to specific nodes according to relationship between nodes. RCBEE analyze changes in income and rebuilt the matrices of icome.is build up the endowment intensity within a period. It maximize Social welfare by reducing bid amount and completing more tasks.to empower endowment effect during holding period of user. According to user cost and quality of data endowment assets initialized. Dividends calculate according to contribution and endowment asset and then intensity effect of user were calculated. The holding time and contribution to motivate user to complete maximum task and reduce bid effect. The requester selects the winner according to the usability and promotion threshold. In algorithm winners selects according to their usability and promotion threshold .The user, by lowering the bid price can reach the promotion threshold. The income-updating algorithm is design for social welfare. The assets endowment, increase and motivate the user to participate in social welfare and reduce payment cost.

In[51], BiCrowd incentive mechanism is a bi objective scheme. The literature is associated with one objective so they investigated the bi objectives. The reverse auction mechanism used for incentives. This scheme consider the online worker arrival. The two objective for sensing applications with main goals. (i) Sensing task completion reliability, by considering and encouraging worker based on their history of task completion. Rating and reliability in which requester rate worker on the task submitted. These rating scores kept in record to calculate reliability of worker. This increases or decreases worker probability for future selection. The future prediction is for the reliable task completion based on this reliability mechanism. (ii).spatial diversity of worker. In Mobile, crowd sensing task of taking photos, worker report their task from different prospective. By modeling spatial diversity of workers, workers sense data and can capture different features of the task. BiCrowd encounter the worker evaluation and optimize incentive mechanism including measuring different properties like computation efficiency, budget feasibility, truthfulness and competitiveness. Two online incentive named EpIM and EaIM. EpIM suppose worker have moderate behavior interested to make best use of their utility. On the other hand, EaIM considers that workers are ambitious and try to find way to utility maximization. Spatial diversity function for worker evaluation on current location. Assign one task when marginal value is greater than a specific threshold density.

In[52],CENTURION, is multi requester mobile crowd sensing system. In existing mechanism that assume one requester, this approach consider multiple data requester.to motivate data requester and worker incentive mechanism based on double auction. Incentive mechanism is not isolated and interact with data aggregation of workers data. The properties desirable are truthfulness, rationality, Computational effectiveness and social welfare. The scenario consider in CENTURION where requester and worker both are self-centered and aim to take full advantage of their own services.(MELON Double Auction) multi requester mobile crowd sensing ,each requester obtain a value ,on her task accomplishment and bid on platform, the payment for task execution. The worker that interested a subset of task bids to the platform against the bidding amount of requester. Requester and workers cost are unknown to the platform. Define utilities of worker and requester. The summation of platform profit and the two entities that are participating all workers and requesters utilization. The requester bid, the platform determine the winner requester, winning requesters and payments to each winner requester. The losing requester, tasks do not execute and they no need to submit payment. Similarly the dropping worker as they not execute any task unable to receive any payment.

In crowd sensing device owner provide information about surrounding by using mobile smart devices. In[53], author proposed data and participants and assessment and remuneration scheme (DPARS). This scheme consists of three stages procedure to estimate reputation based pay off. In first stage consensus based outlier detection technique to assess data efficiency and assign it a score. In second stage, the score is used to measure participant behavior but in corporation statistical management system for reputation. In last stage incentive determine based on cooperative game theory, where participant cooperate to increase utility. The contribution is mature on the bases of first two stages and are used for fair money paid to each participant.

Existing researches mainly emphasis on requester centric mobile crowd sensing (RCMCS). In worker centric requester only, focus on his own benefit in assigning task. Worker in RCMCS unable to get any benefit in this mechanism. While in worker centric mobile crowd sensing (WCMCS), worker maximize their benefits and ignoring the requester and hard to maximize the number of completed task. In[54], task bundling in WCMCS that maximize number of task. Loc Traj Bundling algorithm for bundling of task based on location of task and workers. According to some characteristic task bundling bundle total tasks in to numerous tasks. The attributes are task location, worker tracking and reward for task. The bundle contain number of tasks. The task provide facility to worker to complete all the tasks or not carrying out any task from the bundle. If tasks are bundled with popular and unpopular task then worker, select the bundle have to complete all the tasks to get reward. On contrary task bundle have high reward than an independent task. This motivate worker to select the bundle of task. In some situation where having some cost, task bundling to persuade worker to select unpopular task and complete it. Bundling create a balance between number of bundle and size of bundle packing of task plan.to maximize task bundling heuristic algorithm Loc Traj Bundling that at initial stage use greedy algorithm. Real world data set used by Baidu Map API in experimentation.

Selection of suitable use for optimization of quality of collected data with a budget range is critical that effect the mobile crowd sensing (MCS) effectiveness. The accuracy of sensing data is relevant to mobile user coverage area. The documented reputation of MUs is reflection of past behavior. In [55], author proposed coverage and reputation joint constraint incentive mechanism Algorithm (CRJC-IMA) based on stackelberg game theory. Two stage stackelberg game is applied to determine sensing level of mobile user and obtain maximum incentive mechanism for severe and clients. Nash equilibrium is tested based on response from user. To reach a maximum level of reputation mobile worker priorities of the task in specified time.

When mobile worker upload a computed task EM algorithm evaluates the quality of data, server center evaluate reputation according to sensing data and update historical reputation. Rewards are allocated to user who submitted task according to selected optimal criteria.

2.5 Comparison of reputation and incentives mechanisms

The reputation and incentive mechanism table contain comparisons of different schemes. By briefly discussing about basic idea, mechanism, their advantages and limitation. In the last, the schemes are compared and asses best out of them.

