Truthful Incentive Mechanism for Mobile Crowdsensing

ÖZLEM ZEHRA ÖZYAGCI
Abstract

Smart devices have become one of the fundamental communication and computing devices in people's everyday lives over the past decade. Their various sensors and wireless connectivity have paved the way for a new application area called mobile crowdsensing where sensing services are provided by using the sensor outputs collected from smart devices. A mobile crowdsensing system's service quality heavily depends on the participation of smart device users who probably expect to be compensated in return for their participation. Therefore, mobile crowdsensing applications need incentive mechanisms to motivate such people into participating. In this thesis, we first defined a reverse auction based incentive mechanism for a representative mobile crowdsensing system. Then, we integrated the Vickrey-Clarke-Groves mechanism into the initial incentive mechanism so as to investigate whether truthful bidding would become the dominant strategy in the resulting incentive mechanism. We demonstrated by theoretical analysis that overbidding was the dominant strategy in the base incentive mechanism, whereas truthful bidding was the dominant strategy in the derived incentive mechanism when the VCG mechanism was applicable. Finally, we conducted simulations of both incentive mechanisms in order to measure the fairness of service prices and the fairness of cumulative participant earnings using Jain's fairness index. We observed that both the fairness of service prices and the fairness of cumulative participant earnings were generally better in the derived incentive mechanism when the VCG mechanism was applied. We also found that at least 70% of service requests had fair prices, while between 5% and 85% of participants had fair cumulative earnings in both incentive mechanisms.

Keywords: Vickrey-Clarke-Groves mechanism, mobile crowdsensing, truthful incentive mechanism, Jain's fairness index.
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1 Introduction

Smart devices such as smartphones and tablet computers have become much more popular and widespread over the past decade. They are now fundamental communication and computing devices in people's everyday lives. Moreover, they can embody various sensors, including, but not limited to, microphone, camera, GPS, gyroscope, accelerometer, magnetometer, barometer, temperature sensor, humidity sensor, and ambient light sensor. Through the Internet connection capability of smart devices, such embedded sensors have the potential to form mobile and wireless sensor networks. This potential has led to the emergence of mobile crowdsensing (MCS) [1], which can also be called sensing as a service (S\textsuperscript{2}aaS) [2].

Basically, a MCS system collects sensor outputs from smart devices and analyzes them via cloud computing [3] to provide a sensing service. MCS applications can provide different types of sensing services but their service quality depends on the participation of smart device users regardless of their service type. Nevertheless, providing sensor outputs to a MCS system can decrease the overall performance of smart devices due to battery, memory and CPU consumption. Furthermore, depending on the application, the cost of participating in such sensing services can be not only in terms of money (e.g. owing to the Internet usage) but also in terms of time and effort (e.g. because of going to a specific location for sensing). In addition, MCS applications are subject to privacy and security issues because they typically require participants to share private information like location.

In short, smart device users can have their own valuations of being a sensor output provider, and they may be unwilling to take part in MCS applications if they receive nothing in return. As a result, incentive mechanisms may be necessary for such applications in order to motivate smart device users to become sensor output providers. However, when participants are asked to report their valuations so as to be compensated later on, they cannot be assumed to reveal their true valuations because they may try to increase their monetary gain. In a MCS application, a smart device user's monetary gain can increase either when the service price increases or another user's gain decreases. Therefore, the motivation behind this thesis is to develop an incentive mechanism for MCS systems which can induce participants to reveal their valuations truthfully.
1.1 Background

In mobile crowdsensing, relevant sensor outputs are collected from smart devices and analyzed using cloud computing in order to assess a phenomenon at a particular place [1]. Due to the ubiquity of smart devices and cloud computing, MCS makes large-scale applications possible in a variety of areas. In fact, the sensors on smart devices are not the only data source that can be used in MCS because a smart device can act as a bridge between the cloud and specialized sensors that are not available on smart devices. That is to say, smart devices can also be used to retrieve data from external specialized sensors via wireless interfaces like Bluetooth and transmit the outputs of these sensors to the cloud on behalf of them. Being able to utilize such specialized sensors increases the diversity of MCS applications even further. Contemporary MCS applications can be categorized as environmental, infrastructure, and social applications according to the phenomena they monitor [1]. Some examples of MCS applications are as follows: measuring a city's pollution levels (e.g. air pollution), monitoring traffic congestion, tracking public infrastructure conditions (e.g. road conditions), discovering available parking spaces in a city, sharing eating habits within a community (e.g. diabetics), and comparing exercise details [1].

MCS can be regarded as a subset of mobile phone sensing [4]. Mobile phone sensing is also referred to as people-centric sensing [5] and it is generally classified according to two different criteria. While it can be categorized as personal, group (or social), and community (or public) sensing according to the sensing scale, it can also be categorized as participatory and opportunistic sensing according to the extent that sensing depends on user involvement [4, 5]. The scope of MCS covers both group and community sensing because sensing is performed at large scales in MCS, whereas the degree of user engagement in sensing can vary depending on the application [1]. One of the two opposite ends of this variation is participatory sensing [6], where smart device users cooperate in sensing by supervising the process of generating sensor outputs. The other end is opportunistic sensing [7], in which users do not necessarily know when exactly sensing occurs since producing sensor outputs does not require user intervention. In other words, people do not need to take active part in opportunistic sensing as it is more autonomous than participatory sensing. The less a user is involved, the more quickly a sensor output can be gathered by the cloud. Consequently, opportunistic sensing is better suited to large scale applications like urban sensing systems [7, 8].

A MCS application can be an instance of a combination of previously mentioned categories at the same time. Depending on these combinations, numerous ways can be
used to stimulate people into participating. Some of these approaches include making use of micropayments, emphasizing the public-spirited characteristics of the gathered data, offering personal analytics, exchanging data for extra information, and bringing people in on challenges [9].

1.1.1 Other Related Concepts

Many micropayment based incentive mechanisms in MCS systems utilize reverse auctions, and several of them are discussed in the related work chapter. Essentially, the auctioneer is the buyer, and the bidders are the sellers in a reverse auction. According to our literature survey, the most used reverse auction type in MCS is the sealed-bid reverse auction with multiple winners. In this type of reverse auctions, bidding is done secretly, and depending on the number of units that will be bought by the auctioneer, one or more bidders with the lowest bids win the reverse auction.

The Vickrey-Clarke-Groves (VCG) mechanism [10–12] is one of the most well-known solutions in the literature for making truthful revelation of valuations the dominant strategy for agents [13]. Depending on the context, an agent's valuation can be an outcome's worth or cost for the agent. A strategy is said to be dominant for an agent if the outcome of the strategy is at least as good as any other strategy's outcome for the agent regardless of the strategies other agents choose [14]. A mechanism is called strategy-proof if there is a dominant strategy for the agents in the mechanism, and a mechanism is called truthful (also truth-revealing or incentive compatible) if the agents' dominant strategy is to report true valuations [13]. Further details about the VCG mechanism and why it was chosen to be used in this thesis are briefly explained in the second chapter.

1.2 Problem

Common challenges in MCS systems consist of privacy, security, and data integrity; resource constraints in respect of computing, bandwidth, and energy; finding respective methods for both raw sensor data processing on smart devices and aggregate data analysis in the cloud; and designing an extensible, efficient, and scalable architecture that can accommodate various MCS applications [1]. The problems that an effective MCS application needs to address can be listed roughly as allocating sensing tasks to appropriate smart devices, improving sensor data quality and reliability, reducing the consumption of smart device resources, allocating the resources of a smart device among different applications simultaneously, preventing
duplicate sensing and processing on smart devices, and motivating people to share the capabilities of their smart devices [1].

1.2.1 Problem Formulation

Some MCS systems use micropayments as incentives, and some incentive mechanisms found in these MCS systems are based on the sealed-bid reverse auction with multiple winners. The first focus of this thesis is to make such a reverse auction based incentive mechanism truthful. The other focus is to compare how fair the initial and the resulting incentive mechanisms would be from a service requester's and a sensor output provider's points of view respectively. Essentially, the second focus of this thesis is to compare the fairness of these mechanisms in terms of service prices and earnings per smart device.

