CONTRACT THEORY FRAMEWORK FOR WIRELESS NETWORKING

A Dissertation
Presented to
the Faculty of the Electrical and Computer Engineering
University of Houston

in Partial Fulfillment
of the Requirements for the Degree
Doctor of Philosophy
in Industrial Engineering

by
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May 2016

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WIRELESS NETWORKING

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Acknowledgements

I am so appreciative for everyone that has helped me during my four-year Ph.D. study, which has made my short living in this beautiful country an unforgettable experience.

First, I would like to express my great appreciation to my advisor, Professor Zhu Han, for his esteemed guidance, constant encouragement, and continuous support during my graduate studies. His profound academic background and keen insights has helped me achieve significantly improvement in my Ph.D. research and to be well prepared for future professional development, which will be an invaluable assets for my future career.

Furthermore, I would like to express my sincere gratitude to Professor Ji Chen and Professor Haluk Ogmen whom is also my dissertation committee member. They offered me such a precious opportunity to pursue a doctor's degree at University of Houston, which has indeed changed my life. I would also like to thank the rest of my dissertation committee, Professor Zixiang Xiong, Professor Lijun Qian, Professor Miao Pan, and Professor Saurabh Prasad for their precious time and support on this dissertation.

My appreciation also goes to my dear colleagues Huaqing Zhang, Yunan Gu, Erte Pan, Hung Ngyuen, Yong Xiao, Ali Arab, Nam Ngyuen, Mohammad Esmalifalak, Lanchao Liu, Najmeh Forouzandehmehr, Yi Huang, and Tina Mathews, whom I always having great time with in both on and off work times. I am also grateful to my lovely roommate Huicun Lu, who always welcome me back home after one day's work and sharing me with both happiness and sadness. I am grateful to all my friends who give support during my PhD life, in Houston, back in my hometown China, and all around the world. They are Neng Zhang, Qin Huang, Jianglong Liu, Hui Dong, Qinchuan Guo, and Ke Wang.

Last but by no means least, I want to thank my mom, dad, fiancé, grandmothers, grandfathers, aunts, uncles, cousins, and nephew for their countless love, encouragement, patience, and support during all those years, and bringing us together a wonderful family.

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Abstract

With the rapid development of the modern communication networks, the problem we need to solve is no longer a pure engineering issue. In various heterogeneous network scenarios, there are service providers in need of performing economic analysis on how to ensure third parties' cooperation or attract end-users. In the other way round, third parties or end-users need to evaluate the economic benefits of cooperating or using the services from different service providers. Overall, the current wireless networks are facing a problem in which there is a tight coupling of industry-specific technologies and non-technology related network externality.

Contract theory, the 2014 Nobel Prize of economic science, has been widely used in industries, from banking to telecommunications. Particularly, contract theory is an efficient tool in dealing with asymmetric information between employer/seller(s) and employee/buyer(s) by introducing cooperation. In wireless networks, the employer/seller(s) and employee/buyer(s) can be of different roles depending on the scenario under consideration. Thus, there is a great potential to utilize the ideas, methods, and models of contract theory to design efficient wireless network mechanisms.

Given this background, this dissertation provides a theoretical research between wireless communications, networking, and economics. Especially, different contract theory models have been applied in various wireless networks scenarios. The main contribution of this dissertation are as follows.

- An overview of basic concepts, classifications, and models of contract theory is provided. Furthermore, comparisons with existing economics methods in wireless networks are conducted.

- Applications of contract theory for wireless networks are studied. Specially, three contract theory problems: *adverse selection*, *moral hazard*, and a mixed of the two, are applied into device-to-device (D2D) communication, mobile crowdsourcing, cognitive radio network, respectively.

- Numerical results are provided to show that contract theory can be utilized for developing effective mechanisms for emerging wireless network scenarios such as traffic offloading, mobile crowdsourcing, as well as spectrum trading.
- The potential and challenges of contract theory as a tool for designing mechanisms in future wireless networks are discussed.

This dissertation provides a theoretical research between wireless communications, networking, and economics, in which different contract theory models have been applied in various wireless networks scenarios. This work places a fundamental research on network economics, especially with the framework of contract theory. This research has the potential to contribute to the future of wireless networks network economics area, and have a long term effect on problems such as incentive mechanism and pricing schemes design, resource sharing and trading.

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Chapter 1

Introduction

Owing to the wide adoption of smart devices and fast development of the Internet, various applications and services have been introduced to bring convenience to every aspect of our daily lives; at the same time, this has brought great changes and new challenges to the design and operation of wireless networks. First, The introduction of resource demanding mobile services such as Facebook and YouTube has exponentially raised the desire for wireless access [1]. Moreover, the embedding of advanced sensors in mobile devices has led to the dramatic growth of a wide range of location based services.

On one hand, one can deal with the network capacity crunch by utilizing various forms of cooperation in heterogeneous wireless networking scenarios. Technologies such as device-to-device (D2D) communications, cognitive radio (CR), and small cells have are being developed to offload the cellular traffic, and increase the energy and spectrum efficiency. On the other hand, an attractive solution for location based data crunch is to do mobile crowdsourcing, in which a large group of users (with sensors embedded smart devices) regularly collect and transmit data required from the service provider. In both traffic offloading and data uploading processes, it is necessary to ensure the cooperation from third parties, e.g., D2D devices, small cells, and users.

However, there lies a conflict when participating in such activities, as third parties do consume their resources, e.g., battery capacity and computing power [2]. Such a conflict results in reluctance from third parties to participate, which is a major impediment to the development of practically attractive traffic offloading and mobile crowdsourcing solutions. Therefore, to successfully achieve the benefits, there is a need to develop effective incentive mechanism designs in wireless networks, in order to incentivize third party participation and improve overall operation quality.

Contract theory is widely used in real world economics with asymmetric information to design the contract between employer/seller(s) and employee/buyer(s) by introducing cooperation [3].

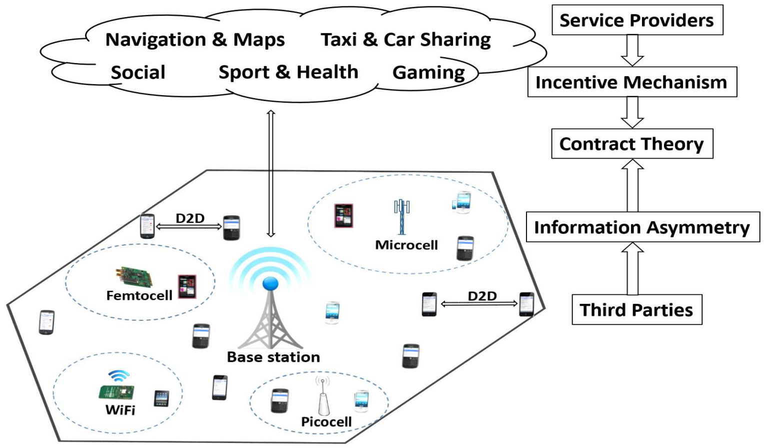


Figure 1.1: General model for cooperation in wireless networks: 1) offloading data traffic through heterogeneous networks (small cell, cognitive radio, and D2D communication); 2) uploading location based data through mobile crowdsourcing.

The information asymmetry usually refers to the fact that the employer/seller(s) does not know exactly the characteristics of the employee/buyer(s). By using contract theory based models, the employer/seller(s) can overcome this asymmetric information and efficiently incentivize its employee/buyer(s) by offering a contract which includes a given performance/item and a corresponding reward/price.

Due to this property of contract theory, we envision that there is a there is a great potential to utilize concepts from contract theory to ensure cooperation and assist the design of incentive mechanisms in wireless networks. In wireless networks, the employer/seller(s) and employee/buyer(s) can be of different roles depending on the scenario under consideration. An employer/seller(s) can be a base station (BS), service provider (SP), and authorized spectrum owner. An employee/buyer(s) can be a small cell, smart device, user, or some other third party that is not part of the current traditional cellular network architecture. The adoption of contract theory for incentive mechanism design in future wireless networks is illustrated in Fig. 1.1.

In this dissertation, we mainly focus our research on how to provide necessary incentives to motivate users' participation in those newly introduced wireless networks, such as heterogeneous network and mobile crowdsourcing. We are going to use the Nobel Prize winning contract theory to formulate the incentive mechanisms in the mobile wireless networks. For each class of the typical contract models, we provide the basic concepts, classification, and models in Section 1.1, as well as comparisons with other economic methods. Beyond providing a self-contained survey on classical contract theory concepts, we will further study in Section 1.2 the design of incentive mechanisms, especially the reward design in a contract. We them emphasize both analytical techniques and novel application scenarios in Section 1.3. Finally, we give the main organization of this dissertation in Section 1.4.

1.1 Contract Theory: Fundamentals and Classification

1.1.1 Basic Contract Concepts

Contract theory has been highly successful and active research area in economics, finance, management, and corporate law for decades. Contract theory allows studying the interaction between employer(s) and employee(s). The performance of employees tends to be better when they work harder, and the probability of a bad performance will be lower if employees place more dedication or focus on the work. By contrast, on the other hand, if an employee's compensation is independent of its performance, the employee will be less likely to put efforts into the work [3]. The design of incentive mechanism plays an important role in addressing the problem of employee incentives.

In contract theory, the solution we need to obtain is a menu of contract for employee, and the object is maximizing the employer's payoff or utility. In most cases, the problem is usually formulated as maximizing an objective function which represents the employer's payoff, subject to the *incentive compatibility* constraint that the employee's expected payoff is maximized when signing the contract, and the *individual rationality* constraint that the employee's payoff under this contract is larger than or equal to its reservation payoff when not participating.

1.1.2 Classification

1.1.2.1 Adverse Selection

The *adverse selection* problem, the information about some relevant characteristics of the employees, such as their distaste for certain tasks and their level of competence/productivity, are hidden from the employer. One of the most common problems in *adverse selection* is the *screening problem*, in which the contract is offered by the uninformed party, i.e., the employer. The uninformed party typically responds to *adverse selection* by the revelation principle which forces the informed party, i.e, the employee, to select contract that fits its true status. Based on the revelation principle, the employer can offer multiple employment contracts (t, r) destined to different skill level employees, where t is the employee's outcome wanted by the employer, and r is the reward paid to the employee by the employer if the given target is achieved. The outcome can be duration of work time, a required performance, or some other outcomes that the employer wants from the employee.

1.1.2.2 Moral Hazard

The problem of *moral hazard*, which refers to situations where the employee's actions that are hidden from the employer: whether they work or not, how hard they work, how careful they are. In contrast to *adverse selection*, the informational asymmetries in *moral hazard* arise after the contract has been signed. In *moral hazard*, the contract is a menu of action-reward bundle (a, r), where a is the action or effort exerted by the employee after being hired, and r is the reward paid to the employee by the employer.

1.1.2.3 Mixed

In practice, it is usually hard to decide which of the two problems is more important, i.e., to figure out if it is a *moral hazard* problem or *adverse selection* problem. Indeed, most incentive problems are the combinations of *moral hazard* and *adverse selection*.

1.1.3 Models

1.1.3.1 Bi-Lateral or Multi-Lateral

Bi-lateral contracting is the basic one-to-one contracting model, in which there are one employer and one employee trading with each other for goods or services. However, in the multi-lateral case, it is usually a one-to-many contracting scenario, in which there is one employer trading with multiple employees. Despite of the increased number of participants in the multi-lateral contracting than in the bi-lateral one, the interactions among the employees/buyers, such as competition and cooperation, making the multi-lateral contracting model more complex and showing the potential of solving more sophisticated problems.

1.1.3.2 One-Dimension or Multi-Dimension

Only one characteristic or task is considered in the one-dimension contracting model. For example, the employer evaluates only one capability of the employee in the one-dimension *adverse selection* model, and there is only one task assigned by the employer to the employee in the one-dimension *moral hazard* model. In contrast, the employer evaluates multidimensional characteristics of the employee, or assigns multiple tasks to the employee in the multi-dimension contracting scenario. As the extension of one-dimension contracting, multi-dimension contracting model can also be analyzed by adapting the similar methods for one-dimension ones.

1.1.3.3 Static or Repeated

Static contracting refers to the one-shot trading between the two parties, in which the employer usually offers a take-it or leave-it contract, and the employee(s) choose to accept or reject it. Every signing of a contract will be regarded as a new one, i.e., previous trading histories will not affect the signing of the next one. While the trading histories affect the next contract in the repeated contracting scenario. Repeated contracting needs to solve the issues that arise with the design and renegotiation of long-term employment contracts, due to the inability of contracting parties to commit to or enforce long-term contractual agreements. The repeated iteration between contracting parties opens up new incentive issues, and thus increases the complexity than in the static contracting.

1.1.4 Comparisons

1.1.4.1 Market Equilibrium

In the market equilibrium, participants paly their own strategy in regarding of the other's actions in each iteration, and then finally reach the equilibrium. While similar to the repeated long-term contracting scenario in contract theory, participants dynamically change their strategy as if they are playing a game. After repeated interactions and renegotiations, both parties can reach an agreement. Thus, we see that the market equilibrium is the repeated contracting case in contract theory, and different scenarios can fit either into the problem of *adverse selection* or *moral hazard*.

1.1.4.2 Auction Theory

In auction theory, there is one seller with an item to sell and multiple bidders with reservation prices competing for it. Meanwhile, in the multi-lateral *adverse selection*, there are one seller and multiple buyers with their own private information which is the same case as the bidder's reservation prices during auction. Thus, we see that auction theory is the multi-lateral *adverse selection* contracting problem in contract theory.

1.1.4.3 Pricing Strategy

The problems that pricing strategy and contract theory can solve have some overlaps. They two are similar to each other in the sense that they can adjust the price/reward to sell a product or service at the seller/employer's maximal profitability. However, pricing strategy and contract theory's major focuses differ from each other. Since pricing strategy mainly focuses on the relation between pricing and marketing, which can be used to beat the business competitors. While contract

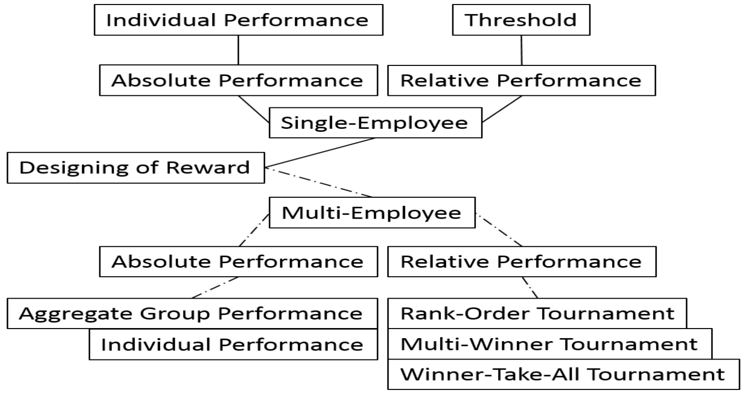


Figure 1.2: Designing of reward in a contract.

theory places the emphasis on studying the interactions between employers and employees, which is helpful in designing incentive mechanisms.

From the three economic models we can see, first, market equilibrium and auction theory, as the special cases of contract theory, have already been widely studied. Second, pricing strategy shows a different research direction as contract theory. To design efficient incentive mechanism, contract theory seems to be an excellent approach and has many unexplored areas to reveal.

1.2 Contract Theory: Reward Design

In contract theory, the objective is to motivate employees by offering a reward, in trading with a level/quality of service, outcome, performance, or target. Thus, we see that the reward determines whether the employee can be fully motivated by the incentive mechanism. Given the large number of models in contract theory, the reward design varies in different contracting scenarios. The design and classification of reward are illustrated in Fig. 2.3b and will be discussed in details in this section.

1.2.1 Dimension of Rewards

From Section 1.1.3.2, we know that there can be one- or multi-dimension contract theoretic models, depending on how many aspects of capability do the employer evaluate the employee, or how many tasks does the employer assign to the employee. Most existing literature on incentive mechanism design in wireless networks adopt the one-dimensional reward model. One example is the reimbursing scheme proposed by [4], which is a usage-based reward design to motivate subscribers to operate as mobile WiFi hotspots to provide Internet connectivity for others.