Table 2.1: Comparison of reputation and incentive schemes

Schemes	Basic idea	Mechanism	Advantages	Limitation
RQRP[4]	• Having Quality of sensing request based on reputation. On new request, data related to MW previous history provided.	• Reputation based recruitment	• Recruit MWs based on reputation result in quality reporting	• No privacy protection is used
Decentralized [5]	• Use block chain based groups to work with, e.g. service provider, user data collectors etc	• Distributed data incorporation	• consistent data achieve, secure communication, increase cooperation , and reviews authentication	• Duplication of resources
Pareto optimal algorithm [32]	• make user participate in network achieve social goal	• use stochastic network model and real world data to find reputation	• Explicit about the assumption made	• Misallocation of productive resources and difficult to achieve social welfare
PACE [28]	• When task request receive and incentives given it secure the privacy	• Data quality based on deviation b/w reliability and ground truth	• sensing data and location privacy preservation	• Do not focus on strategic behavior and assume that all workers are reliable
Beta reputation[40]	• Design the rules for maintaining the values of reputation	• Rating updation based on sensory data received	• Ability to store the feedback values	• Reputation score can be effected by history values

Peer prediction based reputation[40]	• External raters are hired to access the reputation of worker	• Rater checked on logarithmic values	• Truthfulness of rater is checked with logarithmic rule	• History low rating effect the reputation ,rater biasness is not checked
CSP [25]	• Motivate to Contribute information on social network	• Backward induction used	• Optimal incentive and discriminatory rewards	• Computational challenge due to Incomplete Information
DIM[26]	• Based on two groups leaders and followers	• deep reinforcement learning strategy used	• DRL enable service provider to directly learn from experience	• Fake sensing attack can effect
ZD[24]	• Incentive scheme to provide high quality solution for selfish workers	• Ex-ante and ex-post payment schemes used	• Private information is hidden from other workers and quality task delivered	• Free riding exist(taking incentives without desired work result)
Crowd CO-OP[24]	• Workers share risk and achieve rewards	• Reward focused • worker take complex task without financial risk	• Share risk earn fair reward	• Presence of low quality worker increase task rejection rate
RMA[41]	• Reputation and performance based scheme	• Requester adopt environment gradually	• Bonus payments	• Possibility of Reputation inflation
Hierarchical incentive mechanism[31]	• FL based on multiple model owners and federations collaborate	• Model owner collaborate with other models, then select according to profit objective	• Maximization of profit by selecting best model	• Malicious model owner result in heterogeneous cost
E-R[42]	• Indirect sensing with participatory data used in real world usage	• Trust based on experience and reputation	• High quality data ,trust worthy users	• Presence of malicious users
Truthful incentive mechanism [47]	• Partial payments are made depend on previous reputation	• Response time is measured against sensing time	• Maximum utility of platform	• more tasks for reputation result in low data quality
[49]Reputation algorithm	• Filter workers and identify true labels from noisy	• Disagreement based penalties and semi matching	• Identify adversarial/introvert workers	• Small subset of workers

DPARS[53]	• Treating participant as alliance for cooperative game	• Census based technique to identify outliers	• Participant cooperation increase utility on low budget	• Extra communication cost ,no information privacy
CRJC-IMA[55]	• Location and reputation based user selection and stackelberg is applied to analyze data sensing level of user	• EM algorithm is used to evaluate data quality	• Higher coverage rate	• Time conflict occur due to multiple tasks

In RQRP [4], recruit MWs based on reputation result in quality reporting and no privacy protection used for the system. Decentralized [5], consistent data achieve, secure communication, increase cooperation, and reviews authentication is performed but limitation is that resources can be duplicated. Pareto optimal algorithm [32], encourage user to participate but limitation is that productive resources misallocated . PACE [28] , preserves location while sensing data but do not focus on behaviors and assumptions made workers reliability. CSP [19] , optimal incentives and rewards but due to incomplete information computational can be effected. DIM [20], service provider learn from previous experience but fake sensing attack effect the quality of reputation. ZD [18], information is hidden from others that are working in a system but free riding of worker can be found. Crowd CO-OP [18], worker can share their risk by attempting their task and earn rewards .but some low quality work submission can increase the work rejection rate. [32][28][19][20][18][4] are working on same mechanism but RQRP [4] is more effective reputation system due to computational efficiency.

Beta reputation[40] ,this system has capability to store values provided as feedback but these values can affect the reputation of worker. In RMA[41] , bonus payments are made on reputation but due to reputation score more than the actual one. E-R[42], quality of data is high due to trustworthy data but malicious users can effect quality . in [49], reputation algorithm by computing different values opposing workers can be identified , the limitation is data is collected from small number of set. In DPARS[53], participant can work under low budget which benefit the system but disadvantage is that this approach has extra communication cost. In CRJC-IMA[55], having high quality of data and sensing area has high coverage rate but limitation is that multiple task can create time conflict. From [40][42][49][53] and [55], [42] is more convenient due to high quality data.

2.6 Research Gap and Directions

From the analysis of the literature, in crowd sensing reputation system mainly based on the reviews from service consumer or different criterions to measure reputation of mobile workers such as task quality, maximum numbers of task completed in specified. The problems identified in the literature.

- Reputation system updated on reviews can limitize the more factors that act on this system.
- On maximum task, completion within a specified time can cause a problem that the service provider/worker would perform a number of easy tasks and leave the difficult one.
- Reputation ultimately act on the incentive mechanism of a system and without a true picture of reputation, so the platform will unable to distribute incentives fairly.

This work further gives the direction to improve the existing work by taking specific measurements and improvements in reputation system, so that to cover the maximum aspects of research.

2.7 Summary

In this chapter, research paradigms briefly identified. Literature study related to incentive mechanism and reputation conducted to get maximum information about these issues. The literature related to reputation and incentive schemes collected. The schemes providing users, platform and task requester different mechanism to complete their task requirements. Comparison of schemes by enlisting their mechanism, basic idea advantages and limitation in different schemes by providing proper references. Summary of different schemes discussed enlisting their advantages and disadvantages, research gaps discussed for further working on it.

CHAPTER 3

METHODOLOGY

3.1 Overview

In this chapter, methodology is going to be discussed within detail that is used to complete research. A whole map of literature, problem identification and software simulators that are used to accomplish results. In the end, whole chapter is summarized within few words.