1.2.2 Problem Statement

In a MCS system that uses micropayments as incentives, how can an incentive mechanism which is based on a sealed-bid reverse auction with multiple winners be made truthful?

How fair would the initial and the resulting incentive mechanisms be with respect to the amount of money a user pays for a service request and the amount of money a user earns thanks to a smart device?

1.3 Purpose

The underlying purpose of this thesis is to make people more likely to trust a MCS system by making its micropayment based incentive mechanism truthful and thus non-manipulable so that its number of users – who request its services or provide sensor outputs for its sensing tasks – may increase. The other purpose of this thesis is to demonstrate how a truthful incentive mechanism affects service requesters and sensor output providers in comparison with its base incentive mechanism.
1.4 Goal

The main goal of this degree project is to adapt the VCG mechanism to be used in MCS. Another goal is to devise a model of the aforementioned truthful incentive mechanism for a representative MCS system that we envision. The final goal of this degree project is to perform simulations of the truthful incentive mechanism in question and its base incentive mechanism so as to compare their fairness – by using a well established fairness metric called Jain's fairness index [15] – with regard to the prices of service requests and the amounts of money earned per smart device.

1.4.1 Benefits, Ethics and Sustainability

In terms of benefits, the proposed truthful incentive mechanism is intended to be a way for conducting data collection and selection in MCS. For each sensing task, the mechanism is supposed to determine the smart devices whose sensor outputs will be used, and thus the smart device users who will be paid in compensation according to their valuations. In consequence, operators of MCS systems can benefit from this mechanism by using it as a method for not only recruitment but also dynamic price determination.

Regarding ethics, users of MCS applications are vulnerable to privacy threats unless appropriate measures are taken because MCS systems need to use contextual information like location and identity. Sensing tasks are specific to locations in MCS, and in order to know how far a smart device is to the location of a sensing task, smart devices are supposed to send their location information to the cloud along with their sensor outputs. Also, MCS systems should be able to identify the users who provide sensor outputs so that these users can be compensated according to their valuations. Nonetheless, the ethical issues concerning privacy do not arise in this degree project because no real private information of people is used in our simulations.

With respect to sustainability, MCS avoids the installation costs of dedicated infrastructure and sensors, which would be required in traditional sensor networks, by utilizing existing wireless network infrastructure and smart devices. In traditional sensor networks, application specific static sensors need to be deployed over an area that covers the application's range. These specialized stationary sensors are typically installed over a large area, and the cost of installing enough number of them are usually high. On the other hand, a smart device is a platform for a variety of sensors,
and it is capable of wireless connections. Additionally, such sensors can be regarded as mobile since they cover a dynamic range when smart devices are carried by people.

1.5 Method

A research framework has three fundamental components: philosophical assumptions, research strategies, and research methods [16]. Philosophical assumptions are a set of beliefs that a researcher adopts about the truth of knowledge claims and how knowledge can be acquired [17]. They affect how a researcher deals with a problem and conducts data collection and analysis [18]. Research strategies are investigation types that guide a research framework's methodology [16]. Research methods execute research strategies and determine how data is collected, analyzed, and interpreted [16].

Every study corresponds to a point on a continuum where qualitative research and quantitative research are at either end and mixed methods research is in the middle [16]. Basically, qualitative research relates to words, deals with open-ended questions, and inductively investigates subjective meanings that people attribute to a problem, while quantitative research relates to numbers, deals with close-ended questions, and deductively tests objective theories by inspecting the correlation between variables [16]. In mixed methods research, components of qualitative research and quantitative research are integrated to have a better understanding of a problem [16].

The essence of this thesis is more quantitative than qualitative. Therefore, a deductive research approach, postpositivist philosophical assumptions, an experimental research strategy, and an experimental research method were adopted in this degree project. Consequently, data collection and data analysis were performed using experiments and statistics respectively. The details of how our research was conducted as well as the concepts above are described in the third chapter.

1.6 Delimitations

Aspects of privacy, security, sensor data quality and reliability, sensor data processing and analysis, resource constraints, and architecture design in MCS applications are not focused on in this degree project. Further details such as registration and authentication of smart device users, verification of smart device sensors, generating sensor outputs on smart devices, tracking the locations of smart devices, how the
cloud and smart devices communicate, and other cloud computing related parts in MCS systems are not implemented in our model or simulations.

1.7 Outline

The remainder of this thesis is organized as follows. In the second chapter, the VCG mechanism and why it was chosen are mentioned. Also, related works are briefly explained and compared with our work. In the third chapter, further details about our methodology are explained. In the fourth chapter, our system model is described by mentioning how the VCG mechanism is applied on a representative MCS system that we envision. In the fifth chapter, the incentive mechanisms with and without the VCG mechanism are analyzed theoretically, and the results of our simulations are discussed. Our contributions are summarized in the sixth chapter, and finally, possible future directions of our work are mentioned in the seventh chapter.
2 Related Work

The VCG mechanism is a decision making process whose outcome maximizes the overall utilities (i.e. benefits) of a set of agents [14]. The VCG mechanism is often used in allocating resources efficiently (e.g. by auctions) and making group decisions (e.g. by voting) [13, 14]. In consequence, it is also referred to as the generalized Vickery auction or the pivot mechanism depending on the settings it is applied on [19]. Fundamentally, the VCG mechanism achieves being truthful by levying taxes on the agents whose participation has influenced the outcome, but the key point is that the tax of an agent does not depend on what has been reported by the agent [19]. In the VCG mechanism, an agent's tax is equal to the loss in other agents' utilities due to the agent's participation [13, 19]. Let us suppose O is the actual outcome of the mechanism, but O' would have been the outcome if agent i did not exist. Then, the tax levied on agent i is the difference between the sum of the agents' utilities in O' and the sum of the other agents' utilities in O excluding agent i.

2.1 Why VCG Mechanism?

As it was previously mentioned in the problem formulation subsection, we reduced our problem scope to making a truthful incentive mechanism based on a sealed-bid reverse auction with multiple winners for a micropayment using MCS system. The VCG mechanism's applicability to auctions was one of the reasons why we chose it for this task. Furthermore, the VCG mechanism is a well established way to design a truthful and efficient mechanism which can also ensure ex post individual rationality and weak budget balance [19]. Here, the term efficient does not denote computational efficiency but rather economic efficiency. The outcome of an efficient mechanism maximizes the sum of agents' utilities, which are dependent on agents' true valuations instead of their declared valuations [19]. In an ex post individually rational mechanism, agents do not take a loss by participation, and they would never be better off not participating [19]. A weakly budget balanced mechanism may or may not make a profit, but it never makes a loss [19]. Moreover, according to the Green-Laffont theorem, only Groves mechanisms can accomplish an efficient allocation among agents under dominant strategies [19]. The reasons why we did not choose the other truthful mechanisms that were applied on reverse auctions are briefly explained after each truthful mechanism in the literature survey section.
2.2 Literature Survey

In [20], Danezis et al. conduct experiments by applying tools from experimental economics and psychology so as to deduce the price that is required to convince people to have their location monitored. Volunteers in the experiments are told a sealed-bid second-price auction is going to be carried out in order to determine who will participate in the study, so that the volunteers are prompted to disclose the true amount of money that they claim in compensation for their location privacy. The auction of Danezis et al. selects a certain number of people with the lowest bids and pays them the amount that is equal to the lowest bid among the not selected bidders. Their auction is similar to our sealed-bid multiple-winner reverse auction with VCG mechanism, but apart from its name, no other information was mentioned about it in the article.