One-dimensional model becomes inefficient when employees are required to have multiple capabilities, or supposed to work on several tasks. First, the employee's action set becomes richer than what the one-dimensional model has described. Second, there is a risk that one-dimensional reward will induce employees to overwhelmingly focus on the part that will be rewarded and to neglect the other components. Given different aspects of capability or multiple tasks to evaluate, by assigning different weights of rewards in multiple dimensions, the employer can drive employee's incentive on perusing certain capabilities or tasks, which can affect the employer's utility, in return. One current application of multi-dimension reward is from [5], where Karma is a Internet service provider based in the United States. Karma provides 100MB to new guest users for free, and reward users who bring in more users by wirelessly advertising the service.

1.2.2 Rewards on Absolute or Relative Performance

The problem of how can the reward be decided in accordance with the employee's performance also needs attention. Referring the reward designs in job markets, sports, and games, generally there are two methods one can refer to: evaluate the employee's absolute performance or the relative performance.

- *Absolute performance related reward*: The reward is positively related with the employee's absolute performance.
- *Relative performance related reward*: The reward is given based on the ranks that the employees achieved by listing the multiple employees' performance in an ascending or descending order.

Absolute performance related reward is a widely accepted incentive mechanism in real economics as it captures the fundamental aspect of providing necessary and efficient incentives for employees. Piece rate, efficiency wages, and stock options are widely used forms of absolute performance reward in the job market. Despite of the usage-based reward in [4] mentioned previously, the work in [6] also derives the performance and reward dependent function to attract a high amount of sensing data from participating users in wireless networks. Another example is [7], in which incentive mechanism has been developed to encourage the cooperation of mobile terminals (MTs) in wireless cellular networks to reduce the energy consumption the other MTs. The MT who contributes to help will receive a price consistent with its transmitting data rate.

However, there are two disadvantages of the absolute performance related reward. First, in order to pay less reward, the employer has a strong incentive to cheat by claiming that employees had poor performances. Second, this mechanism is vulnerable to *common shock* which is originally used to denote macro-economic conditions such as economic boost or depression [8]. If there is a positive/negative mean that affects employees' performances at the employer's observation, then will lead to an abnormal increase/decrease of reward in the end.

While it has been proven that the relative performance related reward design can filter out this *common shock* problem [8]. As winners receive the amount of reward based on the rank they achieved, which is easy to measure and hard to manipulate [3]. In addition, the employer has no incentive to cheat as it has to offer the fixed amount of rewards no matter who wins. Tournament is the most widely known form of reward by the relative performance, in which the one with better performance ranks higher, and rewarded more. Besides, there are two other special forms of ROT: the Multiple-Winners (MW) and Winner-Take-All (WTA). In the MW tournament, several top winners share the reward equally. While in the WTA tournament, the entire reward is awarded to the highest-ranked user, which is a special case of MW with only one winner.

1.2.3 Reward in Bi-Lateral or Multi-Lateral Contracting

Despite the previous aspects, different trading scenarios also affect the design of incentive mechanism, i.e., the reward. Next, we are going to talk about how to design reward in bi-lateral and multi-lateral contracting scenarios.

1.2.3.1 Contract with Single-Employee

When the employer signs a contract with a single employee, we can design the reward by considering only the single employee's absolute performance instead of the others. Examples in wireless networks are the previous mentioned three works [4, 6, 7]. However, even though there is no other employee to compete with the employee, the relative performance related reward can still be applied. One common form of the relative performance related reward for a single employee is to set up a specific threshold and a reward of the targeted performance. If the employee's absolute performance can achieve the given threshold, a fixed reward will be given to the employee. Otherwise, the employee cannot receive the reward. In fact, we can regard it as the employee competes with the threshold.

1.2.3.2 Contract with Multi-Employee

When the employer designs the contract towards multiple employees, the absolute performance related reward still works quite well, and is a widely accepted method in real economics. Furthermore, there are some other forms of absolute performance related rewards. One widely adopted method is to group employees first, and then reward employees by their aggregated performance in each group. There is a shortcoming with this incentive mechanism, i.e., there is a risk of free riding of some employees on the other employees' efforts. Usually, the absolute performance related reward design is more common seen in contracting with multi-employee. The employees can compete with each other as in a tournament, and have the incentives for higher rewards by performing better.

1.3 Applications in Wireless Networks

In this section, we are going to introduce several applications of contract theory models in wireless networks. To be consistent with the classification of contract theory problems in Section 1.1.2, the following three subsections are wireless network applications of models from *adverse selection*, *moral hazard*, and a mixed of the two, respectively.

1.3.1 Adverse Selection in Wireless Networks

The applications of bi-lateral, one-dimension, and static *adverse selection* in wireless networks are the most widely seen models. This model is first used to solve the problem of spectrum sharing in cognitive radio network (CRN) by [9]. In this work, a primary user (PU) acts as an employer who sets the spectrum trading contract as *(qualities, prices)*, and the second users (SUs) act as an employee to choose which one for purchasing. Another application in CRNs can be found in [10], in which the authors also model the PU and SUs as the employer and employees, respectively. Then designing the *(performance, reward)* in contract as *(relaying power, spectrum accessing time)*.

With the same model, a different application area is by [11] in designing incentive mechanisms for smartphone users' collaboration on both in data acquisition and distributed computing. The SP acts as an employer and smartphone users will be employees. Rewards will be paid according to the amount of data collected and distributed computing users made. In the OFDM-based cooperative communication system, [12] uses contract theory to tackle the source node's relay selection problem. The offers/contracts consist of a menu of desired signal-to-noise-ratios (SNRs) at the destination and corresponding payments. In Chapter 2, we will apply the *adverse selection* model in cellular traffic offloading through D2D communication, by offering rewards to encourage content owners to participate and cooperate with other devices via D2D. We will model the BS as employer and D2D user as employee, and solve contract bundle with a required performance and an absolute performance related reward. The performance is defined as a certain data rate that the

UE must provide during the D2D communication.

1.3.2 Moral Hazard in Mobile Crowdsourcing

Compared to the wide adoption of the *adverse selection* problem, the *moral hazard* problem has hardly been applied in wireless networks by now. However, having seen a great potential of this model, we have done some preliminary applications in mobile crowdsourcing. As mentioned in the beginning of this survey, many users hesitate to participate in mobile crowdsourcing with certain concerns, which results in serious impediment to the exploitation of location based services.

By adopting the *moral hazard*, the incentive mechanism can be designed by regarding the SP "employs" users to upload location based data and reward them by their performance. Thus, one application falls into the multi-dimension *moral hazard* model. Since in mobile crowdsourcing, users are encouraged to take multiple tasks as mentioned in Section 1.2.1. It is intuitive to propose a multi-dimension reward that considers different aspects of user's contributions, and assigns different reward weights on their performance as we will do in Chapter 3. With a large group of users as employees, the multi-lateral *moral hazard* model can be applied. In Chapter 4, we will consider the mobile users competing in the crowdsourcing to win reward as in a tournament, and they are rewarded by their rank orders, i.e., relative performance.

1.3.3 Mixed Problem in Cognitive Radio Networks

Given the applications of the two basic problems: *adverse selection* and *moral hazard*, we can proceed to the mixed problem in wireless networks when both of the two present. The mix problem can also be found in spectrum trading between the PU and SU in CRNs, or infrastructure provider (InP) and SP in virtualized wireless networks. The problem of *adverse selection* arises since the PU/InP may not be fully aware of the SU/SP's capability in utilizing the spectrum to generate revenue, i.e., what is the SU/SP's probability of successfully making profit from the service it provides. Moreover, there is a problem of *moral hazard* as the PU/InP neither knows how much effort the SU/SP will put into running its "business". Thus, the spectrum trading that involves both *adverse selection* and *moral hazard* can be solved by designing a financing contract, as when we buy a car or a house. The main problem that needs to solve is how to design the down payment and installment payment in the financing contract, and the detail work can be found in Chapter 5.

1.4 Dissertation Organization

The rest of the dissertation is organized as follow. In Chapter 2, we formulate the incentive mechanism with adverse selection problem in D2D networks. The incentive mechanism with moral hazard problem in mobile crowdsourcing will be described in Chapter 3 and 4. Finally, some possible future works and a timeline to finish the works are mentioned in Chapter 6.

Chapter 2

Incentive Mechanisms for Device-to-Device Communications in Cellular Networks with Adverse Selection

2.1 Introduction

To deal with this wireless capacity crunch, D2D communication underlaid over cellular network, has recently been proposed as a means to boost the overall wireless network capacity [13]. D2D communication benefits from the fact that two user equipments (UEs) in proximity of one another can establish a direct communication link over the licensed band while bypassing the cellular infrastructure such as the base stations (BSs). One common form of D2D communication is the network-controlled one in which the BS manages the switching between direct and cellular links [14]. Due to the proximity of the involved users, if well designed, D2D communication can dramatically improve the wireless network capacity while reducing energy consumption [15]. It can also assist in offloading the cellular traffic from the BSs while extending their coverage [16].

If UEs' resource blocks (RBs) can be shared, local users will be able to exchange data [17]. For example, the BS can send a frequently requested content to a number of devices who, in turn, can utilize D2D communication to spread the content to other interested users [18]. By doing so, within a certain geographical area, instead of servicing a request multiple times, the BS would only transmit contents which are not locally available. In this case, the BS's traffic is significantly reduced, and thus, the cellular network capacity is increased. One brief illustration can be found in Fig. 2.1, where the BS send the original content to cellular users. If any users are requesting the contents that have already been downloaded, and the content holder is within the D2D transmission distance, the users will be served by D2D communication.

To successfully offload cellular traffic through D2D communication, one main design challenge is to incentivize content owners to participate and cooperate with other devices via D2D. If

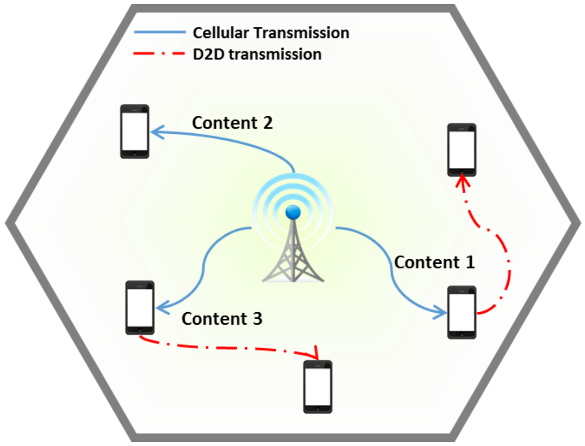


Figure 2.1: An illustration of offloading traffic through D2D communication.

most users are unwilling to provide their contents via D2D communication, then, the BS will still need to serve the users via the conventional cellular network. Consequently, it is unable to increase the network capacity. Clearly, the willingness of users to participate and share data is of great importance to reap the benefits of D2D over cellular in terms of improved capacity and traffic offload.

In order to offload cellular traffic through D2D communication, it is necessary to introduce effective incentive mechanisms that can encourage users to participate in content sharing. To provide incentives, the BS can offer rewards to users' UEs for the usage of their resources (storage, power, time, etc.) as well as for potential privacy risks arising from D2D, since UEs' RBs are open to the BS. For example, if the user is willing to share its content and assists the BS to transmit the data, the BS will offer a reward to compensate for this user's participation. The reward can be in the form of monetary remuneration or free data among others [19].

Intuitively, a well-designed incentive mechanism should reward UEs based on their contributions: devices that contribute more must get higher rewards than devices with less contributions. Users with high preference toward participation will more likely to contribute. However, each user will attempt to harness as much reward as possible by claiming that it is a high preference user, which brings difficulty to the BS in reward design. This problem is exacerbated by *information asymmetry* – the BSs may not be aware of the actual preference, which is naturally known by the users. To this end, our main goal is to propose an incentive mechanism by overcoming this infor-

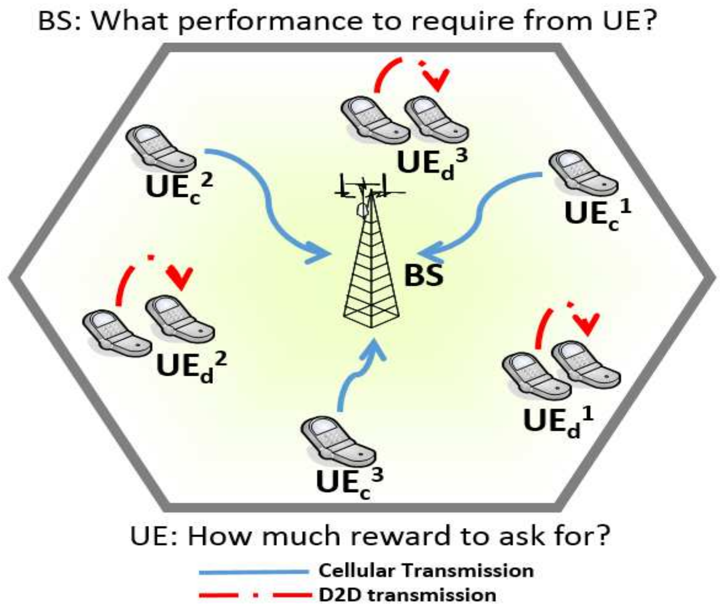


Figure 2.2: The reward assignment problem faced by the BS.

mation asymmetry in a D2D network as shown in Fig. 2.2.

In this respect, there is a need to design a mechanism in which UEs will be rewarded in accordance with their preference. Contract theory, a powerful framework from microeconomics, provides a useful set of tools for modeling incentive mechanisms under information asymmetry [20]. Using contract theory, one can analyze the interactions between an employer who is trying to offer proper contracts to employees whose skills are not known a priori [21]. A contract is essentially a certain reward that will be given to the employee in return for its services. In a D2D context, this contractual situation can be used to study the interactions between BSs, acting as employers and, UEs, acting as devices whose preferences are unknown to the BSs. Here, the contract will represent the rewards provided by the BS to a certain D2D-capable UE who, will provide the required resources and quality-of-service via D2D participation. The main advantages of adopting contract theory in a D2D scenario include: 1) ability to incorporate semi-distributed network control in which the BS can control the D2D communication links; 2) notions such as self-revealing contracts suitable to handle information asymmetry, and 3) ability to devise optimal reward and incentive mechanisms that can induce cooperation between UEs.

The main contribution of this chapter is to leverage the use of contract theory for introducing D2D incentive mechanisms under information asymmetry. In particular, we view the D2D sharing problem, as a contract-theoretic model in which the BS hires the UEs as employees to fulfill the content transmission task. The BS, as an employer, offers contracts to the UEs that specify different performance-reward combinations for different UE preferences. The UEs, as employees, select contracts that are the best fit to their own preferences. Under this scenario, the BS can efficiently reward the users according to their performance, and thus, motivate users to participate in D2D communication.

For the studied D2D contract model, we provide the necessary and sufficient conditions for contract feasibility. Here, contract feasibility implies that when users join in, they receives the reward that covers their cost and in accordance with their true preference. In addition, we study and analyze the problem under two key scenarios: the discrete (finite) type and continuum (infinite) type. To implement the proposed contract-theoretic D2D model, we propose a novel algorithm that can allow the BS and UEs to interact and then optimize the network capacity while guaranteeing a desired network quality-of-service (QoS). Simulation results show that the proposed contract-theoretic model can guarantee UEs receive positive payoffs and compatible incentives. We also study the system performance when the contract-theoretic model is implemented in a D2D underlaid cellular network. The optimal contract gives the highest BS utility and social welfare as shown in the simulations. By varying the cellular network size, maximum D2D communication distance, and UE type numbers, we see the physical layer parameters' impacts on the system performance

The rest of this chapter is organized as follows. Section 2.2 provides a detailed literature survey. The system model is provided in Section 2.3. The optimal contract solution of discrete type case is presented in Section 2.4, followed by the optimal contract solution in continuum type scenario. The simulation results are shown in Section 2.5. Finally, conclusions are drawn in Section 2.6.

2.2 Related Work

D2D communication has been subject to many recent research works such as in [22] and [23]. Due to the shared resources between direct D2D communication and traditional infrastructure-based communication, new resource allocation techniques are needed for D2D deployment [24]. One major challenge in D2D is interference management [17]. The common mechanism is to limit maximum transmit power of D2D transmitter so as not to generate harmful interference from D2D systems to cellular networks [25].

Some interference management strategies are also proposed to enhance the overall capacity of cellular networks and D2D system. For example, the work in [26] introduce the idea of cooperative interference cancellation (CIC) between close-by UEs using D2D communications for improving the throughput of cellular networks in the downlink (DL) period. Another work in [27] formulates the interference between different D2D and cellular communication links as an interference-aware graph, and proposes an interference-aware graph based resource sharing algorithm. Several works study the use of D2D communication as a means to optimize resource usage and maintain an efficient co-existence between the D2D services and main cellular network [28].