3.2 Operational Framework

The operational framework consist of three phase's analysis, design and development and last is performance evaluation phase. These phases elaborate the overall system.

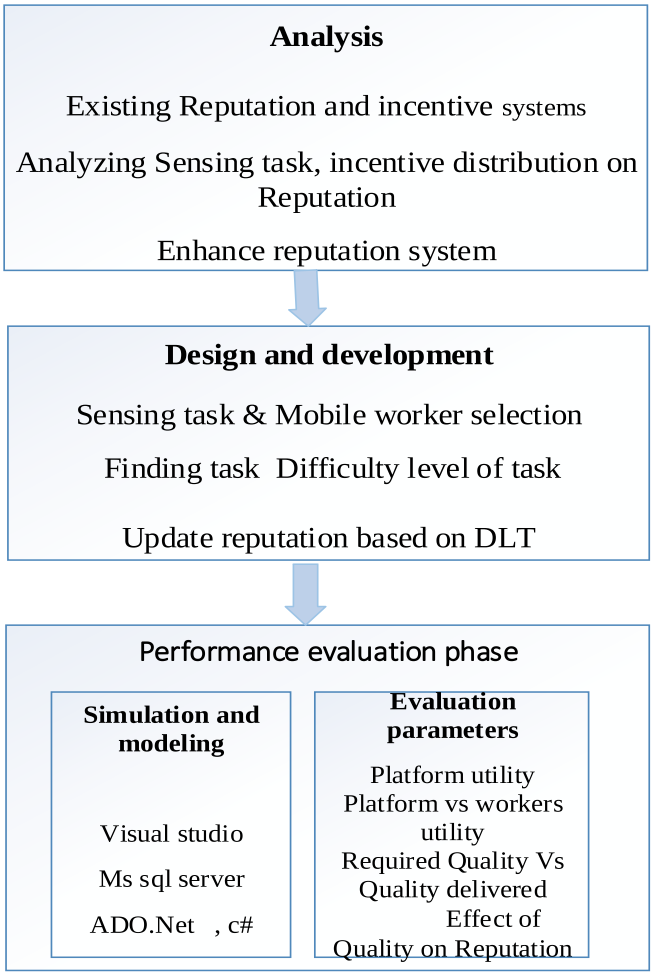


Figure 3.1: Operational Frame Work of the research

3.2.1 Detailed study of literature

The first step is study of literature and collected of related information. The literature study consist of different phases .for the field selection go throw different research material including journal papers and survey papers. The relevant literature is searched through keywords. E.g. mobile crowd sensing, reputation, incentive internet of things. Literature is short listed and select two papers, which were more relevant. Problem is identified from these schemes.

To identify problem statement previous studies identify the problem regrading mobile worker reputation in crowd sensing environment. The factor, which is missing in majority of mobile crowd sensing search, is difficulty level of task. This influence the reputation and incentives mechanism of the whole system.

3.3 Research Design and Development

From the literature, the introduction consists of different survey paper related to crowd sensing. For the literature section, search a lot related to crowd sensing and mobile crowd sensing. From bundle of search, figure out most relevant to our field of study. Almost 25 above general paper selected and discussed their schemes one by one. After writing a critical review about these schemes have included a comparison table consist of their mechanism, advantages and disadvantages.

We categories the schemes in to incentive mechanism and reputation mechanism for mobile worker reputation. These categories are interrelated to each other and have direct influence on each other.

3.4 Simulation

We have done result analysis by using different tools. Made Search for different tools, and then select which was more relevant and suitable to our model. For simulations, we setup testbed by creating Window communication foundation service. Using C# coding and to deploy on window Azure cloud using ASP.net. We maintained Database by entering record in SQL server for evaluating of mobile workers reputation and incentives. Linking that information to window azure cloud.

By drawing different graphs showing values of base scheme and proposed scheme. By using proposed scheme these graphs values provide a clear layout and enhancement for existing schemes.

Table 3.1: Simulation Parameters for DLT

Parameter Descriptions	Notations	Values
Parameter Value Target area	*Area*	1000x1000 m
Number of MWs	*N*	100–500
Tasks announced	-	100, 200, 300
Least task quality factor	α	0.3
Effective mobility region	-	30 m
Reputation score	-	[0–1]
Nttc	-	1, 5, 10
Default reputation value	-	0.5
Ageing factor	-	0.3–0.5

3.4.1Performance Metrics

We explain performance matrices in chapter 5, calculate values, and show results in the form of graphs. The metrics are Platform utility to calculate platform utility, by subtracting all the costs made to the MWs from the total gained revenue. Workers utility the mobile worker utility is n where n ε Nw, the total payment made to the MW on successful accomplishment of task/tasks is P. Required Quality Vs Quality delivered, this performance matric examine the required quality value set by platform with task quality. Quality delivered is the sensing quality of task at the time of completion. Effect of Quality on Reputation this is an important aspect that quality of task can effect reputation. The reputation increase or decrease with the quality of task submitted by mobile worker.

3.4.2 Assumptions and Limitations

This research provide a more refine solution to a platform .By adding more concise solution in the base scheme algorithm, the algorithm will enhances .The reputation system evaluation get better which ultimately benefit all the entities of the system.

Although careful collection of dataset and solution is, provided .but there can be limitation is sensors and at human level .The system can effect by the environmental condition in rare cases, which can effect sensors and provide a little deviation from real values. Apart from that mobile worker, mood and condition can also effect task provision condition.

3.5 Summary

In the methodology chapter, overview of all the research performed is discussed here. From related literature problem identified that, for computation and evaluation of reputation and incentive system different approaches considered. The design and development of base scheme considered by enhancing and adding new scheme. The simulations set up created using visual studio and window communication foundation using window azure cloud.

The performance evaluation matrices compared with base schemes for evaluation and validation of the findings. In chapter 4, proposed solution will discussed.

CHAPTER 4

Difficulty level of task

4.1 Overview

We proposed a reputation-based scheme for reward and incentive distribution to mobile workers. The reputation score is based on the of difficulty level of task (DLT).