In [21] and [22], Lee and Hoh argue that recurring reverse auctions in participatory sensing applications lead to incentive cost explosion because users with higher true valuations often do not end up being winners and eventually cease to participate. When these users drop out of recurring reverse auctions, price competitions are reduced in the following rounds, and remaining users can become winners with higher bids. To solve this problem, Lee and Hoh devise a reverse auction based dynamic price incentive mechanism with virtual participant credit (RADP-VPC), in which virtual credits are assigned to the users that did not win in a round so that these users are more likely to win in the next round when VPCs are subtracted from their bids. This mechanism retains a sufficient number of users for the required service quality while it decreases and preserves the incentive costs, but it is not a truthful mechanism.

In [23], Jaimes et al. present a recurrent reverse auction based incentive mechanism for participatory sensing systems in which the auctioneer – i.e. the platform – has a finite budget per round and winners are chosen by a greedy algorithm according to their locations. Their location and budget dependent incentive mechanism is not truthful because it incorporates Lee and Hoh's RADP-VPC incentive mechanism. Still, their mechanism enhances the geographical coverage of the gathered data and reduces data redundancy while keeping a similar number of participants with a similar budget to RADP-VPC's.

In [24], Yang et al. introduces an incentive mechanism for each of the platform-centric system model and the user-centric system model in mobile phone sensing. In the platform-centric model, the platform determines how much money will be paid in
total to the users, whereas in user-centric model, users determine the minimum amount they want to be paid for their contribution. Yang et al. design their platform-centric incentive mechanism as a Stackelberg game and demonstrate that it is non-manipulable by users and has a unique Stackelberg equilibrium which maximizes the platform's utility. However, their Stackelberg game based platform-centric incentive mechanism is not truthful. They design their user-centric incentive mechanism as a reverse auction which is based on Myerson’s characterization of optimal auctions, and they show it is computationally efficient, individually rational, profitable, and truthful. We did not base our incentive mechanism on Myerson's optimal auction design because it does not guarantee economic efficiency, i.e. an item may not be allocated to the highest bidder [25].

In [26], Koutsopoulos develops an optimal reverse auction with multiple winners, which is also based on Myerson’s optimal auction design, as a solution to the incentive mechanism design for participatory sensing. The optimal reverse auction of Koutsopoulos minimizes the total amount of compensation that is paid to the winners while it ensures that a certain level of service quality is provided to the service requesters. The particular degree of service quality is satisfied by collecting participation levels from users. A user's participation level, as well as payment, is determined by the tracked data quality of the user. This mechanism is both truthful and individually rational. Nevertheless, this mechanism also does not ensure efficient allocation due to the optimal auction design which maximizes the expected utility of the auctioneer [25].

In [27], Zhao et al. address an online scenario of mobile crowdsourced sensing. In their scenario, users become available in the system arbitrarily, and only a user knows his true cost and time interval during which he will be available. In addition, they assume that the value of a group of users' contribution is determined by a non-negative monotone submodular function. Zhao et al. propose two online auction based incentive mechanisms for this scenario, which derive from a multiple-stage sampling-accepting process. In each stage of their incentive mechanisms, a subset of users is chosen before a designated time such that the contribution value of winners is maximized while the total amount paid to winners is not more than a certain budget. Both of the two incentive mechanisms fulfill computational efficiency, individual rationality, budget feasibility, consumer sovereignty, and constant competitiveness. The difference between these mechanisms is that one attains only cost-truthfulness because time-truthfulness is insignificant in it, but the other attains both cost-truthfulness and time-truthfulness. We did not design our incentive mechanism as an online auction because online auctions are a case of random sampling auctions, and a
random sampling auction is not efficient since it may reject allocating items to bidders who value them [19].

In [28], Zhang et al. formulate three online reverse auction based incentive mechanisms for mobile sensing. In these three mechanisms, winners are determined according to users' arrival time to the system and departure time from the system. Their first incentive mechanism aims for maximizing the platform utility near-optimally, but it is not truthful. Their second incentive mechanism attains truthfulness at the expense of platform utility maximization. In both of these two mechanisms, each participant's arrival time is assumed to be equal to his departure time. In the third incentive mechanism of Zhang et al., the intervals between the participants' arrival and departure times are greater than zero. The third mechanism is an extended version of their second mechanism so it is truthful as well. All of these three mechanisms are computationally efficient, individually rational, profitable, and competitive. In addition to the allocative inefficiency of online auctions, the other reason why we did not choose them is because bidders arrive at an online auction one by one, and whether or not a bidder wins need to be determined before knowing the following bid [19].

In [29], Feng et al. conceive a reverse auction based non-VCG mechanism as an incentive mechanism for location-aware collaborative sensing in mobile crowdsourcing. Their incentive mechanism is composed of two parts: the first one designates the winners, and the second one resolves how much each winner is paid. In the first part, sensing tasks are greedily allocated to participants according to their bids and locations, and this task allocation provides an approximate solution in polynomial time. In the second part, winners are paid the amount equal to their respective critical payments. The critical payment of a participant is calculated according to the participant's critical bid, which is the first bid that renders the participant's bid ineffective in the task allocation algorithm. The incentive mechanism of Feng et al. is truthful, individually rational, and computationally efficient. In this mechanism, the optimal allocation – which would have been the outcome of the VCG mechanism – was traded off for computational efficiency by providing an approximation instead. Nevertheless, we did not need to settle for an approximation due to our system design, which is described in the fourth chapter.

In [30], Feng et al. put forward a truthful incentive mechanism which is based on the VCG mechanism. In their system model, a sensing task indicates the total amount of sensing time, which is specified by its requester, to be collected from smartphones. Smartphones has an upper limit on sensing time that they can provide for each task, and users determine a cost per unit sensing time. The incentive mechanism of Feng et
al. consists of two parts. In the first part, the total sensing time is apportioned among a subset of smartphones according to their upper limits such that the total cost of the sensing task is minimum. In the second part, payments of winners are determined, and a winner's payment is equal to the difference that would have been made to the total cost excluding the winner's cost if the winner did not exist at the beginning of the first part. Our incentive mechanism is different from the mechanism of Feng et al. because our mechanism selects a sensing task's winners according to participants' cost and geographical distance to the location specified by the task's requester. Our mechanism does not depend on sensing time because winners are paid per sensor output. In other words, their system model and winner determination is different from ours, and this causes their participant utilities and payments to be different as well. Moreover, the number of winners in their mechanism depends on the values that users submit, whereas user bids do not have any effect on the number of winners in our mechanism.

In [31], Luo et al. propose an all-pay auction based incentive mechanism for participatory sensing. In their incentive mechanism, the auctioneer pays an amount of money to the user whose contribution is the greatest by the end of a task. The amount of money depends on the winner's contribution, and users can start or stop participating in a task anytime throughout the task. This mechanism maximizes the profit of the auctioneer by stimulating users to increase their contribution, whereas keeping the incentives to be paid to users as low as possible. The incentive mechanism of Luo et al. can adapt to a stochastic environment, incomplete and asymmetric information, and risk-averse agents. It is also individually rational but not truthful.

In [32], Luo and Tham develop two incentive mechanisms for participatory sensing. Their first incentive mechanism maximizes fairness, whereas their second mechanism maximizes global utility. Monetary incentives are not used in both of their mechanisms. Instead, they utilize people's inherent call for to receive services. In their mechanisms, users are both service requesters and data contributors. Users are given service quotas by the platform to limit the service they receive depending on their requests and contributions. The mechanisms of Luo and Tham are not truthful, but they also use Jain's fairness index in their work.
3 Methodology

In this thesis, a quantitative research framework and hence a deductive research approach were used. The quantitative research framework consisted of postpositivist philosophical assumptions, an experimental research strategy, and an experimental research method. Accordingly, experiments were used for data collection, and statistics were used for data analysis.

Deductive reasoning is a systematic approach for obtaining specific knowledge from general knowledge by inferring a conclusion from premises [18]. A conclusion that has been reached through deductive reasoning can only be true when its premises are true, but a true conclusion of deductive reasoning still cannot be considered as new knowledge because a conclusion cannot surpass the content of its premises [18]. Nonetheless, what is already known can be arranged by using deductive reasoning to find new connections [18]. Additionally, deductive reasoning can assist not only associating theories with observations but also establishing new hypotheses from existing theories [18].