Despite the large body of work on interference management and resource allocation in D2D communication, to our knowledge, few existing works have addressed to the problem of providing incentives for users to participate in cellular D2D. Moreover, using contract theory for network-controlled D2D has not been studied in existing works.

Here, we note that contract theory has been used in areas such as mobile cloud computing and cognitive radio. For instance, in [29], the authors study the use of contract theory as a means to optimize the economic revenues of a cloud server in a mobile cloud computing environment. Existing works such as [30, 31], and [10] focus on the efficiency of the resource allocation in cognitive radio networks. The work in [32] introduces the concept of insurance into the model, in which if the primary owner (PO) cannot provide the channel purchased by a secondary user (SU), PO needs to pay a certain amount of indemnity to the SU. In [33], the authors develop a contract-theoretic mechanism to model the possibility of secondary users relaying data for primary users to improve data rates. The work in [34] develops the incentive compatible contracts to encourage users to participate in data acquisition and distributed computing programs.

However, potential interference caused by resource sharing makes it difficult to implement existing contract-theoretic models directly into the D2D underlaid cellular network. In summary, while resource allocation and interference management in D2D communication have been widely studied, no literature has investigated the problem of providing incentives for users to engage in D2D underlaid cellular networks using contract theory as proposed here.

2.3 System Model

Consider a cellular network with one BS, several cellular UEs and D2D UE pairs. In each UE pair, there is one content requester (receiver) and one candidate content provider (transmitter). The UE receivers can receive data from the BS, or from their corresponding UE transmitters through D2D communications. In order to offload traffic from the network's infrastructure, the BS will offer contract that can effectively motivate the content provider to use, when possible, D2D communication to deliver the content.

The UEs are heterogeneous with different preference towards joining D2D communication, in terms of personal favor, battery level, storage capacity. Naturally, there is an information asymmetry between the BS and the UE. The UE is aware of its own preference while the BS may not have that information. Thus, to overcome the information asymmetry, the BS will specify a performance-reward bundle contract $(T(R), R)$, where T is the reward to the UE, R is the D2D performance required from the UE, and $T(R)$ is a strictly increasing function of R. Intuitively, better performance should be rewarded more and vice versa, which is called *incentive compatible*.

2.3.1 Transmission Data Rate

The performance R is measured by the UE's transmission data rate. We consider the uplink (UL) scenario since UL resource sharing in D2D communications only affects the BS, and the incurred interference can be mitigated by BS coordination [35].

The transmission data rate is related to the signal to interference plus noise ratio (SINR). In a cellular network with D2D underlaid, the receiver suffers interference from cellular and D2D communications due to resource sharing. When D2D communication is in the UL band, the source UE transmits data to the destination UEs using the uplink band of the cellular band. The interference comes from the other UEs (both cellular UE and D2D UE) [36]. Thus, the transmision data rate of a D2D UE i in the UL band with co-channel interference is given by

$$R_i = W \log_2 \left(1 + \frac{P_i |h_{ir}|^2}{P_c |h_{cr}|^2 + \sum_{i'} P_{i'} |h_{i'r}|^2 + N_0}\right), \tag{2.1}$$

where i' is the UE with $i' \neq i$, P_c, P_i and $P_{i'}$ are the transmit powers of the cellular transmitter UE c and D2D transmitters UE i and i', respectively, h_{cr}, h_{ir} and $h_{i'r}$ are the channel gain between D2D receiver and cellular transmitter c and D2D transmitters i and i', respectively, N_0 is the additive white Gaussian noise (AWGN), W is the channel bandwidth. Hereinafter, without loss of generality, we assume that $W = 1$. $\sum_{i'} P_{i'} h_{i'r}^2$ represents the interference from the other D2D pairs that share spectrum resources with link UE pair i.

2.3.2 User Equipment Type

We define the UE type to be a representation of each UE's preference towards joining D2D communication. Given a fixed reward, a high type UE will be more eager to contribute in the transmission and provide high data rate. Naturally, high type UEs are more preferred by the BS, and will receive more reward. Here, we consider that the number of UE types belong to discrete, finite space. In Section IV.B, we will extend the results to the continuum case.

Definition 2.1. *There are N D2D UE pairs in a D2D underlaid cellular network. The UEs' preferences are sorted in an ascending order and classified into N types: type-1, . . ., type-i, . . ., type-N.*

The type of UE includes properties such as the privacy concern, battery remain, and the willingness to share data. θ_i denotes the type of UE and follows

$$\theta_1 < \cdots < \theta_i < \cdots < \theta_N, \quad i \in \{1, \cdots, N\}. \tag{2.2}$$

A higher θ implies more willingness to participate and contribute to the D2D communication. Here, we write the contract designed for *type-i* UE as (T_i, R_i). The BS does not know the type of UE, however, it has knowledge of the probability that a UE belongs to *type-i*, which is represented by λ_i, with $\sum_{i=i}^{N} \lambda_i = 1$.

Instead of offering the same contract to all UEs, the BS will offer different contract bundles according UE's type θ. The UEs are free to accept or decline any type of contracts. If the UE declines to receive any contract, we assume that the UE signs a contract of $(T(0), 0)$, where $T(0) = 0$. In the following subsections, we will give the utility function of the BS and UEs based on the signed contract.

2.3.3 Base Station Model

For a BS that employs a *type-i* UE as a D2D content provider, a proper utility function can be defined as the increased data rate by establishing a D2D communication

$$U_{\text{BS}}(i) = R_i - cT_i, \tag{2.3}$$

where $c > 0$ is the BS's unit cost, R_i is the required transmission rate UE must provide, and T_i is the reward the BS needs to pay in the contract bundle (T_i, R_i). Here, we assume that the reward to the UE is a certain amount of free data. The utility of the BS is the transmission data rate gained from D2D communication, minus the reward to UEs. For D2D communication to be beneficial for the BS, it is clear from (2.3) that we must have $R_i - cT_i \geq 0$. Otherwise, the BS will choose not to underlay D2D communication.

As there are N types of UE pairs, each with a probability λ_i, the expected utility of the BS can be represented by

$$U_{\text{BS}} = \sum_{i=1}^{N} \lambda_i \left(R_i - cT_i\right). \tag{2.4}$$

2.3.4 User Equipment Model

The utility function of a *type-i* UE employed based on a contract (T_i, R_i) during D2D communication is

$$U_{\text{UE}}(i) = \theta_i v(T_i) - c' R_i, \tag{2.5}$$

where $v(T_i)$ is the evaluation function regarding the rewards, which is a strictly increasing concave function of T, where $v(0) = 0$, $v'(T) > 0$, and $v''(T) < 0$ for all T, and c' is the UE's unit energy cost on providing the required transmission rate. For simplicity, we assume $c' = 1$. The utility of a UE is the received rewards minus the cost in terms of power consumption. Given the utility function in (2.5), the UE chooses the bundle that maximizes its own payoff.

2.3.5 Social Welfare

The network social welfare is the summation of the BS and UEs' utilities. As the number of D2D UE transmitters and number of UE types are all equal to N, the number of UE belongs to each type is 1. Assume that the distribution of the UE type is uniform, then summing up (2.3) and (2.5) from 1 to N, we have

$$\Pi = \sum_{i=1}^{N} [U_{\text{BS}}(i) + U_{\text{UE}}(i)] = \sum_{i=1}^{N} [\theta_i v(T_i) - cT_i]. \tag{2.6}$$

The transmission data rate is the internal transfer between the BS and UE and is canceled out.

2.4 Proposed Solution

In this section, we solve the BS's network capacity maximization problem. First, we will derive necessary constraints that support the feasibility of the contract. Then, we will formulate the optimization problem, and extend to the continuum type case. Finally, we propose an algorithm for practical implementation.

2.4.1 Conditions for Contract Feasibility

To ensure that the UE has an incentive to offload BS traffic via D2D communication, the contract that a UE selects needs to satisfy the following constraint.

Definition 2.2. *Individual Rationality (IR): The contract that a UE selects should guarantee that $U_{UE}(i)$ is nonnegative,*

$$U_{UE}(i) = \theta_i v(T_i) - R_i \geq 0, \quad i \in \{1, \cdots, N\}. \tag{2.7}$$

To motivate a UE's participation, the received reward must compensate its power consumption during D2D communication. If $U_{\text{UE}}(i) < 0$, the UE will choose not to establish the D2D communication. This case can be formally captured by the case in which the UE signs the contract of $(T(0), 0)$.

If a *type-i* UE selects the contract (T_j, R_j) intended for *type-j* UE, the utility that the *type-i* UE receives is

$$U'_{\text{UE}}(i) = \theta_i v(T_j) - R_j, \quad i, j \in \{1, \cdots, N\}, \quad i \neq j. \tag{2.8}$$

As we previously discussed, we want to design a contract such that *type-i* UE would prefer the (T_i, R_i) contract over all the other options. In other words, a *type-i* UE receives the maximum utility when selecting contract (T_i, R_i). The contract is thus known to be as a *self-revealing contract* if and only if the following constraint is satisfied.

Definition 2.3. *Incentive Compatible (IC): UEs must prefer the contract designed specifically for their own types, i.e.,*

$$\theta_i v(T_i) - R_i \geq \theta_i v(T_j) - R_j, \quad i, j \in \{1, \cdots, N\}, \quad i \neq j. \tag{2.9}$$

The IR and IC constraints are the basic conditions needed to ensure the incentive compatibility of a contract. Beyond the IR and IC constraints, there are several more conditions that must be satisfied.

Lemma 2.4. *For any feasible contract (T,R), $T_i > T_j$ if and only if $\theta_i > \theta_j$, and $T_i = T_j$ if and only if $\theta_i = \theta_j$.*

Proof. We prove this lemma by using the IC constraint in (2.9). First, we prove the sufficiency: If $\theta_i > \theta_j$, then $T_i > T_j$.

According to the IC constraint, we have

$$\theta_i v(T_i) - R_i \geq \theta_i v(T_j) - R_j \quad \text{and} \tag{2.10}$$

$$\theta_j v(T_j) - R_j \geq \theta_j v(T_i) - R_i, \tag{2.11}$$

with $i, j \in \{1, \cdots, N\}, \quad i \neq j$. We add the two inequalities together to get

$$\theta_i v(T_i) + \theta_j v(T_j) \geq \theta_i v(T_j) + \theta_j v(T_i), \tag{2.12}$$

$$\theta_i v(T_i) - \theta_j v(T_i) \geq \theta_i v(T_j) - \theta_j v(T_j),$$

$$v(T_i)(\theta_i - \theta_j) \geq v(T_j)(\theta_i - \theta_j).$$

As $\theta_i > \theta_j$, we must have $\theta_i - \theta_j > 0$. Divide both sides of the inequality, we have $v(T_i) > v(T_j)$. From the definition of $v(T)$, we know that v is a strictly increasing function of T. As $v(T_i) > v(T_j)$ holds, we must have $T_i > T_j$.

Next, we prove the necessity: if $T_i > T_j$, then $\theta_i > \theta_j$. Similar to the first case, we start with the IC constraint in (2.10) - (2.12). Using a similar process we can obtain

$$\theta_i[v(T_i) - v(T_j)] \geq \theta_j[v(T_i) - v(T_j)]. \tag{2.13}$$

As $T_i > T_j > 0$ and $v(T)$ is strictly increasing with T, we must have $v(T_i) > v(T_j)$ and $v(T_i) - v(T_j) > 0$. Thus, by dividing both sides of the inequality, we get $\theta_i > \theta_j$. As a result, we have proved that $\theta_i > \theta_j$ if and only if $T_i > T_j$.

Using the same process we can easily prove that $T_i = T_j$ if and only if $\theta_i = \theta_j$. □

From Lemma 2.4, we know that if $\theta_j < \theta_i$, then $T_j < T_i$ must hold. Thus, a UE of high type should receive more reward than a UE of low type. If two UEs receive the same reward, they must belong to the same type and vice versa. Given our assumption in Definition 2.1 that $\theta_1 < \cdots < \theta_i < \cdots < \theta_N$, we have $T_1 < \cdots < T_i < \cdots < T_N$. Indeed, we can give a definition of this property.

Definition 2.5. *Monotonicity: For any feasible contract* (T, R)*, the reward* T *follows*

$$0 \leq T_1 < \cdots < T_i < \cdots < T_N. \tag{2.14}$$

Monotonicity implies that the UEs of higher type, i.e. with higher preference towards participation. With the property in monotonicity, we can have the following proposition.

Proposition 2.6. *As a strictly increasing function of* T*, the contribution* R *satisfies the following condition intuitively*

$$0 \leq R_1 < \cdots < R_i < \cdots < R_N. \tag{2.15}$$

Proposition 2.6 shows that an incentive compatible contract requires a high performance of UE if it receives a high reward and vice versa.

Lemma 2.7. *For any feasible contract* (T, R)*, the utility of each type of users must satisfy*

$$0 \leq U_{UE}(1) < \cdots < U_{UE}(i) < \cdots < U_{UE}(N). \tag{2.16}$$

Proof. From Definition 2.5 and Proposition 2.6 we know that UEs who ask for more rewards must be able to provide larger transmitting rates, i.e., the two constraints $T_i > T_j$ and $R_i > R_j$ are imposed together. If $\theta_i > \theta_j$, we have

$$\begin{aligned} U_{\mathrm{UE}}(i) = \theta_i v(T_i) - R_i &\geq \theta_i v(T_j) - R_j \quad (IC) \\ &> \theta_j v(T_j) - R_j = U_{\mathrm{UE}}(j). \end{aligned} \tag{2.17}$$

Now we have $U_{\mathrm{UE}}(i) > U_{\mathrm{UE}}(j)$ when $\theta_i > \theta_j$. As $\theta_1 < \cdots < \theta_i < \cdots < \theta_N$, then $0 \leq U_{\mathrm{UE}}(1) < \cdots < U_{\mathrm{UE}}(i) < \cdots < U_{\mathrm{UE}}(N)$. □

Thus, higher type UEs receive more utility than the UEs whose types are lower. From the IC constraint and the two lemmas that we proved, we can easily deduce the following. If a high type UE selects the contract designed for a low type UE, even though a smaller transmission data rate is required from the BS, the less reward received will deteriorate UE's utility. Moreover, if a lower type UE selects a contract intended for a high type UE, the gain in terms of rewards cannot compensate the cost in power consumption for the high transmission data rate, and thus the cost surpasses the gain. The UE can receive the maximum utility if and only if it selects the contract that best fit into its preference. Thus, we can guarantee that the contract is self reveal.

2.4.2 Optimal Contract

Given the contract feasibility constraints, we will formulate the system optimization problem in both discrete type case and continuum type case in this subsection .

2.4.2.1 Case of Discrete Type

Under the information asymmetry, the only information available at the BS is the probability λ_i with which a certain UE might belong to type θ_i. Our main focus is to maximize the utility of the BS, which represents the increased data rate when D2D communication is underlaid. Therefore, the problem can be posed as the following maximization

$$\max_{(T,R)} \sum_{i=1}^{N} \lambda_i \left(R_i - cT_i \right), \tag{2.18}$$

$$\begin{aligned} s.t.& \\ &(a)\quad \theta_i v(T_i) - R_i \geq 0, \\ &(b)\quad \theta_i v(T_i) - R_i \geq \theta_i v(T_j) - R_j, \\ &(c)\quad 0 \leq T_1 < \cdots < T_i < \cdots < T_N, \\ &\quad i, j \in \{1, \cdots, N\}, \quad i \neq j. \end{aligned}$$

(a) and (b) represent the IR and IC constraints, respectively, and (c), represents the monotonicity condition. This problem is not a convex optimization problem, however, we can perform the following steps to find a solution:

Step 1: Reduce IR constraints. From (2.18), we can see that in total there are N IR constraints be satisfied. However, from Definition 2.1 we know that $\theta_1 < \cdots < \theta_i < \cdots < \theta_N$. By using IC constraints, we have,

$$\theta_i v(T_i) - R_i \geq \theta_i v(T_1) - R_1 \geq \theta_1 v(T_1) - R_1 \geq 0. \tag{2.19}$$

Thus, if the IR constraint of *type-1* user is satisfied, the other IR constraints will automatically hold. Therefore, we only need to keep the first IR constraints and reduce the others.