4.2 Difficulty level of Task

In Figure 4.1 presents, DLT for MCS is designed. In first section, with required task quality budget and time task requester announce the task. The second section is much important part of proposed mechanism, which is reputation selection of mobile worker and updation of reputation on task participation. Online and offline both worker are picked up, and for achieving high quality sensing, task participants selection is based on reputation of task conclusion and completion. The mobile worker selection, platform announce the task and then observe the bids of mobile worker that is described in base paper. For availability, we suppose that number of mobile workers are willing to participate. Select the bid according to platform requirements and announce the worker. In Algorithm that is linked with the base algorithm. The winner, mobile worker perform task and submit. The platform authenticates the submitted task report with the predefined task criteria. After verification of task, incentives are given to the worker who fulfill at least minimum task criteria otherwise, task will be rejected. This task rejection motivate worker to do best in next sensing task. The requester receive task report from platform. On feedback from requester reputation score is updated. If there is a sensing task that is required by many task requesters, then considering their feedback reputation is updated as a whole. The collective feedback from requester control unfairness in responding about the participants. Final checking is done by platform for quality check. The reputation aware selection is possible through this system. Feedback from task requester helps in selection of mobile worker in the future. Figure shows of DLT, the red arrow represent workers communication, which may contain task announcement, bids selection, reputation, and other platform requirement before

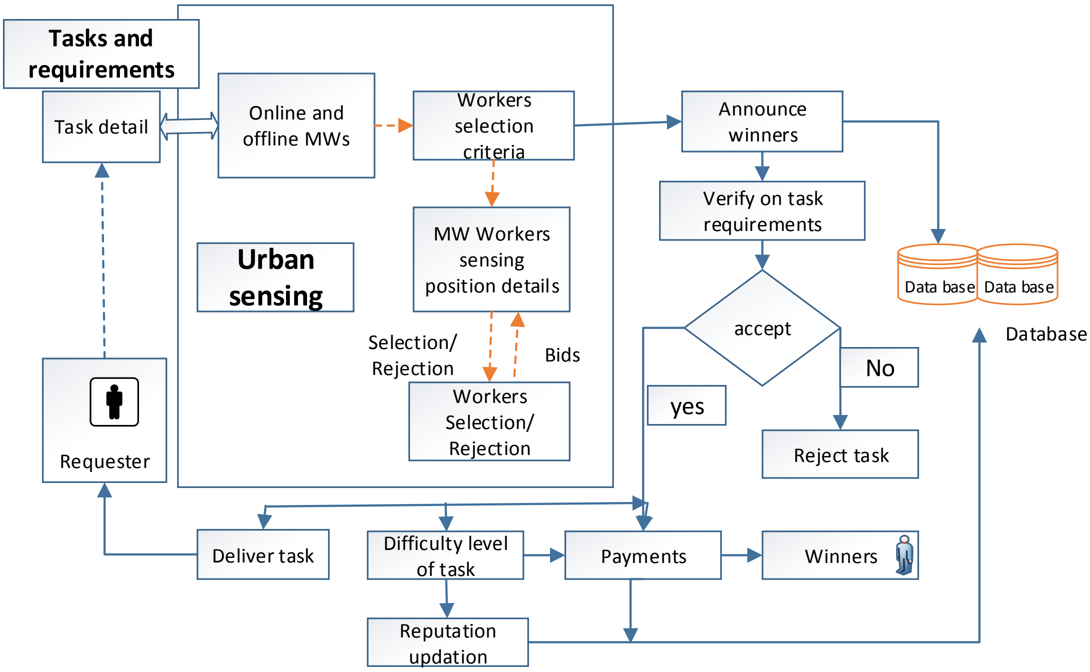


Figure 4.1: System Architecture of Difficulty Level of Task (DLT)

Selection of worker. Blue arrows represent investigation in selection, incentive provision, reputation computation and store in database and giving response to task requester that are main objectives of DLT.

1. Initialize: Nw (Sr) ← Accept (1)/Reject (0), Q Score ←0
2 .**For** (i = 0; i ≤ T; i++)
3. **If**(Sr[i] of h(li) ε H(li)) **then**
4. (Sr[i] – h(li) ≤ β && E(Q) ≥ α && Sr[dt] ≤ Dt)**If** **then**
5. **If** Q_Score = |E(Q) – Rq[ti]| > Q[i] **then**
6. Accept Sr[i] ← Nw[i]
7. $\beta = \sum((Sr[i] - h(li))/Total_{Sr})$
8. $D_{LT_{Sc}}$ = CalcDltScore () // function call
9. $R_{S_c} = R_{S_c-1} + \beta R_{S_c-1} + D_{LT_{Sc}}$ // increase .in reputation
10. **If** $R_{S_c} > 1$ then
11. Set R_{S_c} =1 //R_{S_c} must not exceed
12. **End if**
13. **Else**
14. Reject Sr[i] ← Nw[i] // add the MW's task in rejected array of Reject Sr
15. $R_{S_c} = R_{S_c-1} - \beta R_{S_c-1}$ // decrease in reputation as penalty (beta should be +tive)
16. **End If**
17. **End If**
18. **End For**
19. **For** any Sr[i] ∉ h(li) but Q ≥ α
20. Wu = p
21. h(li) ← Sr[i]
22. $\beta = \sum((Sr[i] - h(li))/Total_{Sr})$
23. $D_{LT_{Sc}}$ = CalcDltScore () // function call
24. $R_{S_c} = R_{S_c-1} + \beta R_{S_c-1} + D_{LT_{Sc}}$
25. Assign weight Sr[i] according to RScore (R_{S_c});
26. **If** Sr[i] is reported by newly recruited MW **then**
27. R Score is initialized by 0.5;
28. **End If**
29. **End For**
30. Return Nw, Nw (R_{S_c}) // winners and their quality scores
31 **Function** CalcDltScore () **Begin**
32. **If** D_{LT} equals 1 **then** // task difficulty levels
33. Set $D_{LT_{Sc}}$ = 0.025 * R_{S_c}
34. **Else If** D_{LT} equals 2 **then**
35. Set $D_{LT_{Sc}}$ = 0.05 * R_{S_c}
36. **Else If** D_{LT} equals 3 **then**
37. Set $D_{LT_{Sc}}$ = 0.075 * R_{S_c}
38. **Else**
39. Set $D_{LT_{Sc}}$ =0.1 * R_{S_c}
40. **End If**
41. **Return** $D_{LT_{Sc}}$ // reputation score for difficulty level
42. **End Function**