Postpositivists believe that even though absolute truth exists, it cannot be discovered – it can only be known imperfectly – because knowledge is based on conjectures instead of solid foundations [16]. Postpositivists have a deterministic standpoint which asserts that causes or conditions can lead to their own particular effects or results and no other [16]. Postpositivism is reductionistic as hypotheses and theories are tested in terms of their fundamental constituents such as variables to analyze the subject of research [16]. Furthermore, postpositivism pursues being objective and avoiding bias [16].

In an experimental research, the researcher manipulates the conditions for treating independent variables to compare how specific treatments of at least one independent variable and withholding these treatments impact dependent variables [17]. In an experiment, some attributes can be measured before as well as after a treatment [17]. There are two kinds of experiments: true experiments – in which subjects are assigned to treatments randomly – and quasi-experiments – where subject assignments to treatments are not random [17].

In this study, a representative MCS system that we envision was defined first to base our system model on it. The incentive mechanism in this representative system was
set as a sealed-bid reverse auction with multiple winners, and it is referred to as the base incentive mechanism. Then, the VCG mechanism was applied on the base mechanism. The resulting mechanism is named as the reverse VCG (rVCG) incentive mechanism to indicate that the VCG mechanism was applied on a reverse auction. After that, the base mechanism and the rVCG mechanism were theoretically analyzed to find out whether truthful bidding would be the dominant strategy for the agents who participate in them. Next, simulations were conducted to discover how independent variables affected dependent variables in both of these mechanisms. Jain's fairness index was used to find how fair the results of both mechanisms were with respect to the manipulated independent variables. Finally, these results were statistically analyzed, i.e. their mean values and confidence intervals were calculated with a confidence level of 95%.

Quality assurance of a quantitative research can be discussed in terms of reliability, validity, and replicability. The consistency of measurements determine a measuring instrument's reliability, while the accuracy of measurements determine its validity [18]. Instead of using measurements of actual instruments, simulations were used in this thesis, and input values were randomly generated using uniform distribution. As a result, this degree project's reliability and validity are trivial since no measurements were made using instruments. Even though our results were obtained from randomly generated inputs, they are replicable, i.e. if other researchers repeat our work, their results would be similar to ours. This is because in order to mitigate the effects of random generation, we repeated our simulations 100 times with different random seeds and calculated both the mean value and the confidence interval for each investigated case.
4 System Model

In this chapter, we first describe what we envision as a representative MCS system whose incentive mechanism uses micropayments and is based on a sealed-bid reverse auction with multiple winners. Then, we explain how the VCG mechanism is applied on this representative system's incentive mechanism. The initial incentive mechanism of the representative system is called the base mechanism, and the resulting incentive mechanism after applying the VCG mechanism to the base mechanism is called the rVCG mechanism. Finally, we describe our system model, which is the representative system with the rVCG mechanism instead of the base mechanism.

4.1 Representative MCS System

The representative MCS system that we envision is composed of the cloud, a set of smart devices which have the service requester role, and a set of smart devices which have the sensor output provider role. The smart devices in these two sets are not necessarily mutually exclusive because a smart device can be used for both requesting service and providing sensor output. The cloud has the auctioneer role in the incentive mechanism and conducts reverse auctions amongst sensor output providers on behalf of service requesters. For that reason, there is no direct interaction between smart devices in our representative MCS system, and they communicate only with the cloud. The overview of this MCS system is depicted in Figure 1.

![Figure 1: MCS System Overview](image)

Roles of smart devices are determined by their users when users log in to our MCS system. If a smart device is a service requester, its user needs to send the following parameters to the cloud so that a sensing task can be initiated: a pair of coordinates, a
radius, and the maximum number of sensor outputs the user is willing to pay for. If a smart device is a sensor output provider, its user needs to report his valuation for providing sensor outputs to the cloud, which is the minimum amount of money the user wants to earn for each sensor output provision. The user interfaces of these functionalities for the Android platform are shown in Figure 2. Also, the smart devices with the sensor output provider role need to send their coordinates to the cloud – in the background – when they become online in the system and whenever there is a change in their locations.

When a service request is received, it is handled by the representative MCS system with the base incentive mechanism as follows. First, among the smart devices which are online in the system as sensor output providers, the ones that are in the area specified in the service request are found. Let us say that there are m number of sensor output providers in the service request's area. So as to determine whose sensor outputs will be used from this group of smart devices, the base mechanism is supposed to select n number of them, where n is the maximum number of sensor outputs specified in the service request. If m is less than or equal to n, then all of the providers are selected. Otherwise, the base mechanism selects n out of m number of
smart devices whose users reported the lowest valuations. If the reported valuations of two users are the same, the preferred smart device is the one which has been online in the system as a provider for a longer period of time since it last provided a sensor output. When smart devices are selected, the payments to their users and the price of the service request are determined as well because users are paid the amounts that are equal to their own valuations, and service price is the sum of what is paid to users. Next, the cloud notifies the selected smart devices and receives their sensor outputs. Finally, after processing the collected sensor outputs, the cloud sends the result to the user who requested the service.

4.2 Application of VCG Mechanism

The following are the definitions that are used to describe and mathematically represent the VCG mechanism's application to the base incentive mechanism:

- **P**: The set of sensor output providers which are in the area that is specified in the service request under consideration.
- **n**: The maximum number of sensor outputs specified in the service request.
- **S**: The set of outcomes for selecting n number of providers from P. Each outcome o in S is a subset of P. If n < |P|, then |o| = n. Otherwise, |o| = |P|.
- **b_i**: The cost that has been reported to the cloud by the user of provider i in P to be regarded as the user's bid.
- **w_i(o)**: The cost which is assumed by the cloud to be incurred by the user of provider i under outcome o. If provider i is selected in outcome o, then w_i(o) = -b_i. Otherwise, w_i(o) = 0.
- **s^***: The outcome in S which minimizes the absolute value of the total reported cost that is assumed to be incurred by the providers in P. This definition is equivalent to the equation 
  \[ s^* = \text{arg max}_o \sum_i w_i(o), \]
  where o \( \in \) S and i \( \in \) P.
- **S_{-i}**: The set of outcomes for selecting n number of providers from P except for provider i. Each outcome o in S_{-i} is a subset of P\{i\}. If n < |P\{i\}|, then |o| = n. Otherwise, |o| = |P\{i\}|.
- **s_{-i}^***: The outcome in S_{-i} which minimizes the absolute value of the total reported cost that is assumed to be incurred by the providers in P\{i\}. This definition is equivalent to the equation 
  \[ s_{-i}^* = \text{arg max}_o \sum_j w_j(o), \]
  where o \( \in \) S_{-i} and j \( \in \) P\{i\}.
- **t_i**: The tax that is allocated to provider i's user by the VCG mechanism. It is the difference between the sum of the reported costs in s_{-i}^* and the sum of the reported costs in s^* excluding the cost reported by the user of provider i. This
definition is equivalent to the equation \( t_i = \Sigma_j w_j(s_{i^*}) - \Sigma_{j\neq i} w_j(s^*) \), where \( j \in P\{i\} \).

In the base incentive mechanism, the users whose smart devices are selected in \( s^* \) are paid according to their bids, while in the rVCG incentive mechanism, they are paid according to the taxes that are assigned to them by the VCG mechanism when it is applicable. The VCG mechanism's applicability depends on whether \( n \) is less than the number of smart devices in \( P \) or not. This is because the ordering relation between \( n \) and \( |P| \) determines the number of selected smart devices in \( s^* \) and \( s_{i^*} \).