Step 2: Reduce IC constraints. The IC constraints between *type-i* and *type-j*, $j \in \{1, \cdots, i-1\}$ are called downward incentive constraints (DICs). Especially, the IC constraint between *type-i* and *type-(i-1)* is called local downward incentive constraints (LDICs). Similarly, the IC constraints between *type-i* and *type-j*, $j \in \{i+1, \cdots, N\}$ are called upward incentive constraints (UICs), and the IC constraint between *type-i* and *type-(i+1)* is called local upward incentive constraints (LUICs). First, we prove that DICs can be reduced.

Proof. As the number of users is N in our model, there exist $N(N-1)$ IC constraints in total. Here, we consider three types of users which follows $\theta_{i-1} < \theta_i < \theta_{i+1}$. Then, we have the following two LDICs

$$\theta_{i+1} v(T_{i+1}) - R_{i+1} \geq \theta_{i+1} v(T_i) - R_i \quad \text{and} \tag{2.20}$$

$$\theta_i v(T_i) - R_i \geq \theta_i v(T_{i-1}) - R_{i-1}. \tag{2.21}$$

In Lemma 2.4 we have shown that $T_i \geq T_j$ whenever $\theta_i \geq \theta_j > 0$, the second inequality becomes

$$\theta_{i+1}[v(T_i) - v(T_{i-1})] \geq \theta_i[v(T_i) - v(T_{i-1})] \geq R_i - R_{i-1} \quad \text{and} \tag{2.22}$$

$$\theta_{i+1} v(T_{i+1}) - R_{i+1} \geq \theta_{i+1} v(T_i) - R_i \geq \theta_{i+1} v(T_{i-1}) - R_{i-1}. \tag{2.23}$$

Thus, we have

$$\theta_{i+1} v(T_{i+1}) - R_{i+1} \geq \theta_{i+1} v(T_{i-1}) - R_{i-1}. \tag{2.24}$$

Therefore, if for *type-i* UE the LDIC holds, the incentive constraint with respect to *type-(i-1)* UE holds. This process can be extended downward from *type* $i-1$ to 1 UEs prove that all the DICs hold,

$$
\begin{aligned}
\theta_{i+1}v(T_{i+1}) - R_{i+1} &\geq \theta_{i+1}v(T_{i-1}) - R_{i-1} \\
&\geq \cdots \\
&\geq \theta_{i+1}v(T_1) - R_1, \\
&\; N > i \geq 1.
\end{aligned} \tag{2.25}
$$

Thus, we have complete the proof that with the LDIC constraint, all the DICs hold, that is

$$\theta_i v(T_i) - R_i \geq \theta_i v(T_j) - R_j, \quad N \geq i > j \geq 1. \tag{2.26}$$

□

Second, we prove all the UICs can be reduced.

Proof. From the IC constraint we have the following two LUICs

$$\theta_{i-1}v(T_{i-1}) - R_{i-1} \geq \theta_{i-1}v(T_i) - R_i \quad \text{and} \tag{2.27}$$

$$\theta_i v(T_i) - R_i \geq \theta_i v(T_{i+1}) - R_{i+1}. \tag{2.28}$$

In Lemma 2.4 we have shown that $T_i \geq T_j$ whenever $\theta_i \geq \theta_j > 0$, the second inequality can be derived as

$$R_{i+1} - R_i \geq \theta_i(v(T_{i+1}) - v(T_i)) \geq \theta_{i-1}(v(T_{i+1}) - v(T_i)) \quad \text{and} \tag{2.29}$$

$$\theta_{i-1}v(T_{i-1}) - R_{i-1} \geq \theta_{i-1}v(T_i) - R_i \geq \theta_{i-1}v(T_{i+1}) - R_{i+1}. \tag{2.30}$$

Thus, we have

$$\theta_{i-1}v(T_{i-1}) - R_{i-1} \geq \theta_{i-1}v(T_{i+1}) - R_{i+1}. \tag{2.31}$$

Therefore, if for $type-(i-1)$ UE, the incentive constraint with respect to $type-i$ UE holds, then all UICs are also satisfied. This process can be extended upward from $type\ i+1$ to N UEs prove that all the UICs hold,

$$
\begin{aligned}
\theta_{i-1}v(T_{i-1}) - R_{i-1} &\geq \theta_{i-1}v(T_{i+1}) - R_{i+1} \\
&\geq \cdots \\
&\geq \theta_{i-1}v(T_N) - R_N, \\
&\; N \geq i > 1.
\end{aligned} \tag{2.32}
$$

Thus, we have complete the proof that with the LUIC constraint, all the UICs hold, that is

$$\theta_i v(T_i) - R_i \geq \theta_i v(T_j) - R_j, \quad 1 \leq i < j \leq N. \tag{2.33}$$

Indeed, with the monotonicity condition $T_{i-1} < T_i$, the LDIC:

$$\theta_i v(T_i) - R_i \geq \theta_i v(T_{i-1}) - R_{i-1}, \tag{2.34}$$

can easily imply that the LUIC

$$\theta_{i-1} v(T_i) - R_i \leq \theta_{i-1} v(T_{i-1}) - R_{i-1}, \tag{2.35}$$

can be satisfied, and thus, can be reduced. Thus, we have proved that, with the LDIC, all the UICs are reduced. □

Step 3: Solve the optimization problem with reduced constraints. Thus, we can reduce the set of UICs and DICs, and only the set of LDICs and monotonicity condition are binding. Therefore, the optimization problem reduces to

$$\max_{(T,R)} \sum_{i=1}^{N} \lambda_i \left(R_i - cT_i\right), \tag{2.36}$$

$$\begin{aligned}
&s.t. \\
&\quad (a)\ \ \theta_1 v(T_1) - R_1 = 0, \\
&\quad (b)\ \ \theta_i v(T_i) - R_i = \theta_i v(T_{i-1}) - R_{i-1}, \\
&\quad (c)\ \ 0 \leq T_1 < \cdots < T_i < \cdots < T_N, \\
&\qquad i \in \{1, \cdots, N\}.
\end{aligned}$$

To solve this problem, we can first formulate and solve the relaxed problem without the monotonicity condition and then consider the standard procedure of the Lagrangian multiplier. Then we check whether the solution to this relaxed problem satisfies the monotonicity condition or not [21].

The optimal contract solved by this optimization problem will give zros utility for the lowest type of UEs. If $N = 2$, there are only two types of UEs, the high type and the low type. By solving this optimization problem, the low type UEs will obtain a zero utility contract, and the high type

UEs can receive a positive utility. In the general cases when $N > 2$, a similar conclusion is also provided in [21], [30], and [33], all type of UEs will get a positive utility except the lowest type UE who will get a zero utility.

2.4.2.2 Case of Continuum Type

In the previous case, there are N type of UEs from θ_1 to θ_N. In practice, the number of UEs types can be infinite. In this subsection, we will give an analysis about the continuum type case with type θ which has the probability density function (PDF) $f(\theta)$ (with cumulative distribution function (CDF) $F(\theta)$ on the interval $[\underline{\theta}, \overline{\theta}]$. The contract that a BS offers to the UE is written as $[T(\theta), R(\theta)]$. T is monotonically increasing in R as in the discrete case. If no trading happens between the BS and the UE, the contract is set as $T(\theta) = 0$ and $R(\theta) = 0$. Similar to the discrete type case, we can write the BS's optimization problem as follows.

$$\max_{\{T(\theta),R(\theta)\}} \int_{\underline{\theta}}^{\overline{\theta}} [R(\theta) - cT(\theta)]\, f(\theta) d\theta, \tag{2.37}$$

$$s.t.$$

$$(a) \quad \theta v[T(\theta)] - R(\theta) \geq 0,$$

$$(b) \quad \theta v[T(\theta)] - R(\theta) \geq \theta v[T(\widehat{\theta})] - R(\widehat{\theta}),$$

$$\theta, \widehat{\theta} \in [\underline{\theta}, \overline{\theta}].$$

Condition (a) is the IR constraints and (b) represents the IC constrains. To solve this continuum type case problem, we follow a similar process as the discrete type case and begin by reducing the IR and IC constraints.

Step 1: Reduce IR Constraints. We first reduce the number of IR constraints as done in the discrete case. Since the IC constraints hold, we have

$$\begin{aligned} \theta v[T(\theta)] - R(\theta) &\geq \theta v[T(\underline{\theta})] - R(\underline{\theta}) \\ &\geq \underline{\theta} v[T(\underline{\theta})] - R(\underline{\theta}). \end{aligned} \tag{2.38}$$

Thus, if the IR constraint of $\underline{\theta}$ is satisfied, the IR constraints for all the other values of θ will automatically hold. Therefore, replace the IR constraints by

$$\underline{\theta}v[T(\underline{\theta})] - R(\underline{\theta}) \geq 0. \tag{2.39}$$

Step 2: Reduce IC constraints. To reduce the IC constrains, we give Lemma 2.8 that using two other constrains to replace all IC constrains [21].

Lemma 2.8. *The IC constrain is equivalent to the following two conditions:*

1. *Monotonicity*

$$\frac{dT(\theta)}{d\theta} \geq 0. \tag{2.40}$$

2. *Local incentive compatibility*

$$\theta v'[T(\theta)]\frac{dT(\theta)}{d\theta} = R'(\theta), \theta \in [\underline{\theta}, \overline{\theta}]. \tag{2.41}$$

Proof. The monotonicity can be easily derived following the steps in Lemma 2.4 and Definition 2.5. The local incentive compatibility can be proved by contradiction. Suppose we have the monotonicity and local incentive compatibility, and the IC constraint cannot be hold. Then, with at least one $\widehat{\theta}$ violates the IC constraint

$$0 \leq \theta v[T(\theta)] - R(\theta) < \theta v[T(\widehat{\theta})] - R(\widehat{\theta}). \tag{2.42}$$

Integrating it from θ to $\widehat{\theta}$ we get

$$\int_{\theta}^{\widehat{\theta}} \left[\theta v'[T(x)]\frac{dT(x)}{dx} - R'(x)\right] dx > 0. \tag{2.43}$$

From the local incentive compatibility, we know $\int_{\theta}^{\widehat{\theta}} \left[xv'[T(x)]\frac{dT(x)}{dx} - R'(x)\right] dx = 0$. If $\theta < x < \widehat{\theta}$, from the monotonicity we have $\theta\frac{dv(T(x))}{dx} \leq x\frac{dv(T(x))}{dx}$. Therefore,

$$\int_{\theta}^{\widehat{\theta}} \left[\theta v'[T(x)]\frac{dT(x)}{dx} - R'(x)\right] dx < 0. \tag{2.44}$$

Thus, we see a contradiction. Similarly, if $\theta > \widehat{\theta}$, we can also get a contradiction. Thus, the two conditions: monotonicity and local incentive compatibility can guarantee the UE's incentive compatible constrains. $\square$

Step 3: Optimization problem with reduced constraints. Finally, the BS's optimization problem can be written as

$$\max_{(T(\theta),R(\theta))} \int_{\underline{\theta}}^{\overline{\theta}} \left[R(\theta) - cT(\theta)\right] f(\theta) d\theta, \tag{2.45}$$

$$\begin{aligned} s.t.& \\ &(a) \quad \underline{\theta} v[T(\underline{\theta})] - R(\underline{\theta}) \geq 0, \\ &(b) \quad \theta v'[T(\theta)] \frac{dT(\theta)}{d\theta} = R'(\theta), \\ &(c) \quad \frac{dT(\theta)}{d\theta} \geq 0, \\ &\qquad \theta \in [\underline{\theta}, \overline{\theta}]. \end{aligned}$$

Similar to the discrete type case problem, constraints (a) and (b) represent the IR and IC constraints, and constraint (c) is the monotonicity condition. The procedure for solving this problem is also similar to the discrete type case problem. First ignore the monotonicity condition and solve the relaxed problem with constraints (a) and (b). Then, check whether the solution to this relaxed problem satisfies the monotonicity condition or not.

2.4.3 Practical Implementation

By solving the proposed problem, we could provide UEs with the optimal contract that can incentivize them to participate in D2D communication. To implement the proposed approach in a practical D2D network, we can follow the next steps. From the system model, we have the initial information such as the cellular network radius S, the cellular users' transmit power P_c, the number of UE types N, and the probability λ_i that UE belongs to θ_i. With those initial values, the BS can obtain the optimal contract (T, R). Once there are UEs requesting contents, the BS acts in the following stages.

In the first stage, when the BS receives UEs' requests for contents, the BS will detect if the contents are locally accessible in other UEs within the maximum D2D communication distance L. If the content is locally available, then, the BS will broadcast the optimal contracts to the candidate content providers. By evaluating the contracts, UEs will send feedback signals to indicate whether they are willing to participate in according the estimated utility. After getting the feedback from UEs, the BS will sign the contract with the UE that accepts it. If all UEs reject the contract, the BS will serve the content requester directly, which is the same procedure as if the content is not locally accessible.

After signing the contract, the employed UE will set up the D2D communication and forward the content to the content requester. The BS will stand by to watch the communication by sending control signals, and also receiving feedback signals from UEs. If the transmission is successful, the BS reward the involved UEs based on their contract. Otherwise, if the transmission failed, the BS serve the user directly and the "employed" UE will not receive the reward. The proposed D2D communication algorithm is summarized in Algorithm 1. This algorithm gives the practical implementation steps of the theoretical model.

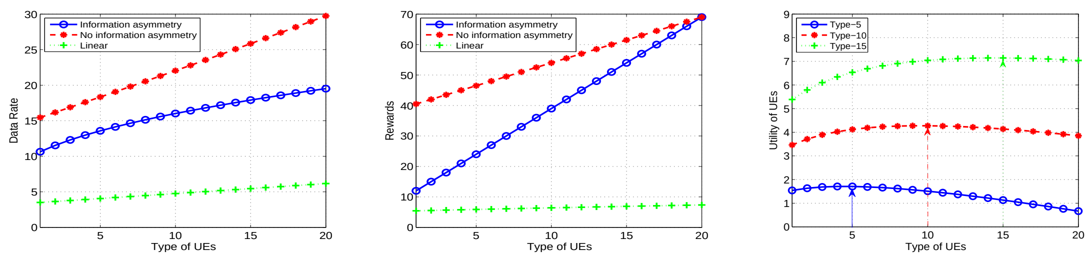
2.5 Simulation Results and Analysis

In this part, we will first evaluate the feasibility of the proposed contract, then analyze the system performance when D2D communication is underlaid in the cellular network.

First of all, we donate the optimal contract solved in the previous section by *information asymmetry*. For comparison purposes, we introduce another two incentive mechanisms. The first one is the optimal contract under *no information asymmetry* (i.e., the BS is aware of the types of UEs), which is the optimal outcome that we can achieve and serves as the upper bound. The second contract is the *linear pricing* which is also under the information asymmetry that the BS has no acknowledgement of the UE type. In this *linear pricing* mechanism, the BS will only specify a unit

Table 2.1: Physical Layer Parameters

Parameter	Value
Cellular Area Radius	500 m
Maximum D2D Distance	30 m
number of UE Types	20
Noise Spectral Density	-174 dBm/Hz
Noise Figure	9 dB at device
Antenna Gains	BS: 14 dBi; Device: 0 dBi
Transmit Power	BS: 46 dBm; Device: 23 dBm



(a) Data Rate (b) Rewards (c) Utility of UE

Figure 2.3: Contract monotonicity and incentive compatibility.

price P for data rate, and the UEs will request the amount of reward T which corresponding to a certain amount of data rate, to maximize their own utilities.

We assume $N = 20$ and give the simulation with 20 types of UEs. For simplicity, we consider a uniform distribution of UE type, i.e., $\lambda_i = 1/N$. We set the unit payment cost of the BS $c = 0.01$. The main parameters of the D2D underlaid cellular network are shown in Table 2.1.

2.5.1 Contract Feasibility

2.5.1.1 Monotonicity

In Fig. 2.3a and 2.3b, we compare required transmission data rate and reward of different type UEs to show the monotonicity of the contract.

In Fig. 2.3a, we see that required transmission data rate increases with the UE type, which is consistent with our system model. The difference among the three mechanisms is that the required data rate under *no information asymmetry* and *linear pricing* are linear function of type, and is a concave function of type under *information asymmetry*. Among the three mechanisms, the *no information asymmetry* contract requires the highest data rate from the UE, followed by the optimal contract under *information asymmetry*. The lowest data rate is required under the *linear pricing* contract. Similarly, the reward shown in Fig. 2.3b also proves our assumption that reward T is a strictly increasing function of UE type.