Figure 4.2: Algorithm for MW reputation using difficulty level of task

This algorithm contains steps for task acceptance or rejection and reputation updation of MW. Step 1-17 if the information about a sensing location is available the basis of ground truth the data is fetch from database. If sensing location data is not in database then it is labelled as new location. sr[i] is a sensing report received from a mobile worker, Q[i] is quality of task T[i] and payment p. if the β that is threshold function (acceptance criteria from history) is accepted quality that is alpa and within task deadline then this task is accepted otherwise rejected in steps 13. Reputation quality score Rq[ti] of selected mobile worker Nw[i] in accepted category. Reputation is increased/updated in step 9. In steps 10-11 there is limit in reputation score it should be between [0-1], set reputation score equals to 1 if it exceeds 1.

If sensing report of mobile worker's task is rejected then reputation score will decrease and worker sensing report added in rejected array in step 13. If the reputation is drop every time, the score decreases from a certain level then those mobile workers are included in blacklist. These processes repeated for every sensing task and mobile workers whose has history and incentives are assigned appropriately.

Step 18-29 if the sensing report of task is not available then we consider it as new worker. We assign an initial value and reputation score updated for future use. Then payment made to mobile workers having the updation of reputation score. The parameter β also updated and used as future recruitments. Step 30 -41 Function of CalcDltScore is declared, there are four difficulty levels of tasks. If difficulty level of task is 1 the then set assign value 0.025, multiplying it with reputation value from history and store it in Set$D_{LT_{Sc}}$. By using if else condition if DLT is 2, 3 and 4 assign values 0.05, 0.075 and 0.1 accordingly. Return DLT score and End function.

4.3 Proposed Data flow for quality of data

Sensing is not limited to situations; it may include images, measuring temperature, videos, and environment and so on. DLT aim to dive quality sensing and rewards based on participation. It is based on 'Beta reputation system' after enhancement it is suitable to MCS. In figure [] when requester generate task with the task requirements, platform that contain many servers take necessary steps. The accomplishment feasibility check on platform. The certified server store the history of tasks and mobile workers and provide authentication services. The flexibility of our system is that it not deny the task due to constraints. It make necessary discussions with requester about quality and budget before declaring task to participants. On task announcement MW bid on task. If the task is not, accomplished in budget with required quality then requester is informed to make changes.