Let us suppose \( n < |P| \), and \( b_{n+1} \) is the minimum reported cost among the users of the smart devices that are in \( P \) but not selected in \( s^* \). Then, for any provider \( i \) in \( s^* \), provider \( n+1 \) whose user reported \( b_{n+1} \) would replace \( i \) if \( i \) did not exist. That is to say, \( s_{i^*} = (s^* \{i\}) \cup \{n+1\} \), and in consequence, \( \Sigma_j w_j(s_{i^*}) = (\Sigma_{j\neq i} w_j(s^*)) + w_{n+1}(s_{i^*}) \). After substituting the right-hand side of the latter equation for \( \Sigma_j w_j(s_{i^*}) \), \( t_i \)'s equation becomes \( t_i = (\Sigma_{j\neq i} w_j(s^*)) + w_{n+1}(s_{i^*}) - \Sigma_{j\neq i} w_j(s^*) \). In the end, \( \Sigma_{j\neq i} w_j(s^*) \) and \( -\Sigma_{j\neq i} w_j(s^*) \) cancel each other out, and \( t_i \)'s equation becomes \( t_i = w_{n+1}(s_{i^*}) = -b_{n+1} \). This means that each user of the selected providers in \( s^* \) is paid the amount equal to the bid of provider \( n+1 \)'s user.

Let us suppose \( n \geq |P| \). Then, for any provider \( i \) in \( s^* \), there would be no other provider to replace \( i \) if \( i \) did not exist. That is, \( s_{i^*} = s^* \{i\} \) and \( \Sigma_j w_j(s_{i^*}) = \Sigma_{j\neq i} w_j(s^*) \). After substituting \( \Sigma_{j\neq i} w_j(s^*) \) for \( \Sigma_j w_j(s_{i^*}) \), \( t_i \)'s equation becomes \( t_i = \Sigma_{j\neq i} w_j(s^*) - \Sigma_{j\neq i} w_j(s^*) = 0 \). For this reason, the VCG mechanism is not applicable when \( n \geq |P| \). Instead of not paying anything to the users of the selected providers in \( s^* \), the rVCG incentive mechanism pays them the amounts equal to their own bids, just as the base incentive mechanism does.

### 4.3 Overall System

The system model that we propose is our representative MCS system with the rVCG incentive mechanism. Further details of our system model are discussed with respect to the agents that make a decision at any point in the overall system. These agents are comprised of the sensing service operator leasing or owning the cloud computing infrastructure, the users of service requesting smart devices, and the users of sensor output providing smart devices.
Before sending a service request to the cloud, a user needs to decide on both the maximum number of sensor outputs he is willing to pay for and the area he wants the sensing task to cover. The maximum number of sensor outputs to be used and the number of sensor output providing smart devices in the area of the sensing task together determine the number of winners in our incentive mechanism's reverse auction. That is, besides the locational distribution of provider smart devices, only the user who requests the sensing service determines the number of winners. This is consistent with the assumption of Aggarwal et al. which states in [33] that the number of slots sold in their forward auction is not dependent on the submitted bids.

A user who requests service determines the sensing task's area by deciding on a radius and a location which will be regarded as its center. In our system model, the sensing service operator provides a scale which limits the possible values for a radius, and a user determines a sensing task's range by selecting a value from it. For that reason, the operator needs to decide on this scale's upper bound, lower bound and interval. In addition, the operator needs to provide a map – which may or may not restrict the possible locations for a sensing task's center – so that a user can select a pair of coordinates from this map.

Before a user's smart device starts providing sensor outputs to the cloud, its user needs to decide on the minimum amount that he wants to earn per sensor output. This amount is regarded as the user's bid in our incentive mechanism's reverse auction until it is changed by the user at a later time. Since these bids are not known by other users, a user who wants to request the service cannot know the price of his service request before he sends it. Therefore, the operator of the sensing service needs to decide on an upper limit for the bids so that the maximum price possible for a service request can be known by the user who requested it.

A user must be able to control the sensor output provision of his smart device by determining when his smart device becomes online or offline in the system as a sensor output provider. Also, whenever it is possible, the providers that have been online in the system for a longer period of time but selected for a fewer number of service requests must be given priority. So as to indicate such a situation, a sensor output provider's online waiting time can be recorded, which we describe as the total period of time the smart device has been online in the system as a provider since it last provided a sensor output for a sensing task.

Assuming the online waiting times as well as the locations of provider smart devices are tracked by the cloud, and the above-mentioned decisions are made by the agents, a
service request is handled by the representative MCS system with the rVCG incentive mechanism as follows:

1. The cloud finds the online provider smart devices (P) which are in the area of the service request. The providers whose users' bids are greater than the upper limit determined by the operator are discarded.
   a. If P is empty, the cloud finds the minimum distance between the service request's location and an online provider whose user's bid is not greater than the upper limit. The cloud sends this distance to the user who has sent the service request and asks him whether he wants to update the radius in his service request.
      I. If the user updates his service request, the first step is repeated using the updated radius.
      II. If the user does not update his service request, the cloud stops handling the service request.
   b. If P is not empty, only then the cloud continues handling the service request.
2. The cloud implements the rVCG mechanism.
   a. If the maximum number of sensor outputs (n) specified in the service request is less than the number of smart devices in P:
      I. The smart devices in P are sorted in ascending order according to the bids of their users. If some of these bids are the same, the smart devices correlated with the same bids are sorted among themselves in descending order according to their online waiting times.
      II. The first n number of smart devices are selected from this arrangement to provide sensor outputs. The payment of each selected provider's user is determined to be equal to the bid of the n+1\textsuperscript{st} smart device's user.
   b. Otherwise, all smart devices in P are selected to provide sensor outputs. The payment of each selected provider's user is determined to be equal to his own bid.
3. The cloud notifies the selected smart devices and receives their sensor outputs. The online waiting times of the providers whose sensor outputs have been received are reset to 0.
4. The cloud only pays the users whose smart devices' sensor outputs have been received. The service price is equal to the sum of what is paid to these users, and the user who requested the service is charged this amount by the cloud.
5. The cloud processes the received sensor outputs and sends the result along with the service price to the user who sent the service request.
5 Results

In this chapter, we first theoretically analyze the base and the rVCG incentive mechanisms to find out whether bidding truthfully is the dominant strategy for the agents in these mechanisms. Then, we describe how we conducted our simulations to compare the fairness of service prices and provider earnings in these mechanisms. Lastly, we explain the analysis of our simulation results.

5.1 Theoretical Analysis

In order to find out whether truthful bidding is the dominant strategy in the base and the rVCG incentive mechanisms, we compare truthful bidding with underbidding and overbidding respectively in terms of the agents' utilities (benefits). In addition to the definitions in the fourth chapter, the following definitions are used to describe and mathematically represent how these comparisons are done:

- $c_i$: For provider $i$, its user's true valuation of what providing a sensor output can cost.
- $v_i(o)$: The true cost that is incurred by the user of provider $i$ under outcome $o$. If provider $i$ is selected in outcome $o$, then $v_i(o) = -c_i$. Otherwise, $v_i(o) = 0$.
- $u_i(o)$: The utility that provider $i$'s user gets under outcome $o$. It is equal to the difference between the user's true valuation of the outcome and what he actually ends up with under that outcome.
  
  - For the base mechanism, this definition is equivalent to the equation $u_i(o) = v_i(o) - w_i(o)$. This is also the case for the rVCG mechanism when the VCG mechanism is not applicable ($n \geq |P|$). If provider $i$ is selected in $s^*$, $u_i(s^*) = v_i(s^*) - w_i(s^*) = -c_i - (-b_i) = b_i - c_i$. Otherwise, $u_i(s^*) = 0$.
  
  - For the rVCG mechanism when the VCG mechanism is applicable ($n < |P|$), this definition is equivalent to the equation $u_i(o) = v_i(o) - t_i$. If provider $i$ is selected in $s^*$, $u_i(s^*) = v_i(s^*) - t_i = -c_i - (-b_{n+1}) = b_{n+1} - c_i$. Otherwise, $u_i(s^*) = 0$.