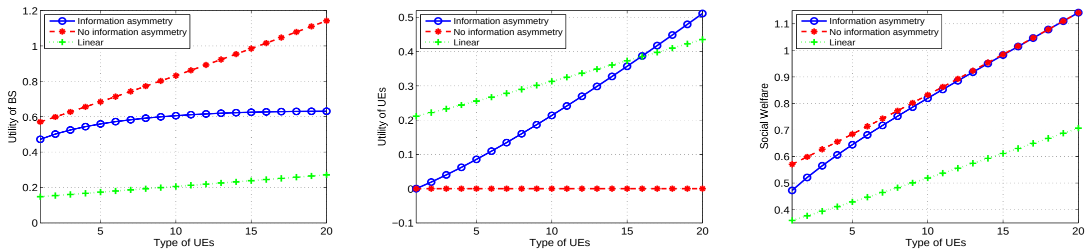
2.5.1.2 Incentive Compatibility

In Fig. 2.3c, we evaluate the incentive compatibility of our proposed contract, the optimal scheme. We show the utilities of *type-5*, *type-10*, and *type-15* UEs when selecting all the contracts offered by the BS. The utility of each user is a concave function. Each UE can achieve their maximum utility if and only if it selects the type of contract that is intended its own type, as shown clearly in Fig. 2.3c. Thus, by designing a contract in this form, the type of an UE will be automatically revealed to the BS after its selection. In other words, the optimal contract under *information asymmetry* enables the BS break the information asymmetry and retrieve the information related to UE type.

Moreover, Fig. 2.3c shows that when the three types of users select the same contracts, their utilities follows the inequality $u_5 < u_{10} < u_{15}$. This corroborates the result shown by the (2.16) in Lemma 2.7: the higher the type of the UE, the larger the utility it can receive when selecting the same contract.

2.5.2 System Performance

To evaluate the performance of the D2D underlaid cellular network, we try to see the impacts of different parameters on the utility of BS, UE, and social welfare.



(a) Utility of BS (b) Utility of UE (c) Social Welfare

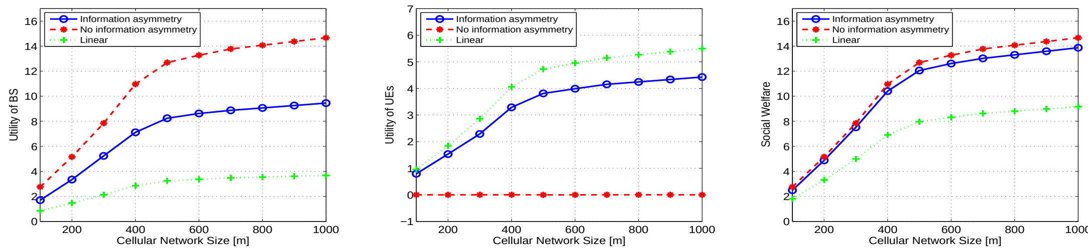
Figure 2.4: System performance of different type UEs.

2.5.2.1 The UE Type

First we take a close look at the three values of different type UEs in Fig. 2.4. The three figures show the monotonicity of the contract that the higher the UE type, the larger utility it will bring to the BS and UE, as well as the social welfare.

Fig. 2.4a shows that the BS achieves the highest utility when there is no information asymmetry, since the BS has full knowledge of UE types. Nonetheless, we can see that the proposed solution with information asymmetry yields an utility for the BS that outperforms the linear pricing case. Here, we note that, even though the optimal contract under *information asymmetry* can force the UEs to reveal their types, the exact value of the UE type is still unavailable to the BS. Thus, the BS can only achieve a near optimal utility under *information asymmetry*, which is always upper bounded by the *no information asymmetry* case. The *linear pricing* mechanism does not place any restriction on the UEs choice of contract and less information is retrieved, which prevents the BS from obtaining more utility.

In Fig. 2.4b, we compare 20 types UEs' utilities. This results proved the monotonicity of the contract that the higher the type of UE, the larger the utility it can receive under *information asymmetry*. All the type of UEs enjoy a positive utility except the lowest type (i.e., *type-1*) UE, which consistents with our conclusion in Section IV.B. However, the UE's utility remains 0 disregarding the type of UE under *no information asymmetry*. This is due to fact that when the BS is available of the UE's type, it will adjust the contract to maximize its own utility while leave the UE a 0 utility. Overall, we see that *linear pricing* gives the UEs the highest utility, followed by the optimal con-



(a) Utility of BS. (b) Utility of UEs. (c) Social Welfare

Figure 2.5: The system performance when the size of cellular network varies.

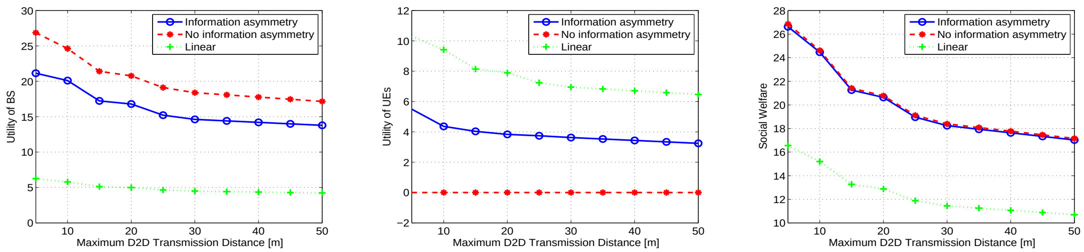
tract under *information asymmetry*, then the ideal case with *no information asymmetry*. However, for some of the high type UEs can obtain higher utility from the optimal contract under *information asymmetry* than the *linear pricing*.

In Fig. 2.4c we see that the social welfare shows similar performance with that of the BS. One interesting point is that, the social welfare of the highest type UE has the same value under *no information asymmetry* and *information asymmetry*. This is in accordance with the conclusion we made in Section IV.B that the highest type UE will result in an efficient trading as if there is no information asymmetry. For other high type UEs under *no information asymmetry*, they also have close optimal efficient trading with the BS. The *linear pricing* mechanism gives the lowest social welfare (i.e., trading efficiency) since no in formation retrieving strategy has been apply.

2.5.2.2 The Cellular Network Size

In a small-sized network, cellular communication will generate severe interference on D2D communication, which will decrease the transmission data rate of UEs. The interference will decrease as the size of network increases. In Fig. 2.5, we show the impact of network size on the system's performance.

In Fig. 2.5a and Fig. 2.5b, we show the utility of the BS and UEs when the cellular network size varies, when the transmission power and antenna gain of the BS are fixed. As the size of cellular decreases, D2D UE pairs and cellular UEs are located in a more dense area, and suffering from a larger interference from other cellular and D2D UEs. Thus, the transmission data rate decreases, as



(a) Utility of BS. (b) Utility of UEs. (c) Social Welfare

Figure 2.6: The system performance when the maximum D2D communication distance varies.

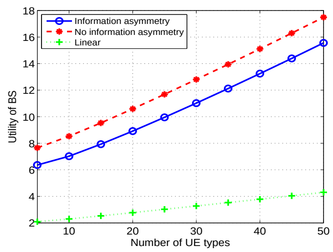
well as the rewards. As a result, the utilities of the BS and UE also decrease.

From Fig. 2.5a we see that, the utility of BS achieves the maximum utility under *no information asymmetry*. Followed by the optimal contract under *information asymmetry*. The *linear pricing* gives the worst utility to the BS compares to the other two. The utility of the UE has one similar property as Fig. 2.4b, that the UE utility under *no information asymmetry* remains 0. The UE achieves the maximum utility by the *linear pricing*, followed by the optimal contract under *information asymmetry*. The UEs benefit from the information asymmetry, while the BS can increase its utility by removing the information asymmetry.

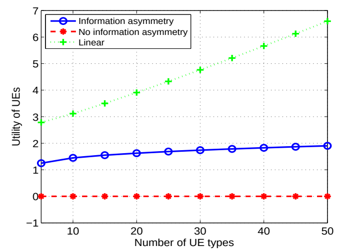
From Fig. 2.5c, we can also see the differences in the social welfare under the three different contracts. Social welfare under *no information asymmetry* achieves the highest among the other two. As the BS is informed of the UE type, the transaction achieves the highest efficiency. Then, followed by the optimal contract achieved under *information asymmetry*. The *linear pricing* presents the worst efficiency. The optimal contract achieved under *information asymmetry* achieves a near optimal social welfare, as it breaks the information asymmetry when the UEs select contracts, their types are revealed to the BS automatically. The *linear pricing* does not account for any type of information and, thus, has the lowest social welfare.

2.5.2.3 The Maximum D2D Communication Distance

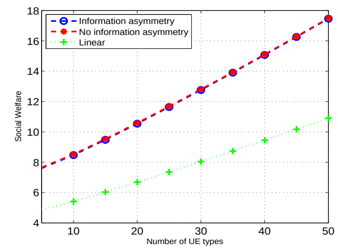
When the size of cellular network and the BS transmission power are fixed, the interference from cellular communication will be in a certain range. Under this condition, we change the maxi-



(a) Utility of BS.



(b) Utility of UEs.



(c) Social Welfare

Figure 2.7: The system performance when the number of UE types varies.

mum transmission distance of D2D pairs, to see the effects on system performance, in Fig. 2.6.

For the utility of the BS and UEs, they still exhibit similar properties as in Fig. 2.5a and Fig. 2.5b. The utility that the BS receives is maximized under *no information asymmetry*, followed by *information asymmetry* and *linear pricing*. The UE achieves the maximum utility under *linear pricing*, and followed by *information asymmetry* and *no information asymmetry* which equals to 0 all the time. The highest social welfare is achieved under *no information asymmetry*, *information asymmetry* is the second, *linear pricing* results in the worst social welfare.

2.5.2.4 The Number of UE Types

In Fig. 2.7, we study the system performance when the number of UE types increases, while the other parameters are fixed. An increase in the number of types will automatically yield an increase in the total number of UEs pairs. Thus, the utilities of the BS and UE, and the social welfare will also increase.

Similar to the conclusions drawn from the Fig. 2.5 and 2.6, the BS has the highest utility under *no information asymmetry*. The optimal contract under *information asymmetry* gives the second highest BS utility. The *linear pricing* still gives the worst utility to the BS. The *linear pricing* gives the highest UE utility, the optimal contract under *information asymmetry* gives the second highest one, and the *no information asymmetry* remains 0. The case under *no information asymmetry* achieves the highest social welfare among all schemes. The optimal contract under *information asymmetry* yields the second highest social welfare. The *linear pricing* still achieves the lowest efficiency in social welfare.

2.6 Conclusions

In this chapter, we have proposed a contract-theoretic model for addressing the problem of incentivizing UEs to participate in D2D communication underlaid over a cellular system. Under the case with information asymmetry in which the UEs' preferences are not available at the BS, we have proposed a self-revealing mechanism based on the framework of contract theory. We have considered the type of UEs under two different scenarios, the discrete type case and continuum type case. Simulation results have shown that our proposed approach can potentially incentivize UEs to participating in D2D communication. Further more, the optimal contract under *information asymmetry* has been proved to obtain the performance close to the ideal case with *no information asymmetry*, and higher than the *linear pricing* when not trying to retrieve any information at all.

Chapter 3

Multi-Dimensional Incentive Mechanism in Mobile Crowdsourcing with Moral Hazard

3.1 Introduction

Nowadays, people are used to accessing various sophisticated location based services (e.g., Yelp and Google Map) by their smartphones via/through wireless access networks [37]. Most location based services are essentially based on crowdsourcing which is a technology that requires user to regularly transmit data to the for the service provider which is denoted as principal here after. The data is obtained by the embedded sensor such as GPS, accelerometer, digital compass, gyoscope, and camera, or users themselves [2]. Once the data is aggregated and processed by the principal, the location-based service is provided to the users for free or with purchase. The brief illustration of crowdsourcing is shown in Fig. 4.1. One well-known application is the live auto traffic map offered by Google. Smartphone users transmit the traffic information which includes the time, location, and velocity to Google. Google collects and processes the data to provide free live traffic map to mobile users [38].

With the drastic growth in the global location based service market, and the rapid development of big data technology, more data as well as user participation are required to support more sophisticated services [39]. Although the users receive the satisfaction from enjoying the location based service, there are many concerns that stop users from providing location based data for the principal. When participating in a crowdsourcing activity, users contribute their effort, time, knowledge and/or experience, and consume the battery power and computing capacity of their smartphones. In addition, the users expose their locations with potential privacy threats [6]. Hence, many users hesitate to participate in with those concerns, which becomes one of the serious impediments to the development of location based services [40]. Thus, necessary incentive mechanisms that motivate the users to participate in crowdsourcing are needed to address those critical demands.

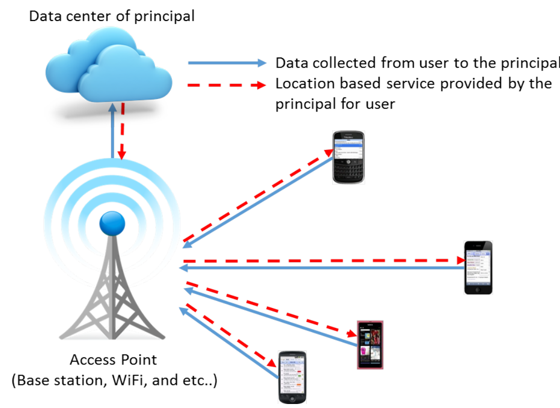


Figure 3.1: An illustration of crowdsourcing.

Many researches have already noticed that there is an urgent need to alleviate these challenges by providing incentive mechanisms to the users. The design proposed in [5] is to give users a one-time reward after users have accomplished a certain task. A problem with this mechanism is its inability to provide continuous incentives to users to stay active after receiving the opening reward [4]. Inspired by the effort-based reward from the labor market, several works studied this problem by providing users with the amount of reward that is consistent with their performances. The work in [6] and [11] have derived the performance and reward dependent function for users that induces the maximum profit for the principal. In one of our previous works [41], we have also proposed a contract that includes user's current performance related reward and user's satisfaction from enjoying the free service in the reward package.

The works above capture the fundamental aspect of providing necessary incentive for user to participate in the crowdsourcing activity. However, beyond these insights, the simplified one-dimensional models are too abstract to capture the main features of the user's contributions, since users are supposed to work on several different tasks [42]. For example, a user's contribution to Yelp involves many dimensions and cannot adequately be reduced to a simple problem of effort choices. Users do not only make location based check-ins, upload photos, and write reviews for the restaurants and bars. But, they are also encouraged to invite new friends to sign up, and to give feedbacks and suggestions to Yelp for the website to determine the future overall strategy. Generally speaking, in the real world crowdsourcing, the user's action set is considerably richer than in the previous literatures have described, and the variables in the contract can be conditioned on are much more difficult to specify or to observe precisely.

The complexity of real world scenarios makes one dimensional incentive mechanisms hard to adapt; in addition, other considerations also arise if we only reward users based on one aspect of the performance [43]. Still taking Yelp for example, suppose we introduce a mechanism that links user's reward to the number of his/her reviews, the advantage of this mechanism is that it provides an independent measure of the user's performance. But there is also an disadvantage that it measures only a part of what users are encouraged to contribute to the website. To put it in another way, if the crowdsourcing is a single-task problem, in which the only thing user needs to do is writing reviews, the quality of a review such as length, correctness, and objectiveness is not considered. If the crowdsourcing is a multi-task problem such as Yelp, the other tasks such as checking-ins, uploading photos, and inviting friends will be ignored. In a nutshell, there is a definite risk that this policy will induce users to overwhelmingly focus on the part that will be rewarded and to neglect the other components that can enrich the content of the crowdsourcing activity [44].

Thus, a qualified mechanism can both reward user's effort in a comprehensive way, and drive user's incentive to undertake actions that affect the principal's utility, in return. To capture the incentive problem in crowdsourcing, the one-dimension incentive mechanism needs to be modified into a number of dimensions. At the very least the user's action set must include the range of different tasks it is responsible for. Furthermore, performance measures must be multi-dimension rather than one-dimension for all, so that the principal can drive user's incentives by assigning different reward weights on different tasks [45].