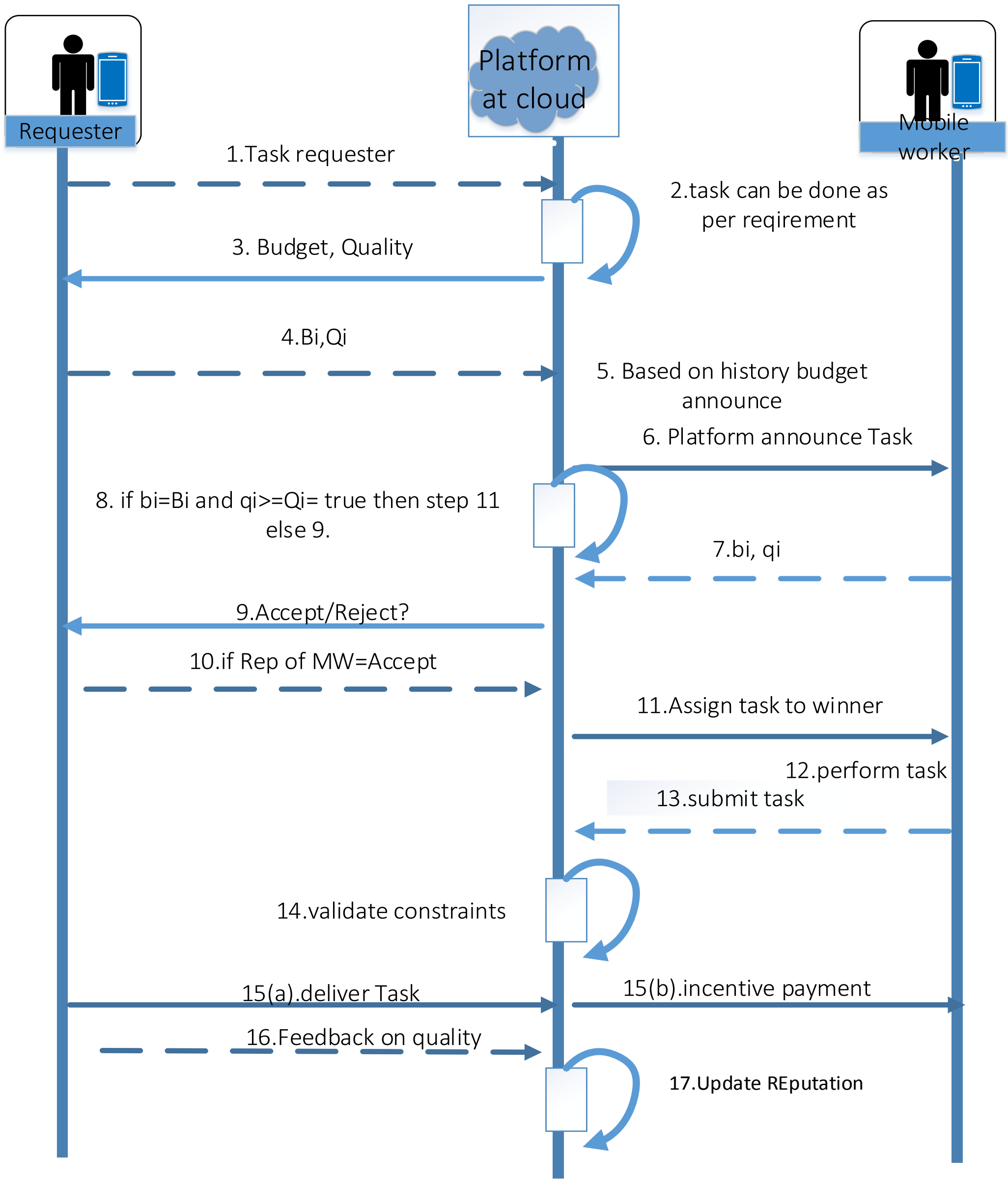


Figure 4.3: Data Flow diagram for DLT quality of information

This situation is a result of imperfect information, even after consulting from history. Otherwise winners selected if bi≤ Bi that is budget of task should be less than total budget and qi≤ Qi and quality is in range of total required quality of task. After completion task Mobile worker submit their report to platform, which analyze it on requirements and deliver it as shown in step 15(a). In step, 15(b) rewards based on quality of task are given. The reputation of, MW is updated, for future decisions that is based on feedback from task requester in step 17.

4.3.1 Participant effective Reputation

The reputation can be effective in two scenarios. The feedback from one or more task requesters, depend on the number of tasks requests by requester and completed by mobile worker (MW). The other aspect is the calculations performed by platform based on history. The platform calculations for trust evaluation is done because taking feedback from user can be error prone and biased due to human nature of tendency for (like and dislikes). with the time ageing factor is considered important for the selection of mobile worker ,reputation can vary time to time ,new workers do a better task than the old one .the history value with the time become zero , reduce selection time of mobile workers, save space and easy to maintain record.

4.3.2 Mobile worker reputation on feedback

The feedback from task requester has very important influence in reputation procedure of mobile worker. If multiple requesters' requests for the same task we give write to vote to those requester so that it only limited to one requester. Eq () give reputation of mobile workers according to requester rating assigned .Wi is the requester feedback and Rtk is reputation score.

$$R_T = W_1 \, {}^{R}_{T1} + W_2 \, {}^{R}_{T2} + \ldots\ldots W_N \, {}^{R}_{TN} = \sum_{K=1}^{N} W_K \, {}^{R}_{TK} \qquad (4.1)$$

4.3.3 Requester rating weightage

For more effective system requester feedback rating is equal important as reputation of mobile worker .it minimize biasness effects of reputation system in Mobile crowd sensing.W1,W2,……. WN are the requester weightage for different tasks, if every requester rate honestly then other requester have same rating assigned for task. The weightage of requester can increase or decrease accordingly. To calculate weight, the weight from history and average weight as

$$W_T = \sum_{K=1}^{n} \frac{W_{n-K}}{n} \qquad (4.2)$$

4.6 Summary

The overall chapter is about proposed system diagram, data flow and algorithm. The difficulty level of task is assigned by the platform after necessary calculations. The architecture of system contain different phases for sensing and assigning task to MW. The algorithm contains stepwise flow of task sensing and if meeting particular criteria accept/reject then according to that reputation system updated and store for future use. The data flow shows the whole system flow and the interaction with the platform.

CHAPTER 5

PERFORMANCE EVALUATION OF DIFFICULTY LEVEL OF TASK (DLT)

5.1 Overview

This chapter will present and discuss simulation results to evaluate our proposed reputation system and algorithms introduced in Chapter 4. This section contains two sections. Results and Analysis i.e. performance evaluation of difficulty level of task with different parameters and Comparison of reputation system with others schemes and with base scheme as shown below.

5.2 Results and Analysis

This section is going to provide analysis of effect of difficulty level of task on reputation platform and worker utility, effect of quality on reputation.

5.2.1 Platform utility

To analyze platform utility different schemes are assessed in Figure 5. With the time, DLT presented a regular increase as the trust level on the MWs is increased. The main reason for this constant variation is only in our approach reputation with respect to DLT is considered. The platform's utility displayed a increasing tendency when the number of MWs is increased. The platform needed to pay less with respect of reputation that created a economical environment for platform. A large number of MWs may need to be recruited, in the absence of reputation system, which requires financial incentives. Our approach DLT disallowed many candidates based on low reputation score, which also saved the platform's assets. As the general a MW whose score was less than 0.3 from the maximum value of one, was rejected. The score value increase or decrease according to the participation level. As more choices are available, with the increase rate of available users' platform utility increases directly. For example, on the arrival rate of 0.8 users, the platform utility for DLT was 3900 and RQRP was 3700, whereas 2800, 2300, 1800, 1300, were the utility values for arbitrary, OMZ (online)[56], OMG (online)[56], OMZ[57], OMG[57], methods respectively. On the scale, the approaches compared are presented on the large integral values for result clarity.

In MCS paradigm, we selected these approaches for comparison as they have similar input /output as ours; and they are state of the art schemes; these are lack in reputation system based on difficulty level of task, which is an important aspect in increasing the efficiency of the system in MCS. These approaches taking sample from a large set and then accept it, which is closely similar to our approach. However, the difference is that we considered reputation of MW on the very first stage of selection for a task.