- $s_{b^*}$: The set of providers selected by the incentive mechanism ($s_{b^*} = s^*$) if provider $i$ reports $b_i$.
- $s_{c^*}$: The set of providers selected by the incentive mechanism ($s_{c^*} = s^*$) if provider $i$ reports $c_i$. 
• \( b_n \): The maximum reported cost among the users whose smart devices are selected in \( s_b^* \).

• \( b_{n+1} \): The minimum reported cost among the users whose smart devices are not selected in \( s_b^* \).

• \( c_{n+1} \): The minimum reported cost among the users whose smart devices are not selected in \( s_c^* \).

5.1.1 Base Mechanism

The theoretical analysis is the same for both the base mechanism and the rVCG mechanism when the VCG mechanism is not applicable \( (n \geq |P|) \). It is done by first comparing truthful bidding with underbidding and then with overbidding:

1. Let us say the user of provider \( i \) has underbid by reporting \( b_i \) instead of \( c_i \) such that \( b_i < c_i \).
   a. If provider \( i \) is not selected in \( s_b^* \), \( b_i \) cannot be less than \( b_n \), and \( u_i(s_b^*) = 0 \). Had the user of provider \( i \) bid truthfully by reporting \( c_i \), provider \( i \) would not be selected in \( s_c^* \) because \( b_n \leq b_i < c_i \), and \( u_i(s_c^*) = 0 \). In this case, truthful bidding and underbidding have the same utility.
   
   b. If provider \( i \) is selected in \( s_b^* \), \( b_i \) cannot be greater than \( b_{n+1} \), and \( u_i(s_b^*) = b_i - c_i < 0 \). Had the user of provider \( i \) bid truthfully by reporting \( c_i \):
      I. If \( c_i < b_{n+1} \), provider \( i \) would be selected in \( s_c^* \) because \( b_i < c_i < b_{n+1} \), and \( u_i(s_c^*) = c_i - c_i = 0 \). In this case, truthful bidding's utility is better than underbidding's utility.
      II. If \( c_i > b_{n+1} \), provider \( i \) would not be selected in \( s_c^* \) because \( b_i \leq b_{n+1} < c_i \), and \( u_i(s_c^*) = 0 \). In this case, truthful bidding's utility is better than underbidding's utility.
      III. If \( c_i = b_{n+1} \), provider \( i \) might or might not be selected in \( s_c^* \) because \( b_i < c_i = b_{n+1} \). In any case, truthful bidding's utility is better than underbidding's utility.

2. Let us say the user of provider \( i \) has overbid by reporting \( b_i \) instead of \( c_i \) such that \( b_i > c_i \).
   a. If provider \( i \) is selected in \( s_b^* \), \( b_i \) cannot be greater than \( b_{n+1} \), and \( u_i(s_b^*) = b_i - c_i > 0 \). Had the user of provider \( i \) bid truthfully by reporting \( c_i \), provider \( i \) would be selected in \( s_c^* \) because \( c_i < b_i \leq b_{n+1} \), and \( u_i(s_c^*) = c_i - c_i = 0 \). In this case, overbidding's utility is better than truthful bidding's utility.
b. If provider i is not selected in \( s_b^* \), \( b_i \) cannot be less than \( b_n \), and \( u_i(s_b^*) = 0 \).

Had the user of provider i bid truthfully by reporting \( c_i \):

I. If \( c_i > b_n \), provider i would not be selected in \( s_c^* \) because \( b_n < c_i < b_i \) and \( u_i(s_c^*) = 0 \). In this case, truthful bidding and overbidding have the same utility.

II. If \( c_i < b_n \), provider i would be selected in \( s_c^* \) because \( c_i < b_n \leq b_i \), and \( u_i(s_c^*) = c_i - c_i = 0 \). In this case, truthful bidding and overbidding have the same utility.

III. If \( c_i = b_n \), provider i might or might not be selected in \( s_c^* \) because \( b_n = c_i < b_i \). In any case, truthful bidding and overbidding have the same utility.

A strategy weakly dominates another strategy if it is better in at least one case and as good in the other cases [13]. In the base incentive mechanism, truthful bidding weakly dominates underbidding, and overbidding weakly dominates truthful bidding. For this reason, overbidding is the dominant strategy in our reverse auction when the VCG mechanism is not applied.

### 5.1.2 rVCG Mechanism

The theoretical analysis of the rVCG mechanism when the VCG mechanism is applicable (\( n < |P| \)) is also done by first comparing truthful bidding with underbidding and then with overbidding:

1. Let us say the user of provider i has underbid by reporting \( b_i \) instead of \( c_i \) such that \( b_i < c_i \).

   a. If provider i is not selected in \( s_b^* \), \( b_i \) cannot be less than \( b_n \), and \( u_i(s_b^*) = 0 \).

      Had the user of provider i bid truthfully by reporting \( c_i \), provider i would not be selected in \( s_c^* \) because \( b_n \leq b_i < c_i \), and \( u_i(s_c^*) = 0 \). In this case, truthful bidding and underbidding have the same utility.

   b. If provider i is selected in \( s_b^* \), \( b_i \) cannot be greater than \( b_{n+1} \), and \( u_i(s_b^*) = b_{n+1} - c_i \). Had the user of provider i bid truthfully by reporting \( c_i \):

      I. If \( c_i < b_{n+1} \), provider i would be selected in \( s_c^* \) because \( b_i < c_i < b_{n+1} \), and \( u_i(s_c^*) = c_{n+1} - c_i = b_{n+1} - c_i > 0 \). In this case, truthful bidding and underbidding have the same utility.

      II. If \( c_i > b_{n+1} \), provider i would not be selected in \( s_c^* \) because \( b_i \leq b_{n+1} < c_i \) and \( u_i(s_c^*) = 0 \). In this case, since \( u_i(s_b^*) = b_{n+1} - c_i < 0 \), truthful bidding's utility is better than underbidding's utility.
III. If \( c_i = b_{n+1} \), provider i might or might not be selected in \( s_c^* \) because \( b_i < c_i = b_{n+1} \). In any case, since \( u_i(s_b^*) = b_{n+1} - c_i = 0 \) while \( u_i(s_c^*) = b_{n+1} - c_i = 0 \), truthful bidding and underbidding have the same utility.

2. Let us say the user of provider i has overbid by reporting \( b_i \) instead of \( c_i \) such that \( b_i > c_i \).

   a. If provider i is selected in \( s_b^* \), \( b_i \) cannot be greater than \( b_{n+1} \), and \( u_i(s_b^*) = b_{n+1} - c_i \). Had the user of provider i bid truthfully by reporting \( c_i \), provider i would be selected in \( s_c^* \) because \( c_i < b_i \leq b_{n+1} \), and \( u_i(s_c^*) = c_{n+1} - c_i = b_{n+1} - c_i > 0 \). In this case, truthful bidding and overbidding have the same utility.

   b. If provider i is not selected in \( s_b^* \), \( b_i \) cannot be less than \( b_n \), and \( u_i(s_b^*) = 0 \). Had the user of provider i bid truthfully by reporting \( c_i \):

      i. If \( c_i > b_n \), provider i would not be selected in \( s_c^* \) because \( b_n < c_i < b_n \) and \( u_i(s_c^*) = 0 \). In this case, truthful bidding and overbidding have the same utility.

      ii. If \( c_i < b_n \), provider i would be selected in \( s_c^* \) because \( c_i < b_n \leq b_n \) and \( u_i(s_c^*) = c_{n+1} - c_i = b_n - c_i > 0 \). In this case, truthful bidding's utility is better than overbidding's utility.

      iii. If \( c_i = b_n \), provider i might or might not be selected in \( s_c^* \) because \( b_n = c_i < b_i \). In any case, since \( u_i(s_c^*) = 0 \) or \( u_i(s_c^*) = b_n - c_i = 0 \), truthful bidding and overbidding have the same utility.