Based on this motivation, we aim at offering a contract that considers different aspects of user's contributions, and assigns different reward weights on their performance in order to incentivize them to provide high quality information to the principal. Fortunately, the moral hazard problem from contract theory provides us a useful tool to design such a mechanism that can solve the employees' multi-dimension action problems when performing multiple tasks [3]. Indeed, the moral hazard model can be adopted to solve the crowdsourcing incentive problem. From the principal's perspective, it "employs" the users to upload location based data and reward them by multi-dimension measures. The principal makes profit by extracting useful information from the collected data, which also incurs a cost such as the reward given back to users. Thus, to maximize its own payoff, the principal needs to find an optimal mechanism that can properly reward user's efforts and drive user's incentives [20].

The main contributions of this paper are summarized as follows. First, we are first to propose a performance and reward consistent contract to maximize the principal's utility as well as to provide users with a continuous incentive to participate in crowdsourcing activities. Second, we extend the incentive mechanism from one-dimension to multi-dimension, which characterizes the general situation in real world and provides comprehensive reward package to the users. Third, we present detail analysis of the multi-dimension case which accounts for the scenarios such as *zeros incentive*, *missing incentive clauses*, and *grouping of tasks*. Last, through simulations, we reveal different parameter's impacts on the optimal reward package, and compare the principal utility under six different incentive mechanisms. Our results show that by using the proposed incentive mechanism, the principal successfully maximizes the utilities and the users obtain the continuous incentives to participate in the crowdsourcing activity.

The remainder of this paper is organized as follows. First, we will introduce the network model in Section 3.2. Then, the problem formulation is described in Section 3.3, and we give the extended analysis of the multi-dimensional case. The performance evaluation is conducted in Section 3.4. Finally, Section 3.5 draws the conclusion.

3.2 System Model

In this section, we will first introduce the principal-user model by constructing the reward package offered by the principal. Then, we will give the utility functions of both the user and principal before proceeding to the solution of the optimal contract. We assume that the crowdsourcing is a multi-task problem, in which there are n tasks that the user can work on and will be rewarded based on its performances on the different tasks.

3.2.1 Operation Cost

When crowdsourcing for the principal, the user encounters an operation cost which includes the consumption of power due to signal processing, execution, and data uploading activities, in addition to power consumption due to data transmission. But the operation cost does not only restrict to the power consumption, but also the user's effort, time, knowledge and/or experience. Consider a user who participates in a crowdsourcing activity who makes a one-time choice of a vector of efforts $a = (a_1, \ldots, a_n)$, $n \geq 1$, for those tasks. When exerting efforts, the operation cost incurred is defined in a quadratic form [46],

$$\psi(a) = \frac{1}{2} a^T C a, \tag{3.1}$$

where C is a symmetric $n \times n$ matrix with the form of

$$C = \begin{bmatrix} c_{11} & \cdots & c_{1n} \\ \vdots & \ddots & \vdots \\ c_{n1} & \cdots & c_{nn} \end{bmatrix}. \tag{3.2}$$

The diagonal element c_{ii} of C reflects the user's task-specific operation cost coefficient, and the off-diagonal elements c_{ij} represent the relationship between two tasks i and j.

The sign of c_{ij} indicates technologically substitute, complementary, independent between two tasks i and j, if $c_{ij} > 0$, < 0, $= 0$, respectively. If two tasks are technologically substitute, raising the effort on one task raises the marginal operation cost of the effort on the other task. The example of technologically substitute is dynamic route planning and traffic jam detection. When the roads are detected as highly congested, the navigation app will start to recalculate the route so that the driver can avoid them. Thus, more power is consumed. In contrast, raising the effort on one task decreases the marginal operation cost of the effort on the other task if they are technologically complementary. There are two examples for technologically complementary: 1) mapping GPS traces to road segments and route/travel time estimation, 2) traffic jam detection and visualization.

In both examples, good achievements in one task ease the work in the other task, and thus save the power. For technologically independent tasks, their operation cost is not dependent on how much efforts are exerted on other tasks. There are many technologically independent examples in crowdsourcing, such as reporting of location, time, and speed in the dynamic traffic map.

Therefore, under different scenarios, the exact form of the operation cost function $\psi(a)$ varies. In return, the optimal reward varies with the shape of the operation cost functions. In particular, the user decision on the effort level for one task affects the marginal operation cost of undertaking other tasks, will be discussed in the next section. In this paper, we do not consider the technologically complementary case, since it does not provide further insights of this model, but increases the mathematical complexity. Thus, the operation cost coefficient matrix is a positive semi-definite matrix with every element in C is non-negative.

3.2.2 Performance Measurement

The location based data received by the principal may differs from the user's actual situation. The error may come from the measurement system. For example, there are usually GPS position errors due to the device and signal diversity, especially in "urban canyons" near tall buildings or tunnels [47]. Another example is the urban noise mapping system, in which the sound level meter (SLM) has a precision of ± 2.7 dB [48]. The phone position and context can induce errors and enlarge the variance of errors.

We assume that the effort a the user exerts is hidden from the principal, but the user's contribution can be observed as a vector of information $q = (q_1, \ldots, q_n)$, $n \geq 1$, which can be regarded as the user's performance. Due to the previous mentioned reasons such as the different measurability on tasks, the received information q varies [49]. Therefore, the performance of the user is a noisy signal of its effort

$$q = a + \varepsilon, \tag{3.3}$$

where the random component $\varepsilon = (\varepsilon_1, \ldots, \varepsilon_n)$, $n \geq 1$, is assumed to be normally distributed with mean zero and covariance matrix Σ. Thus, the user's performance follows the distribution of $q \sim N(a, \Sigma)$.

The variance Σ is a symmetric $n \times n$ covariance matrix with the form of

$$\Sigma = \begin{bmatrix} \sigma_1^2 & \cdots & \sigma_{1n} \\ \vdots & \ddots & \vdots \\ \sigma_{n1} & \cdots & \sigma_n^2 \end{bmatrix}, \tag{3.4}$$

where σ_i^2 denotes the variance of ε_i, and σ_{ij} is the covariance of ε_i and ε_j [50]. The variance denotes the difficulty to guarantee the correctness of measuring effort [51], and also reflects the relationship between the effort exerted by the user and the performance observed by the principal. If the variance is large, the measurability of the performance is difficult, and there is a high probability that the performance is poorly measured and far away from the true effort user exerted. An example is the use of a smartphone microphone as a SLM, which incurs large errors when the phone is put in a pocket or when making a phone call [52]. In contrast, if the performance is easy to measure, the variance will be small or even zero. For example, the report of time is an independent measure with variance 0. The covariance of two measurements exists because the measurement on one task may affect the measurement of the others; for example the detection of a pothole and a bump have a strong connection. Due to this measurement error, both the principal and user will face the measurement cost when integrating multiple tasks.

3.2.3 Reward Package

Inspired by the manager's reward package in industry, which comprises a fixed salary, a bonus related to the firm's profits, and stock options related reward based on the firm's share price [53], we define the user's reward package w in crowdsourcing as a linear combination of a fixed salary and several performance related rewards [54]. By restricting the reward package offered by the principal in the linear form, the reward package w user receives by participating in the crowdsourcing activity can be written as

$$w = t + s^T q, \tag{3.5}$$

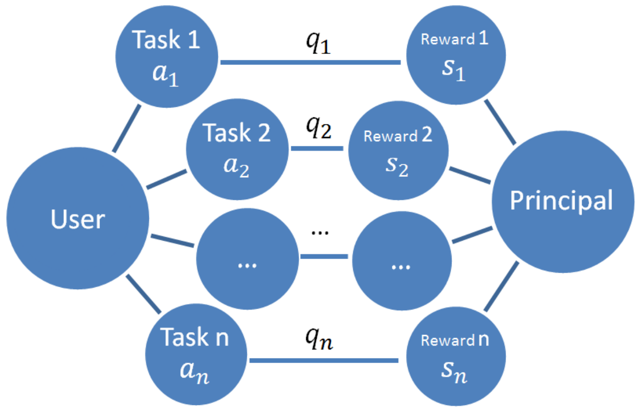


Figure 3.2: The multi-task reward contract.

where t denotes the fixed reward salary, which is a constant and is independent of performance, and $s = (s_1, \ldots, s_n)$, $n \geq 1$, is the reward related to the user's performance q. As q is a random variable which follows $q \sim N(a, \Sigma)$, the reward package w is also a random variable with a mean of $t + s^T a$. From the scaling property of covariance, we know that $Var(s^T q) = s^T \Sigma s$. Thus, the reward package follows the distribution $w \sim N(t + s^T a, s^T \Sigma s)$.

At this point, we can propose the contract that is offered by the principal as (a, t, s), where a and s are $n \times 1$ vectors, and t is a constant value. Under this contract, the principal offers the user a reward package which includes a fixed salary t, and n performance related rewards $(s_1, \ldots, s_n)$. Fig. 3.2 illustrates how this contract works. The user exerts effort a_i for task i, which is observed as a performance q_i by the principal. The principal offers a reward related to q_i, with the reward assigned to the task as s_i.

3.2.4 Utility of User

In this model, we assume that the user has constant absolute risk averse (CARA) risk preferences, which means the user has a constant attitude towards risk as its income increases. Thus, user utility is represented by a negative exponential utility form [55]

$$u(a, t, s) = -e^{-\eta[w - \psi(a)]}, \tag{3.6}$$

where $\eta > 0$ is the agent's degree of absolute risk aversion

$$\eta = -\frac{u''}{u'}, \tag{3.7}$$

where u is the user's utility function. A larger value of η means more incentive for the user to implement an effort. The utility and operation cost of the user are measured in such monetary units that they are consistent with the reward from the principal.

From (3.6), we see that the user's utility is a strictly increasing and concave function. For lower computation complexity, we can make use of the exponential form of the utility function, and use *certainty equivalent* as a monotonic transformation of the user's expected exponential utility function [56].

Proposition 3.1. *The user's utility can be equally represented by certainty equivalent*

$$CE_u = t + s^T a - \frac{1}{2}a^T Ca - \frac{1}{2}\eta s^T \Sigma s. \tag{3.8}$$

The certainty equivalent consists of the expected reward minus the operation cost and measurement cost.

3.2.5 Utility of Principal

In this model, we regard the principal as a "buy and hold" investor, who cares only about the direct performance of the user [57]. That is, the principal is not concerned about its profit from the location based service in the secondary market (e.g., advertisement selling). Therefore, the effort a leads to an expected gross benefit of $V(a)$, which accrues directly to the principal. Thus, we define the utility of the principal as the expected gross benefits of $V(a)$ minus the reward package w to the user. Thus, the principal's expected utility is written as

$$U(a, t, s) = V(a) - w, \tag{3.9}$$

where $V(\cdot)$ is the evaluation function which follows $V(0) = 0$ and $V'(\cdot) > 0$. Different from the user who has CARA risk preferences, the principal here is assumed to be risk neutral, i.e.,

$V''(\cdot) = 0$. Thus, the expected profit of the principal can be simplified to

$$U(a, t, s) = \beta^T a - w, \tag{3.10}$$

where $\beta = (\beta_1, \ldots, \beta_n)$, $n \geq 1$, characterizes the marginal effect of the user's effort a on the principal's utility $V(a)$. Similar to the definition of user's certainty equivalent, we can derive the principal's certainty equivalent as

$$CE_p = E[\beta^T a - w] = \beta^T a - s^T a - t. \tag{3.11}$$

3.2.6 Social Welfare

With the definitions of both user's and principal's utility functions and certainty equivalent payoffs, we can have the social welfare defined as their joint surplus, i.e., the summation of user's and principal's equivalent certainty

$$R = CE_u + CE_p = \beta^T a - \frac{1}{2} a^T C a - \frac{1}{2} \eta s^T \Sigma s. \tag{3.12}$$

The social welfare is the effort exerted by the user, minus the operation cost and the cost incurred by inaccurate measurement. Notice that this expression is independent of the fixed salary t, which serves as an intercept term in the contract. Thus, the fixed salary t can only be used to allocate the total certainty equivalent between the two parties [58]. Later we will see that, under the optimal contract, the social welfare has the same value as the utility of the principal, as the user receives zero utility in crowdsourcing by receiving the optimal reward package.

3.3 Problem Formulation

With the system model, we can formulate the principal's utility maximization problem while providing the user necessary incentives to participate. The principal's problem can be written as

$$\max_{a,t,s} \quad U(a^*, t, s), \tag{3.13}$$

$$s.t. \qquad (a) \;\; a^* \in \arg\max_a u(a, t, s),$$

$$(b) \;\; u(a^*, t, s) \geq u(\overline{w}),$$

where $u(\overline{w})$ is the reservation utility of the user when not taking any effort ($a = \mathbf{0}$) in the crowd-sourcing. The principal maximize its own utility under the incentive compatible (IC) constraint (a) that the user selects the optimal effort a^* maximizing its own utility, and the individual rationality (IR) constraint (b) that the utility user received is no less than its reservation utility.

In the following subsections, we will first solve this problem in the one-dimension case. Then, we will extend this problem to multiple dimensions, which is the general case in reality. Then, we will exam three specific scenarios to have deeper understanding of the multi-dimension incentive problem.

3.3.1 One-Dimension Moral Hazard

When this incentive problem is one-dimension, i.e., $n = 1$, the user makes a single effort choice a, and the distribution of the effort measurement error ε reduced to $N(0, \sigma_1^2)$. Therefore, the user's performance distribution is $q \sim N(a, \sigma_1^2)$. As a result, the reward package now is written as

$$w = t + sq, \tag{3.14}$$

where s is also a constant value. The user's operation cost is reduced to

$$\psi(a) = \frac{1}{2}c_{11}a^2. \tag{3.15}$$

Typically, the user's utility and its certainty equivalent can be written, respectively, as

$$u(a, t, s) = -e^{-\eta(t+sq-\frac{1}{2}c_{11}a^2)} \quad \text{and} \tag{3.16}$$

$$CE_u = t + sa - \frac{1}{2}c_{11}a^2 - \frac{1}{2}\eta s^2\sigma_1^2. \tag{3.17}$$

Similarly, the principal's utility and its certainty equivalent form can be written as, respectively,

$$U(a, t, s) = \beta a - w \quad \text{and} \tag{3.18}$$

$$CE_p = \beta a - sa - t. \tag{3.19}$$

As we have stated previously that the certainty equivalent is a monotonic transformation of the expected utility function. Thus, maximizing the principal's and user's expected utilities is equivalent to maximizing their equivalent certainty payoffs. Thus, we can rewrite the optimization problem in terms of their certainty equivalent wealth, and thus obtain the following simple reformulation of the principal's problem

$$\max_{a,t,s} \quad (\beta - s)a - t, \tag{3.20}$$

$$s.t. \qquad (a) \;\; a^* \in \arg\max_a [t + sa - \frac{1}{2}c_{11}a^2 - \frac{1}{2}\eta s^2 \sigma_1^2],$$

$$(b) \;\; t + sa - \frac{1}{2}c_{11}a^2 - \frac{1}{2}\eta s^2 \sigma_1^2 \geq \overline{w},$$

where $\overline{w}$ denotes the reservation reward of the user when not participating in the crowdsourcing activity.

This one dimensional problem is easy to solve by using the first-order approach. In the first step, we reduce the IC constraint in (a) by taking the first derivative of the user's certainty equivalent regarding a, and setting $u'(a, t, s) = 0$. Then, we obtain the effort $a = s/c_{11}$. Accordingly, we substitute the IR constraint in (b) with the optimal effort a^* and simplify the principal's problem to

$$\max_{a,t,s} \quad (\beta - s)\tfrac{s}{c_{11}} - t, \tag{3.21}$$

$$s.t. \quad (a) \;\; s\tfrac{s}{c_{11}} + t - \tfrac{1}{2}c_{11}\left(\tfrac{s}{c_{11}}\right)^2 - \tfrac{1}{2}\eta s^2 \sigma_1^2 = \overline{w}.$$

Substituting for the value of t in the IR constraint and maximizing with respect to s, we then have the fraction of reward s^* related to performance in the optimal linear reward package as

$$s^* = \frac{\beta}{1 + \eta c_{11}\sigma_1^2}. \tag{3.22}$$

With s^*, we have the optimal effort

$$a^* = \frac{\beta}{c_{11} + \eta c_{11}^2 \sigma_1^2}. \tag{3.23}$$

Representing t by $\overline{w}$, s^* and a^*, we obtain the fixed salary t in the optimal linear reward package as

$$t^* = \overline{w} + \frac{1}{2}\left(\eta\sigma_1^2 - \frac{1}{c_{11}}\right)s^2 \tag{3.24}$$

$$= \overline{w} + \frac{1}{2}\left(\eta\sigma_1^2 - \frac{1}{c_{11}}\right)\left[\frac{\beta}{1 + \eta c_{11}\sigma_1^2}\right]^2.$$

The user's reward package expressions vary as a function of the stochastic structure of the performance or the quality of received data to the user's effort [3]. Under the single task problem, we see that the user's reward package and optimal effort are all decreasing with the operation cost coefficient and the variance of measurement. In other words, the higher the operation cost, or the more difficulty to measure a performance, the user will be less likely to exert effort in the crowdsourcing.