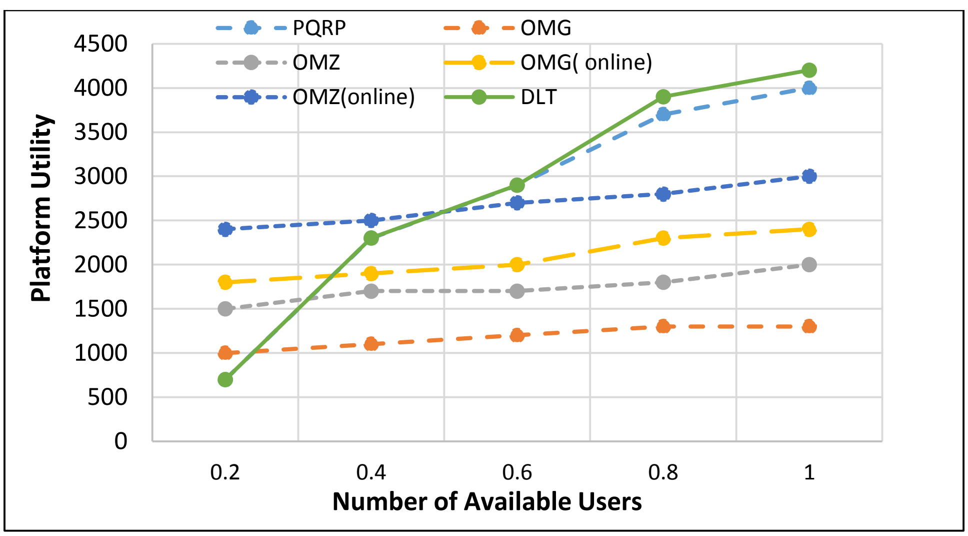


Figure 5.1: Effect of change of Mobile workers on the platform utility

5.2.2 Platform vs workers utility

The effect on MW and platform utility analyzed with respect to online Mobile workers available is depicted in **Figure 5.2**. The graph shows that platform utilization increases with the increase in number online mobile workers in **Figure a**. The increase observed due to competition among mobile workers large sample size. Due to competition in online environment, platform pay less but its utility was increased. On the other side, as the number of workers increased the utility of a single worker decreased in **Figure b**. the reason of this decrease is the fixed budget for their task. In our proposed work, workers paid according to their participation level, worker feel satisfaction for their contribution. As the platform, utility increases it also result in increasing the online Mobile workers. The increase in number of participant decrease worker utility .we took average as 100 values for simulations. For platform and workers took same values as the participant can be selected on its same or may be on little variation in values.

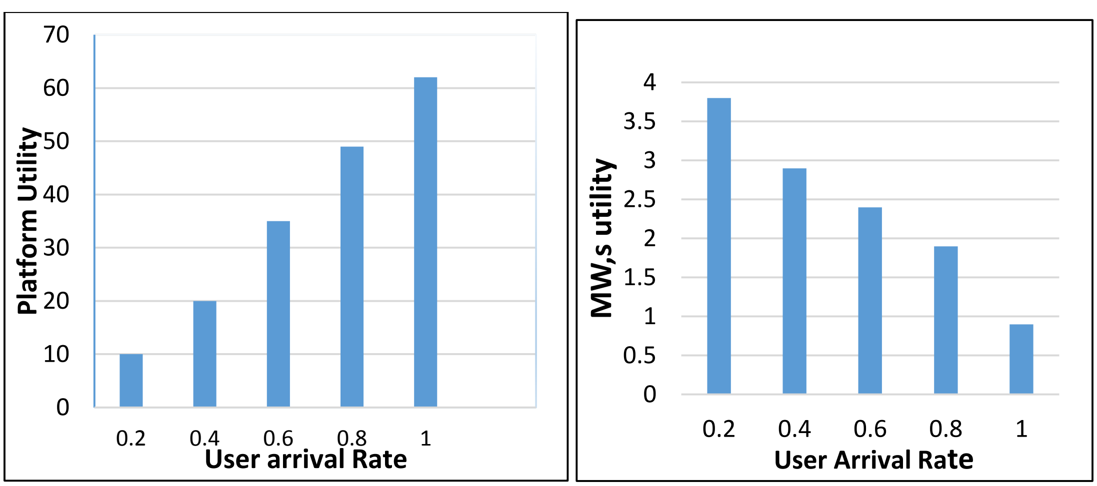
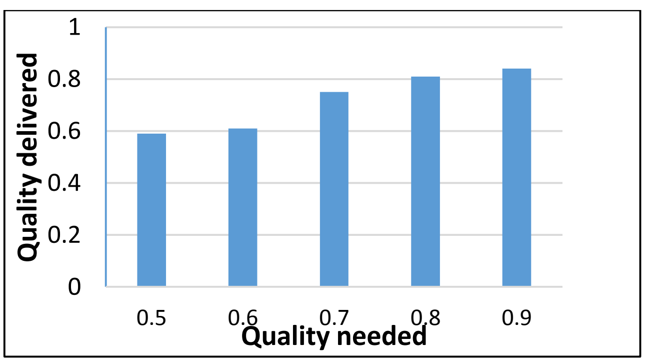


Figure 5.2: Comparing User Arrival Rate with (a) Platform utility (b) Mobile worker Utility

5.2.3 Required Quality Vs Quality delivered

In proposed DLT, based reputation system the comparisons between task quality required vs delivered is shown in figure a. There is a slow continuous increase in quality until it reaches the required one. The selection of user not made until a desired reputation restraint were met. The selection of user depends on his contribution of sensing task and probably he score similar or higher reputation score in the selected task. Thus, the average of task quality delivered than required constraints. Incentives are not paid to MW until the task accepted criteria is fulfilled. For example, the quality constraint was 0.6 but received 0.65, which is higher than required. There is a challenge to achieve accurate quality due to different working factors.(e.g hardware, software, working experience).

In figure (b), the required quality is, compared, with number of MW. Due to challenges and diverse mobile devices owned by people, that are malicious and workers may lack of work experience, 100% quality a challenge. The needed quality is on x axis and selected users for desired quality is on y-axis. For example, we noticed, that with the increase in quality, few workers were, selected on desired criteria. For 0.5 maximum users contributed and for, 1 no worker sensed the task. It is possible that with the increase in quality, it is possible no worker contribute.as in 0.7 the workers were 5 but in 0.9 there was only one. The tough the task completion criteria the fewer workers contribute.