When the agents are paid independently of their bids in the rVCG incentive mechanism, truthful bidding weakly dominates both underbidding and overbidding. For this reason, truthful bidding is the dominant strategy in our reverse auction when the VCG mechanism is applied.

### 5.2 Simulations

In order to evaluate the performance of our system model, we compared the rVCG incentive mechanism with the base incentive mechanism in regard to the fairness of service request prices and sensor output provider earnings. We performed simulations and investigated how fair the prices of service requests and the earnings of sensor output providers were in these incentive mechanisms by using a metric called Jain's fairness index. This index of fairness is always between 0 and 1, and a fairness of 0.1 denotes being unfair to 90% [15].
5.2.1 Setup

The independent variables in our simulations consisted of the number of service requests (sr), the number of provider smart devices (pd), the radius of sensing tasks (r), and the maximum number of sensor outputs – or winners – (n). Consequently, there were four parameter sets for our simulations, and in each set, a different independent variable was manipulated. The number of requests and the number of providers varied from 100 to 1000 with the increment of 100, similar to [24] and [28]. The radius varied from 50m to 500m with the increment of 50m, and the maximum number of winners varied from 5 to 50 with the increment of 5. When the independent variables were not manipulated in the parameter sets, their default values were equal to the half of their maximum values. The equivalent notation for the parameter sets is as follows:

- A = \{sr = [100, 1000] + 100, pd = 500, r = 250, n = 25\}
- B = \{sr = 500, pd = [100, 1000] + 100, r = 250, n = 25\}
- C = \{sr = 500, pd = 500, r = [50, 500] + 50, n = 25\}
- D = \{sr = 500, pd = 500, r = 250, n = [5, 50] + 5\}

The setting \{sr = 500, pd = 500, r = 250, n = 25\} was common in all parameter sets, and each parameter set had 9 other settings. There were 37 unique settings in total, and all settings corresponded to one simulation. We conducted 100 simulations, and for each simulation, 1000 service request locations, 1000 provider locations, 1000 true valuations, and 1000 overbids were randomly generated using the pseudorandom number generator in the Java platform's 8th standard edition. A different random seed was used per simulation, and according to each setting, the base and the rVCG mechanisms were applied on the randomly generated values respectively. For example, for the setting \{sr = 500, pd = 100, r = 250, n = 25\}, the rVCG mechanism was applied on the first 500 service request locations, the first 100 provider locations, and the first 100 true valuations, whereas the base mechanism was applied on the first 500 service request locations, the first 100 provider locations, and the first 100 overbids.

Without loss of generality, we limited the locations of sensing tasks and provider smart devices to a 1000m x 1000m region, similar to [24]. Latitudes and longitudes of these locations were randomly generated using a uniform distribution over the interval between 0 and 1000 such that each value had at most 6 decimal digits. Some areas of service requests and locations of sensor output providers – which were generated under different settings in our simulations – are graphically represented in Figure 3.
Locations of sensing tasks are represented by hexagons, and smart device locations are represented by diamonds. Matching colors are used to depict a sensing task's center and its border, but different colors are used to indicate the varying radiiuses of sensing tasks.

The upper limit of the true valuations was 10, similar to [27] and [28], and the maximum overbid ratio was 150%, similar to [21], [22], and [23]. The true valuations of providers were randomly generated using a uniform distribution over the interval between 0 and 10, and each value had at most 2 decimal digits. The overbids of providers were also randomly generated using a uniform distribution such that each value had at most 2 decimal digits, but the intervals depended on the true valuations. Each interval's lower bound was the corresponding true valuation, while its upper bound was the minimum of 10 and 1.5 times the true valuation.

5.2.2 Analysis and Evaluation

For each setting, four fairness indexes were calculated because the dependent variables in our simulations were the prices and the earnings in both incentive mechanisms. We averaged out the respective fairness indexes that belonged to the same setting across all simulations. We also found the confidence intervals of these mean values by using a confidence level of 95%. The results of our analysis are depicted in Figure 4-11, where each data point is averaged over 100 instances – similar to [24] and [28].
The effect that the number of service requests – parameter set A – has on the fairness of service prices is shown in Figure 4. Increasing the number of service requests does not cause a substantial change in the average Jain's fairness index of prices aside from a negligible decrease. This impact might be because of using a uniform distribution when pseudorandomly generating bids and locations. Given the configuration of our simulations, the values of our parameters must be adequate to utilize the providers with similar bids – across settings – most of the time so that altering the number of service requests does not affect the service price variety. Still, the rVCG incentive mechanism's fairness of prices is slightly better than the base incentive mechanism's fairness of prices. This might be because the selected providers are paid the n+1\textsuperscript{st} bid in the rVCG mechanism. In consequence, if the n+1\textsuperscript{st} bids in two service requests are the same, their service prices are the same as well since n does not change in parameter set A.

Figure 4: Effect of Parameter Set A (sr) on Fairness of Prices
The effect that the number of service requests – parameter set A – has on the fairness of provider earnings is shown in Figure 5. Increasing the number of service requests causes a gradually diminishing increase in the average Jain's fairness index of earnings. This impact is because more smart devices can be selected when there are more service requests. The rVCG incentive mechanism's fairness of earnings is marginally better than the base incentive mechanism's fairness of earnings. This might also be because the selected providers are all paid the $n+1^{\text{st}}$ bid in the rVCG mechanism, whereas they are paid the bids of their own users in the base mechanism. Additionally, why the fairness indexes are below 0.4 might be due to the providers that are never selected and hence earn nothing because of their relatively higher bids.

Figure 5: Effect of Parameter Set A (sr) on Fairness of Earnings
The effect that the number of provider smart devices – parameter set B – has on the fairness of service prices is shown in Figure 6. Increasing the number of provider smart devices first increases, then decreases, and at the end does not affect the average Jain's fairness index of prices. This impact might be because there are less than $n$ number of providers in the areas of some sensing tasks at first and these service requests have different number of winners. Then, as the density of providers increase, more service requests have the same number of winners, and the fairness of service prices increase as well. The decrease afterwards might be due to the heterogeneous increase in the variety of bids that are found in the areas of sensing tasks. As the number of providers increase, the number of lower bids found in some areas can increase as well, causing the price of these service requests to decrease, whereas the other service requests still have to select the providers with higher bids. After 500 smart devices, increasing the number of providers does not have a substantial effect on the fairness of prices. This is most probably because increasing the number of providers does not change the selected bids in the service requests after that point. The rVCG incentive mechanism first appears to be less fair than the base incentive mechanism, but later on, the fairness of prices becomes slightly better in the rVCG mechanism than it is in the base mechanism. This outcome must be also because there are less than $n$ number of providers in the areas of some sensing tasks at the beginning. In such service requests, the VCG mechanism is not applicable, and the rVCG mechanism works the same as the base mechanism. However, true valuations ($t_i$), which can be between 0 and 10, are used in the rVCG mechanism, while

![Figure 6: Effect of Parameter Set B (pd) on Fairness of Prices](image-url)
overbids, which can be between \( t_i \) and \( \min(10, 1.5 \times t_i) \), are used in the base mechanism. Since overbids have less variety, the service prices in the base mechanism end up being more similar, which causes its fairness index to be better. Later, when the VCG mechanism becomes applicable, same number of winners are paid the \( n+1^{st} \) bid by the rVCG mechanism, and the prices in the rVCG mechanism becomes more fair than the prices in the base mechanism.