3.3.2 Multi-Dimension Moral Hazard

When this problem has multiple dimensions, i.e., $n \geq 2$, the problem becomes more complicated to solve. In this subsection, we will first solve the general case where we assume that the measurement error is stochastic dependent and the user's effort is technologically dependent. After this general solution, we will move on to the bench mark case with both stochastic and technological independence.

Under the assumption of stochastic dependent, the error terms are stochastically interacted, i.e., $\sigma_{ij} \neq 0$. For technologically dependent, we mean that the activities are technologically correlated with each other, i.e., $c_{ij} > 0$ and C is a positive definite matrix.

Similar to the previous section, we still solve this multi-dimensional problem by using certainty equivalent model with the following simple reformulation of the principal's problem

$$\max_{a,t,s} \quad \beta^T a - s^T a - t, \tag{3.25}$$

$$\begin{aligned} s.t. \qquad & (a) \;\; a^* \in \arg\max_a [t + s^T a - \frac{1}{2} a^T C a - \frac{1}{2}\eta s^T \Sigma s], \\ & (b) \;\; t + s^T a - \frac{1}{2} a^T C a - \frac{1}{2}\eta s^T \Sigma s \geq \overline{w}, \end{aligned}$$

where $\overline{w}$ also denotes the reservation reward of the user when not participating in the crowdsourcing activity. The IC constraint represents the rationality of the user's effort choice. The IR constraint in (b) ensures that the principal cannot force the user into accepting the contract.

Similar to the one-dimension case, we first solve the optimal effort by reducing the IC constraint first. The user's certainty equivalent is concave, since its second-order derivative with respect to a is a negative definite matrix $-C$. Thus, the optimal effort can be determined by taking the first-order derivative of the user's certainty equivalent regarding a, and set $u'(a,t,s) = 0$. In the matrix differentiation, if we define $\alpha = a^T Ca$, as C is a symmetric matrix, we have $\partial\alpha/\partial a = 2a^T C$ [49]. Since C is symmetric positive definite, its inverse is existent. Thus, through numerical derivations, we can finally have $a = C^{-1}s$ in this multi-dimension case. Accordingly, we substitute the IR constraint in (b) with the optimal effort a^* and simplify the principal's problem to

$$\max_{a,t,s} \quad \beta^T C^{-1}s - s^T C^{-1}s - t, \tag{3.26}$$

$$s.t. \qquad (a)\ \ t + s^T C^{-1}s - \frac{1}{2}(C^{-1}s)^T C(C^{-1}s) - \frac{1}{2}\eta s^T \Sigma s = \overline{w}.$$

Substituting the value of t in the IR constraint to the objective and differentiating the objective function with respect to s, we have the performance related reward s^* in the optimal multi-dimension reward package as

$$s^* = (C^{-1} + \eta\Sigma)^{-1}C^{-1}\beta = (I + \eta C\Sigma)^{-1}\beta. \tag{3.27}$$

With s^*, we have the optimal effort in the multi task case as

$$a^* = C^{-1}(I + \eta C\Sigma)^{-1}\beta. \tag{3.28}$$

Representing t by $\overline{w}$, s^* and a^*, we obtains the fixed salary t in the optimal linear reward package as

$$\begin{aligned} t^* &= \overline{w} + \frac{1}{2}s^T(\eta\Sigma - C^{-1})s \qquad (3.29)\\ &= \overline{w} + \frac{1}{2}\left[(I + \eta C\Sigma)^{-1}\beta\right]^T \left(\eta\Sigma - C^{-1}\right)\left[(I + \eta C\Sigma)^{-1}\beta\right]. \end{aligned}$$

Comparing this equation with the first order results, we see that the first order reward package is one special case of this general case and can be derived from this general case directly by setting the matrixes as one dimension ($n = 1$).

Using the formulas (3.27) for s^* we can indeed determine how the optimal linear incentive reward varies with the accuracy of output measures for each task and the operation cost coefficient of each task. Assume, for example, when two tasks are technologically substitution $c_{ij} > 0$, if the measurability of task i worsens, that is, σ_i^2 increases, then, as is intuitive, s_j^* goes up, but s_i^* goes down. Thus, there is a measurement complementarity between the s_i^* and s_j^* in the presence of technologically substitutes problems [3].

A higher incentive reward can induce the user to implement a higher effort, but it will also expose the user to a higher risk. It, therefore, requires a premium to compensate the risk averse user for the risk he/she bears. The optimal power of incentive is therefore determined by the tradeoff between incentive and insurance.

3.3.2.1 Stochastic Independent and Technologically Independent

In this benchmark case, the error terms are stochastically independent (i.e., $\sigma_{ij} = 0$, Σ is a diagonal matrix), and the tasks are technologically independent (i.e., $c_{ij} = 0$, C is a diagonal matrix). Thus, the optimal incentive contract for each task is similar to the single-task problem, and the solution in (3.27) simplifies to

$$s_i^* = \frac{\beta_i}{1 + \eta c_{ii} \sigma_i^2}, \quad \forall i \in \{1, \dots, n\}. \tag{3.30}$$

The user's optimal choice of effort becomes

$$a_i^* = \frac{s_{ii}}{c_{ii}} = \frac{\beta_i}{(1 + \eta c_{ii} \sigma_i^2) c_{ii}}, \quad \forall i \in \{1, \dots, n\}. \tag{3.31}$$

Representing t by $\overline{w}$, s^* and a^*, we obtain the fixed salary t in the optimal linear reward package as

$$t_i^* = \overline{w} + \frac{1}{2} \left(\eta \sigma_i^2 - \frac{1}{c_{ii}} \right) \left[\frac{\beta_i}{1 + \eta c_{ii} \sigma_i^2} \right]^2 . \tag{3.32}$$

In this case, efforts are set independently of each other since the operation cost of inducing the user to perform any given task is independent of the other tasks. As expected, s is decreasing in risk aversion degree η, operation cost coefficient c_{ii} and measurement error variance σ_i^2. We can also prove the relationship between reward s_i and effort a_i from $a = C^{-1}s$. As in this technologically independent case, C is a diagonal matrix with elements c_{ii} on the diagonal. Thus, we can take the partial derivatives as

$$\frac{\partial s_i}{\partial a_i} = c_{ii} \quad \text{and} \quad \frac{\partial a_i}{\partial s_i} = c_{ii}^{-1}. \tag{3.33}$$

Thus, we see that the reward s_i for effort a_i is decreasing in c_{ii}, and the higher of s_i, the more effort the user is like to exert.

3.3.3 Extending Analysis

3.3.3.1 Zero Incentive

In this part, we analyze one special case, in which the principal does not provide any incentive for some tasks. In other words, the reward s_i for Task i is less than or equal to zero. In the general multi-dimension case, the optimal effort a is affected by those cross-partial of C due to technological substitutes. To illustrate how the operation cost coefficients affect the principal to assign a zero reward, we consider the two-dimension case with stochastic independent, i.e., $\sigma_{12} = \sigma_{21} = 0$. We assume that Task 2 is easy to measure, i.e., σ_2^2 is finite and small, while Task 1 is impossible to measure, i.e., $\sigma_1^2 \to \infty$. From (3.27), we have the optimal reward for Task 2 under this case as

$$s_2 = \frac{\beta_2 - \beta_1 \frac{c_{12}}{c_{11}}}{1 + \eta\sigma_1^2(c_{22} - \frac{c_{12}^2}{c_{11}})}. \tag{3.34}$$

However, as effort a_1 is impossible to measure, the reward s_1 cannot be determined, neither. Under the assumption that Tasks 1 and 2 are technologically substitutes, i.e., $c_{12} > 0$. If we increase c_{12}, the reward s_2 will decrease correspondingly. If we assign a high value of s_2, the user will substitute effort from Task 1 to Task 2. The extreme case is that, user only works for Task 2 but no effort exerts for Task 1, as in the one-dimension case.

Proposition 3.2. *When efforts are technologically substitutes, providing incentives for a given task can be implemented either by increasing the reward for that task or by reducing the rewards for the other tasks.*

In this case, effort a_1 cannot be measured, nor can we assign specific reward s_1 to Task 1. Thus, the only way to provide incentives for Task 1 is to reduce the reward s_2 for Task 2. If Task 1 is a critical work that the principal cares extremely about, it may be optimal to punish effort on Task

2 ($s_2 < 0$) or give no reward at all for Task 2 ($s_2 = 0$). In this case, *zero incentive* happens for Task 2.

The second case when *zero incentive* may happen is, when $c_{12} = \sqrt{c_{11}c_{22}}$, the effort for the two tasks are "perfect substitutes," i.e., $a = a_1 + a_2$. Thus, we have $s_1 = s_2$ as the user must equate the marginal return to effort in various tasks. In the case of $\sigma_1^2 \to \infty$, we thus have $s_1 = s_2 = 0$.

The third case when *zero incentive* happens is that the user has a deep love for Task 1. Then it will be willing to exert all its effort even in the absence of any financial reward. This *zero incentive* case can be found in many online applications, in which the user receives incentives through the other user's praise and self-esteem, instead of the principal's reward. In this case, the effort choice of the user will also equate the marginal nonfinancial benefit with the marginal cost [3].

3.3.3.2 Missing Incentive

In some cases, the incentive mechanism cannot provide specific incentives for some aspects of user's contribution. *Missing incentive* differs from *zero incentive* in the sense that, in *zero incentive*, the principal measures the user's performance on the task, but rewards zero. However, the principal neither takes into consideration of user's contribution on the task, nor give any reward in the *Missing incentive*. One example in crowdsourcing is the NoiseTube which is designed to measure and map urban noise pollution using smartphones sensors such as microphone and GPS. Those data can be used directly to construct the dynamic noise map. Furthermore, they can be used to support decision and policy making in different domains such as public health, urban planning, environmental protection and mobility, which will bring far more great benefit in the future [52]. Even though those contributions are important, the principal is unable to account for such explicit incentive provisions in actual contracts.

Again, we use the two-dimension model in the previous case with stochastic independent and perfect effort substitutes to illustrate why that contribution should not be considered. The performance for Task 1 is still hard to measure, such as attention to detail, or helpful advice. But Task 2 is measurable, such as the quantity achieved in a task. We additionally assume that Task 1 is "very important" and that both tasks are valuable.

Proposition 3.3. *For such a case described in the last paragraph, the optimal reward package should only include a fixed wage t, but contain no performance related reward, i.e., $s = 0$.*

Proof. When the principal does not provide any performance related reward, i.e., $s = 0$, the user will choose the total effort $\bar{a}$ that maximize its certainty equivalent in (3.8). Since the efforts are perfect substitutes, we can choose $a_1 \in [0, \bar{a}]$ to maximize the utility $V(\bar{a}) = \beta_1 a_1 + \beta_2(\bar{a} - a_1)$, since $a = a_1 + a_2$. In this case, the principal's utility will be $V(\bar{a}) - \psi(\bar{a})$.

However, if the principal decides to provide performance related reward, i.e., $s > 0$, then user will choose to set a_1 as zero since Task 1 is hard to measure, and thus $s_1 = 0$. In contrast, the user will work on Task 2 with effort $a_2 = \bar{a}$. Then, we have the following inequality for the principal's utility

$$0 - \psi(a_2) - \frac{1}{2}\eta s_2^2 \sigma_2^2 \leq -\psi(\bar{a}) < V(\bar{a}) - \psi(\bar{a}). \tag{3.35}$$

Thus, we see that if the principal provides incentives for the user, the utility will decrease compared to the case when no incentive is provided.

If the principal punish user's effort, i.e., $s < 0$, the user will not work on Task 2, and thus $s_2 = 0$. We must have $a_1 < \bar{a}$ since $\psi'(a_1) < 0 = \psi'(\bar{a})$. Hence, the principal's utility follows the inequality as

$$V(a_1) - \psi(a_1) - \frac{1}{2}\eta s_1^2 \sigma_1^2 < \beta_1 \bar{a} - \psi(\bar{a}) < V(\bar{a}) - \psi(\bar{a}). \tag{3.36}$$

If the principal imposes fine (negative incentive) on user's effort, the utility will decrease compare to the case when no incentive is provided.

By now, we have proved that, only when $s = 0$, the principal's utility can be maximized. Thus, it is optimal to pay a fixed wage t, and contains no performance related reward, i.e., $s = 0$ to the user. □

3.3.3.3 Groupings of Tasks

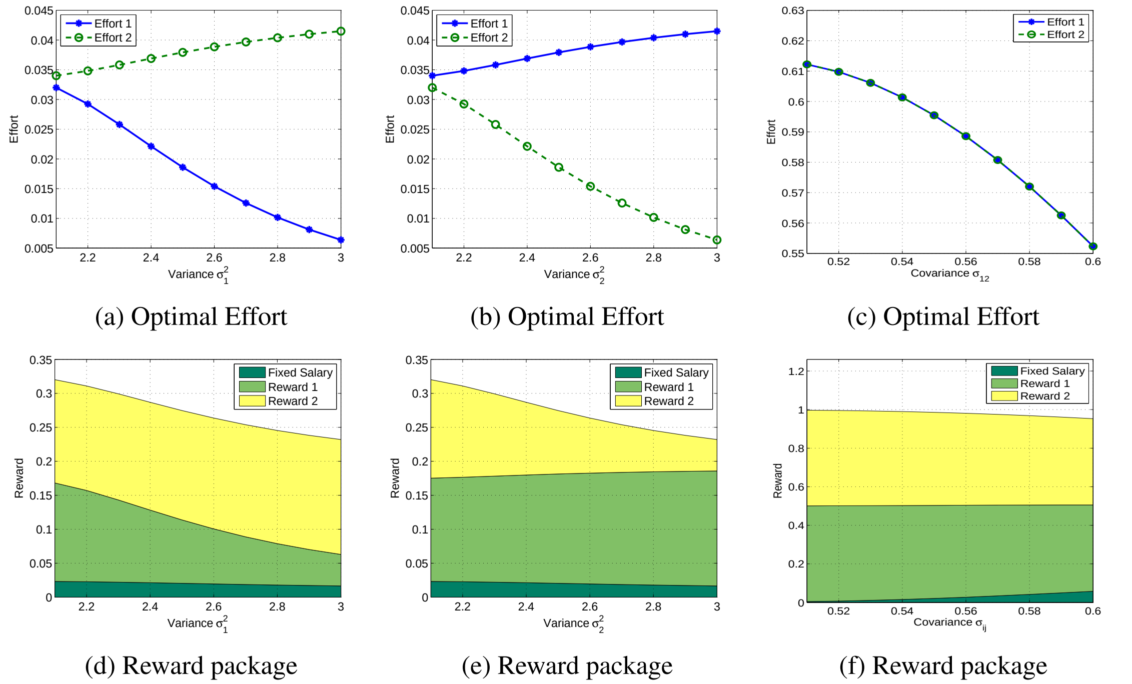
In the single-user multi-task problem, the performance related rewards $(s_1, \ldots, s_n)$ serve three purposes: allocating risk, motivating work, and directing the user's efforts among the various tasks [58]. However, a trade-off arises when these objectives are in conflict with each other. For example, risk-sharing may be inconsistent with motivating work, and motivating hard work may distort the user's effort allocation across tasks. If we have multiple users, the principal can group the tasks, which enables lowering the cost of incentive by using more sensitive measure of actual performance.

To alleviate those conflicts, we consider grouping tasks into different jobs that can assign to different users. One application can be used in Nericell [59], in which varied road and traffic condition need to be detected. The part of common traffic detection tasks such as traces, traffic flow speed, and driving patterns can be grouped and assigned to users with basic sensing functions, such as GPS and accelerometer. The other parts of the newly introduced tasks such as the detection of crashes, potholes and bumps, can be grouped and assigned to users equipped with a special-purposed device with 3-axis accelerometers.