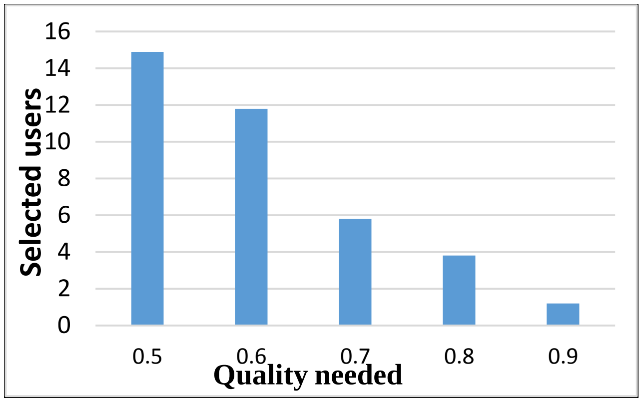


Figure 5.3: Quality needed is presented (a) delivered quality (b) number of selected users

5.2.4 Effect of Quality on Reputation

To ensure quality of sensing report or data various measures are considered. Reputation is top most priority in this research. By considering workers as honest and dishonest, change shown in Figure. The honest workers reputation increases and they will considered best for future selection. Workers having well reputation are surety of better-expected quality of task. On the other hand MW, which are dishonest having gradual decrease in reputation also shown. Low contribution quality result in to decrease in reputation and deregistration from platform and ultimately added to blacklist. Punishment is a penalty for low reputation. This research also tackled the reputation system efficiently by penalizing the non-serious behaviors of the participants.

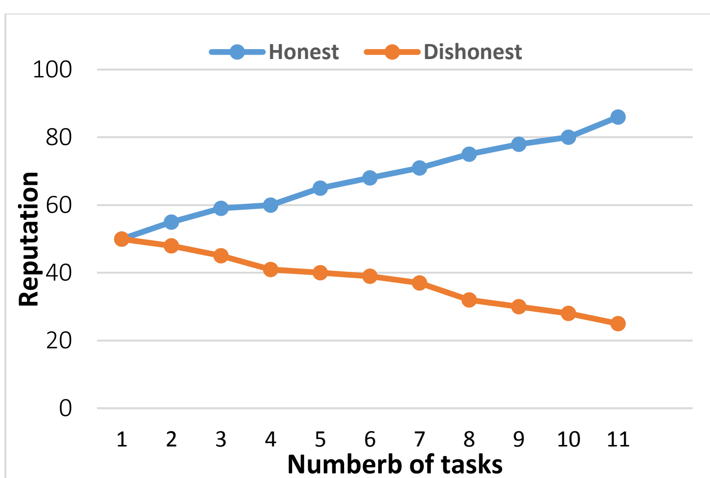


Figure 5.4: Reputation of honest vs dishonest workers

5.2.5 Time Computation

From history and reputation calculations, the proposed system shows the feasibility in figure. The algorithm measures the credible sensing and updation of reputation. The starting steps are execution and evaluation of the task sensing report, the constraints of time as number of reports. The algorithm update, reputation values according to difficulty level of task, and have a constant time. The time complexity of this Algorithm with respect to task sensing reports submitted is constant. The running time is similar to the other schemes.

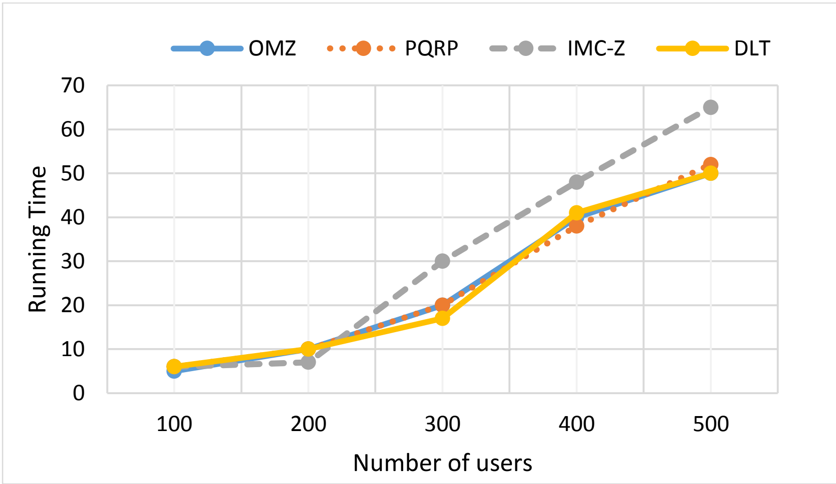


Figure 5.5: Time computation with other schemes: IMC-Z is incentive mechanism under zero case; IMC-G general case incentive mechanism

5.3 Summary

This chapter consists of graphs and their computation with different schemes. The platform utility and moble worker utility showing values of the system usage. The quality needed for a task to complete analyzed in the system . if the number of users increase then the platform utility increse and paricipants get maximum benefits out of it. The other graph showing honest/dishonest worker peputation increases and decreases with the tasks submission. The time computation of algorithm shows that manageable time is required by this scheme.

CHAPTER 6

CONCLUSION AND FUTURE WORK

6.1 Overview

The thesis focuses on a better reputation system, and different parameters used to evaluate this system. The contribution of this research described below.

6.2 Summary of contribution

In this thesis, we discussed Reputation system of Mobile workers .Mobile crowd sensing provides an efficient way to conduct large scale sensing reporting for different tasks, with the help of large crowd owing up to date sensor equipped smart phones. There are three roles in Mobile crowd sensing, the platform, participant /MW and requester. There are many challenges exist when a requester send task request on platform. The suitable participant to whom work to be assign should have different social and moral values. In our proposed approach, difficulty level of task (DLT) the Reputation of a Mobile worker is an important attribute .our target was to improve reputation system based on Difficulty level of task. As the workers, which participate and efficiently complete different level of tasks their reputation graded accordingly. The computations according to level of tasks helps us find a reputation value that is from [1-100] limit. This value is stored for future hiring, and making platform profitable and efficient in working. This approach ensures the computational efficiency, trustworthiness and profitable for all the entities involved.

6.3 Future Work

For future direction, this research shall be further directed for the security of Mobile workers. More equipped sensors used for vehicles coverage area, which was limited in mobile phone scenario.

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