The effect that the number of provider smart devices – parameter set B – has on the fairness of provider earnings is shown in Figure 7. Increasing the number of provider smart devices mostly decreases the average Jain's fairness index of earnings. This impact must be because as the density of providers increases, more number of lower bids become available. Since the providers with lower bids are selected instead of the providers with higher bids, the difference between the earnings of the former and the latter escalates, and the fairness index decreases. The rVCG incentive mechanism's fairness of earnings is better than the base incentive mechanism's fairness of earnings in general. This must be because the rVCG mechanism pays the same amount to a service request's selected providers when the VCG mechanism is applicable. The only increase in the fairness index happens between the first and the second data points of the rVCG mechanism, which must be also because there are less than \( n \) number of providers available for some service requests in these data points, and as the number of providers increase, the ratio of the providers that gets selected at least once to the providers that are never selected increases as well.
The effect that the radius of service requests – parameter set C – has on the fairness of service prices is shown in Figure 8. Increasing the radius of sensing tasks first increases, then decreases, and towards the end increases the average Jain's fairness index of prices again. The first steep increase must be because the initial radius values are not enough to enclose at least n number of providers for some service requests, similar to the case in Figure 6. When there are less than n number of providers to choose from, the fairness index of prices can be lower because different number of providers would be selected in the service requests and then paid. As the radius increases, more providers become available, and the service prices become more similar. The decrease afterwards might be caused by the heterogeneous increase in the variety of bids when there are at least n number of providers available to choose from for most service requests. Like in the case of Figure 6, due to this heterogeneity, the providers with higher bids might still have to be selected in some service requests, while the providers with lower bids can be selected in the other service requests. The gradual increase after the 6th data point (300m) must be because the heterogeneity decreases as the providers with lower bids become available for more service requests. The rVCG incentive mechanism first appears to be less fair than the base incentive mechanism, but later on, the fairness of prices becomes slightly better in the rVCG mechanism than it is in the base mechanism. This outcome must be also because the initial radius values are not enough to enclose at least n number of providers for some service requests. In such service requests, the VCG mechanism is not applicable, and the rVCG mechanism works the same as the base mechanism.
Similar to the case in Figure 6, the difference between the possible values of true valuations and overbids causes the service prices in the base mechanism to be more similar, which leads to its fairness index being better. However, when the VCG mechanism becomes applicable, n number of winners are paid the same amount by the rVCG mechanism, and the prices in it becomes more fair than the prices in the base mechanism.

The effect that the radius of service requests – parameter set C – has on the fairness of provider earnings is shown in Figure 9. Increasing the radius of sensing tasks first increases and then decreases the average Jain's fairness index of earnings. This impact must be because as the density of providers increases until there are at least n number of provider smart devices available for most service requests, more number of providers get selected and avoid not earning anything since they are not in the area of any service request. Therefore, the fairness index of earnings increases. After there are at least n number of providers to choose from for most service requests, the fairness of earnings decreases similar to the case in Figure 7. This is because more number of lower bids become available as the radius increases, and more number of providers with higher bids earn less or never get selected. The rVCG incentive mechanism first appears to be less fair than the base incentive mechanism. Later, the fairness of prices becomes better in the rVCG mechanism than it is in the base mechanism, but eventually, the base mechanism's fairness surpasses the rVCG mechanism's fairness slightly. At first, the initial radius values must be not enough to enclose at least n
number of providers for some service requests, which causes the selected providers in these service requests to be paid the amounts equal to their true valuations in the rVCG mechanism. Thus, similar to the cases in Figure 6 and 8, the base mechanism appears more fair since the values of true valuations are more diverse than the values of overbids. Then, the rVCG mechanism becomes more fair than the base mechanism because the radius values must have become enough to enclose at least n number of providers for most service requests, and the selected providers are paid the n+1\textsuperscript{st} bid by the rVCG mechanism. At the end, most of the providers must have become available to most service requests, and the providers with the lowest bids must be selected frequently. At these points, the lowest overbids can be less than the lowest n+1\textsuperscript{st} true valuations, and as there would be more providers that are never selected – usually the ones with the highest bids – the base mechanism appears to have a slightly better fairness of earnings than the rVCG mechanism.

The effect that the maximum number of winners – parameter set D – has on the fairness of service prices is shown in Figure 10. Increasing the maximum number of winners increases the average Jain's fairness index of prices. This impact might be because as more providers are selected per service request, more providers with higher bids can get selected. As the bids of the selected providers get higher, the possible values that the n+1\textsuperscript{st} bids can take become more similar since there is an upper limit for the bids. This causes the service prices in the rVCG incentive mechanism to become more similar as well. Also, when the variety among the

Figure 10: Effect of Parameter Set D (n) on Fairness of Prices
selected bids increases in each service request, the service prices in the base incentive mechanism become more similar because these prices are the sum of the selected bids. The rVCG mechanism's fairness of prices is generally better than the base mechanism's fairness of prices. This might be because the sums of the \( n+1 \)st bids have more similar values, whereas the sums of the first \( n \) bids have more different values. At the end, the base mechanism appears to be more fair than the rVCG mechanism. This is probably because the density of the provider smart devices does not change as the number of winners increases, and the density of providers becomes insufficient. When the number of providers available for a service request is not greater than the maximum number of winners, the rVCG mechanism behaves the same as the base mechanism. Similar to the cases in Figure 6, 8, and 9, since the number of different values that true valuations can take is more than the number of different values that overbids can take, the rVCG mechanism appears to be less fair when the VCG mechanism is not applicable.

![Figure 11: Effect of Parameter Set D (n) on Fairness of Earnings](image)

The effect that the maximum number of winners – parameter set D – has on the fairness of provider earnings is shown in Figure 11. Increasing the maximum number of winners increases the average Jain's fairness index of earnings. This impact is because more providers are selected per service request as the maximum number of winners increases. When more providers with higher bids get selected, there would be less providers that are never selected and earn nothing. The rVCG incentive mechanism's fairness of earnings is better than the base incentive mechanism's
fairness of earnings. This might be because all selected providers in a service request are paid the same bid in the rVCG mechanism when the VCG mechanism is applicable. Additionally, as the maximum number of winners increases, the n+1\textsuperscript{st} true valuations might have more similar values in comparison to the cases with fewer number of winners, whereas individual overbids might have more different values in comparison to the n+1\textsuperscript{st} true valuations.
6 Conclusions

We investigated two problems related to a micropayment using MCS system in this thesis. First, we applied the VCG mechanism to the MCS system's reverse auction based incentive mechanism and analyzed whether this made the incentive mechanism truthful. We demonstrated that overbidding was the dominant strategy in the base incentive mechanism, whereas truthful bidding was the dominant strategy in the VCG applied incentive mechanism. Then, we measured how fair the prices of service requests and the cumulative earnings of sensor output providers were in the base and the rVCG incentive mechanisms using Jain's fairness index. We compared the fairness of both incentive mechanisms in terms of how the number of service requests, the number of provider smart devices, the radius of sensing tasks, and the maximum number of winners in service requests affected the service prices and the cumulative earnings of providers. We observed that both the fairness of prices and the fairness of earnings were generally better in the rVCG incentive mechanism when the VCG mechanism was applicable, i.e. when the maximum number of winners in a service request was less than the number of available providers in a sensing task's area. We also found out that the fairness of prices in both of our incentive mechanisms was better than the fairness of earnings: The lowest fairness of prices was greater than 0.7, while the lowest fairness of earnings was less than 0.1. That is, at most 30% of service prices was unfair at worst, whereas at least 90% of cumulative earnings was unfair at worst. The reason for the low fairness index of cumulative earnings is because the participants with lower bids become winners more frequently in reverse auctions since they are selected instead of the participants with higher bids. Some participants may never get selected, and a truthful mechanism alone is not sufficient to prevent that.
7 Future Work

For future work, our study can be merged with another work in the literature – such as [22] or [23] – which decreases the likelihood of participants' dropping out of the system due to being not selected frequently. Our system model can be extended to accommodate different sensing service types and price options with different upper limits for bids. Also, the mobility of participants can be included in our simulations. Moreover, the privacy in our system can be enhanced as the users of sensor output provider smart devices need to report their location even when their smart devices are not selected for a service request and they earn nothing. Furthermore, ensuring the data quality can be integrated into our incentive mechanism.
References


[27] D. Zhao, X.-Y. Li, and H. Ma, ‘How to Crowdsource Tasks Truthfully without Sacrificing Utility: Online Incentive Mechanisms with Budget Constraint’, in