To illustrate how this grouping of tasks brings works, first assume that there is a continuum of tasks indexed by $i \in [0, 1]$, and the measurement errors of each task are stochastic independent. We consider two identical users indexed by $k = 1, 2$, and use $a_k(i)$ to denote the effort that User k exerts on Task i. Again we assume that the two users can share a task and their efforts are perfectly substitutes, i.e., the total effort input for Task i from both users follows $a(i) = a_1(i) + a_2(i)$. Likewise, the measurement error variance for Task i is $\sigma^2(i)$. The total effort User k induced on all task is given by

$$\bar{a}_k = \int_0^1 a_k(i)di. \tag{3.37}$$

Proposition 3.4. *Under this symmetric system model, it is optimal to allocate the two users to be solely responsible for Task i, i.e., $s_k(i) > 0$, and $s_{k'}(i) = 0$, $k \neq k'$, instead of jointly responsible for any Task i, i.e., $s_k(i)s_{k'}(i) > 0$.*



(a) Optimal Effort (b) Optimal Effort (c) Optimal Effort

(d) Reward package (e) Reward package (f) Reward package

Figure 3.3: The optimal effort and reward package as the measurement error covariance Σ matrix varies.

Proof. Let I be a set of tasks that both users are jointly responsible, i.e., $s_1(i)s_2(i) > 0$, $i \in I$. From (3.37), we see that the total effort that User k induced on the task set I is $a_k(I) = \int_I a_k(i)di$. Within set I, we can always find another subset $I' \subset I$ such that we can have $\int_{I'} a(i)di = a_1(I)$, where $a(i) = a_1(i) + a_2(i)$. Similarly, we can also have $\int_{I''} a(i)di = a_2(I)$, where $I' \cup I'' = I$ and $I' \cup I'' = \emptyset$.

By now, we can define a new set of effort and reward package $\{\hat{a}_k(i), \hat{s}_k(i)\}$ for $i \in I$.

1) If $i \in I'$, for Task 1 we set $\hat{a}_1(i) = a(i)$, $\hat{s}_1(i) = s_1(i)$. For Task 2 we set $\hat{a}_2(i) = \hat{s}_2(i) = 0$.

2) If $i \in I''$, for Task 1 we set $\hat{a}_1(i) = \hat{s}_1(i) = 0$, $\hat{a}_2(i) = a(i)$. For Task 2 we set $\hat{s}_2(i) = s_2(i)$,

By this setup, the total effort devoted to each task and the total effort exerted by each user are unaltered. This scheme minimizes the payment cost for the principal, as some of the rewards are lowered to zero for a set of tasks of nonzero measure. $\square$

Providing incentives for an user in any task incurs a fixed cost such as the measurement error. Thus, in the two-dimension case, assigning joint responsibility for any task would incur two fixed costs, which is unnecessary. If some tasks are jointly responsible, it is optimal to split them among the users without affecting either the total effort required from each user or the total effort allocated to any task. This grouping of tasks is possible to eliminate some of the user's risk, so increasing the utilities of both the principal and users [45].

The issue of how the tasks should be grouped can be found in [58]. For the two-dimension case, tasks should be grouped such that all the hardest-to-monitor tasks are assigned to user 1 and all the easiest-to-monitor tasks are assigned to user 2. Separating tasks according to their measurability characteristics allows the principal to give strong incentives for tasks that are easy to measure without fearing that the user will substitute efforts away from other harder-to-measure tasks.

3.4 Simulation Results and Analysis

In this section, we will first give a detailed analysis of reward package in the multi-dimensional case. We will look at how different reward items in the reward package change by varying the parameters such as the operation cost coefficients and measurement error covariance. Then, we will conduct a comparison of the principal's utility among different incentive mechanisms.

In the simulation set up, we assume that, the reservation reward of the user $\overline{w} = 0$ when not participating in the crowdsourcing ($a = 0$). The reason we do not consider the user's utility is that, from the optimal reward package we have derived, no matter how those parameters change, the user's utility will remain the same. The optimal reward package will bring user the utility the same as the reservation utility $-e^{-\eta\overline{w}}$, which in our case is -1 as we set $\overline{w} = 0$.

3.4.1 Optimal Reward Package Analysis

3.4.1.1 Measurement Error

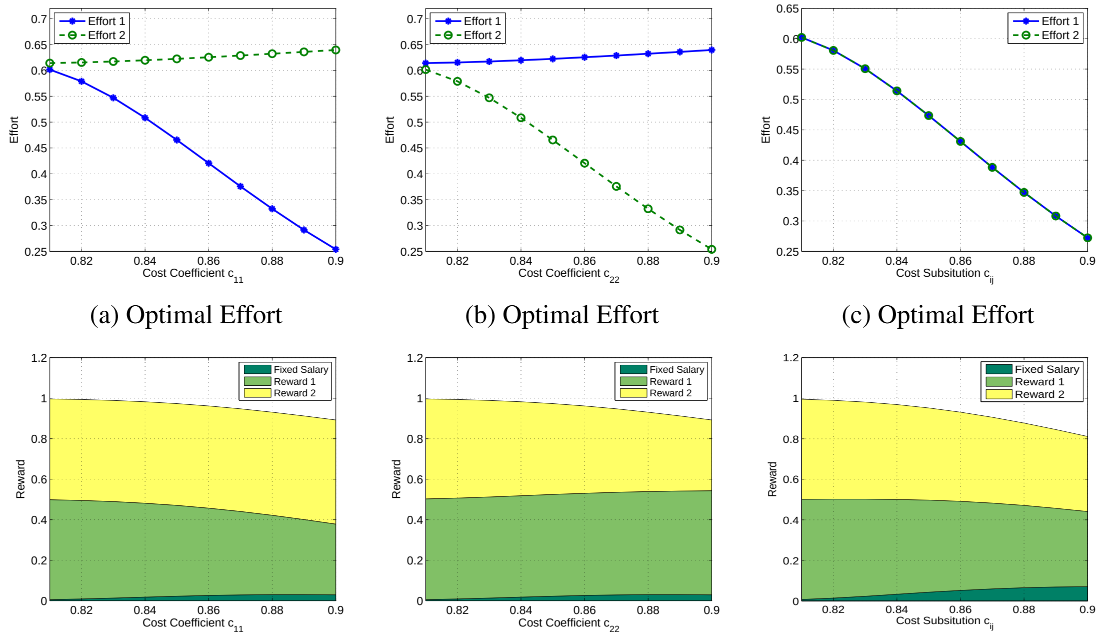
To look into the detail of how the variance and covariance of measurement error affect the optimal effort and reward package, we set up the multi-dimensional space as $n = 2$. Since the measurement error covariance matrix is symmetric, there are three variables that we can vary: the variances of measurement error for Task 1 and Task 2: σ_1^2 and σ_2^2, and the covariance σ_{12}/σ_{21}. We fix the operation cost matrix C, and risk averse degree η, and show the results in Fig. 3.3, where the first row gives the optimal efforts, and the second row gives the reward packages.

In Figs. 3.3(a, b, d, e), we are going to see how the variances of the measurement error on the performances affect the user's selection of efforts for the two tasks and the rewards offered by the principal. When we vary one variance, the other one keeps fixed.

Fig. 3.3a show the measurement error variance σ_1^2 for Task 1 increases, the optimal effort a_1 for Task 1 decreases, while the effort a_2 for Task 2 shows opposite properties. From Fig. 3.3d, we see that as measurement error variance σ_1^2 for Task 1 increases, reward package w, the fixed salary t and reward s_1 are decreasing, while the reward for Task 2 is increasing. This result is because the measurement error becomes more volatile (σ_1^2 increases), the user's benefit from Task 1 decreases (s_1 becomes smaller), but the share from Task 2 increases so that the use's utility can be maintained at the reservation utility.

Figs. 3.3(b, e) show similar properties as Figs. 3.3(a, d). At this time we fixed σ_1^2 but increase σ_2^2, thus Figs. 3.3(b, e) show the opposite behavior compare to the previous case. As σ_2^2 increases, i.e., the measurement error for Task 2 becomes more volatile, user prefers to exert more effort for Task 1 instead of Task 2. As we can see from Fig. 3.3b that, the effort for Task 1 is increasing while effort for Task 2 is decreasing. Similarly, from Fig. 3.3e we see that the user's reward from the Task 2 and the fixed salary t are decreasing at the same time, but the reward from the Task 1 goes up.

From Figs. 3.3(d, e), we have learned that, as the user's utility remains the same (i.e., -1) in all situations, the reward package offered to the user will mostly rely on the part that is more stable,



(a) Optimal Effort (b) Optimal Effort (c) Optimal Effort

(d) Reward package (e) Reward package (f) Reward package

Figure 3.4: The optimal effort and reward package as the operation cost coefficient C matrix varies.

such as the reward with fixed measurement error variance: Reward 2 when σ_1^2 increases and Reward 1 when σ_2^2 increases. In summary, the reward design lowers the proportion of bonus from the less predictable part. By this mechanism, the risk of losing user's incentive in all kinds of situations can be canceled.

In Figs. 3.3(c, f), we investigate the impacts of covariance σ_{12}/σ_{21} on the optimal effort and reward package, while fixing σ_1^2 and σ_2^2 the same. The simulation results show that, as the covariance σ_{12}/σ_{21} increases, the optimal effort a and reward package w are all decreasing. Since we assign the same operation cost for Task 1 and Task 2, the optimal effort of them overlaps in Fig. 3.3c. Meanwhile, from Fig. 3.3f we see that, within the reward package, Reward 1 and Reward 2 are decreasing except the fixed salary t. When the relationship between the performance observed by the principal and the effort exerted by the user becomes more volatile, it is harder to predict them to identify an effort. Thus, the user becomes more reluctant to exert effort, and the principal receives less utility and rewards the user less.

3.4.1.2 Operation Cost

To see how the operation cost coefficients affect the optimal effort and reward package, we also set up the multi-dimensional space as $n = 2$. The operation cost coefficient is also a symmetric matrix, and we can vary three of the elements: task-specific operation cost coefficient for Task 1 and Task 2: c_{11} and c_{22}, and the technologically substitution coefficient c_{12}/c_{21}. We fix the measurement error covariance matrix Σ, and risk averse degree η, and show the results in Fig. 5.4, where the first row gives the optimal efforts, and the second row gives the reward packages as what we have done in Fig. 3.3.

Figs. 5.4(a, b, d, e) show how the task-specific operation cost affects the user's effort choice for the two tasks and the reward items in reward package. We keep one operation cost coefficient fixed when vary the other operation cost coefficient.

In Fig. 3.4a, we see that as the operation cost coefficient c_{11} for Task 1 increases, the optimal effort a_1 for Task 1 decreases, but effort a_2 for Task 2 increases. In Fig. 3.4d, reward package w and reward s_1 are decreasing, while the reward for Task 2 and fixed salary t are increasing. This result is intuitive, since if exerting effort for task 1 encounters more operation cost, (c_{11} increases), the user will be more likely to switch effort to Task 2, which consumes less operation.

Figs. 5.4(b, e) show similar properties as Figs. 5.4(a, d). At this time we fixed c_{11} but increase c_{22}, thus Figs. 5.4(b, e) shows the opposite behavior compared to the previous case. As c_{22} increases, i.e., the operation cost for Task 2 increases, user prefers to exert more effort for Task 1 instead of Task 2. We can see from Fig. 3.4b that the effort for Task 1 is increasing while effort for Task 2 is decreasing. Similarly, from Fig. 3.4e we see that the user's reward from the Task 2 is decreasing. While the reward from the Task 1 and the fixed salary t go up at the same time.

From both Fig. 3.4d and Fig. 3.4e, we observe that, the user is more likely to exert effort on the task that incurs less operation cost, and thus the reward package will reward more on the task with a smaller operation cost coefficient. Thus, we see that the principal Reward 2 when c_{11} increases and Reward 1 when c_{22} increases.

In Figs. 5.4(c, f), we investigate the impacts of technologically substitution c_{12}/c_{21} on the optimal effort and reward package, while fixing the task specific operation cost coefficients c_{11} and c_{22} the same and unchanged. As the technologically substitution c_{12}/c_{21} increases, the optimal effort a and reward package w are all decreasing. Since we assign the same task-specific cost coefficients for both tasks, the optimal effort of them two overlap in Fig. 3.4c. Meanwhile, from Fig. 3.4f we see that, reward s_1 and s_2 are both decreasing except the fixed salary t. This is due to less efforts are exerted from the user, less performance related rewards will be offered. However, in order to keep user incentivized, the principal has to increase the fixed salary t, so that the user's utility is guaranteed.

3.4.2 Incentive Mechanism Comparison

In the previous section, we have solved the optimal reward package when the measurement error is stochastic dependent and effort is technologically dependent. As this multi-dimensional case is the most general case in reality, we name this mechanism by *General*. In addition, we also obtained the optimal reward package when the measurement error and effort are independent, and thus we name it by *Independent*. We also have a third one called *Single Bonus* that is the reward package obtained in the one dimensional case. In this one-dimensional case, we can regard the principal rewards user on only one task. In this subsection, we will propose another three incentive mechanisms as the comparisons with the previous two. Those three mechanisms are generally based on our current model, while they are different from each other in the construction of their reward packages.

The first two are special cases of the *General*: one is stochastic independent but technologically dependent, the other one is technologically independent but stochastic dependent, and are named by *Stochastic Independent* and *Technologically Independent*, respectively. The last one is called *Opening Reward*, that is the reward package only contains a fixed salary t. We can regard this mechanism as a company which will offer each user an opening reward as the Karma which is mentioned in Section I. But this *Opening Reward* mechanism does not care about user's future performance.

3.4.2.1 Stochastic Independent

When tasks are stochastic independent, the co-variances of the error measurement are zero, and we have $\sigma_{ij} = 0$ and Σ becomes a diagonal matrix. The optimal performance related rewards for each task in (3.25) is simplified to

$$s^* = (I + \eta C \mathrm{Diag}(\Sigma))^{-1}\beta, \tag{3.38}$$

where $\mathrm{Diag}(\Sigma)$ is the a $n \times n$ diagonal matrix with element σ_i^2, $\forall i \in \{1, \ldots, n\}$ on the diagonal. Based on $a = C^{-1}s$ and (3.29), we can easily obtain the user's optimal choice of effort and the fixed salary t in this stochastic independent but technologically dependent package.

3.4.2.2 Technologically Independent

When tasks are technologically independent, the cross-partials of the cost function are zero, i.e., $c_{ij} = 0$ and C becomes a diagonal matrix. The optimal incentive contract for each task in (3.25) simplifies to

$$s^* = (I + \eta \mathrm{Diag}(C)\Sigma)^{-1}\beta, \tag{3.39}$$

where $\mathrm{Diag}(C)$ is the a $n \times n$ diagonal matrix with element c_{ii}, $\forall i \in \{1, \ldots, n\}$ on the diagonal. Based on $a = C^{-1}s$ and (3.29), we can easily obtain the user's optimal choice of effort and the fixed salary t in this technologically independent but stochastic dependent package.

3.4.2.3 Opening Reward

When no performance related reward is offered, the problem is formulated as

$$\max_{a,t} \quad \beta^T a - t, \tag{3.40}$$

$$s.t. \qquad (a) \;\; a = \arg\max_a [t - \frac{1}{2}a^T C a - -\frac{1}{2}\eta s^T \Sigma s],$$

$$(b) \;\; t - \frac{1}{2}a^T C a - -\frac{1}{2}\eta s^T \Sigma s = \overline{w}.$$

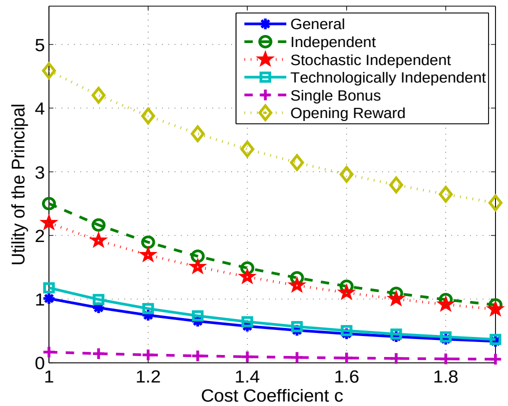


Figure 3.5: The principal's utility as the operation cost coefficient c_{ii} varies.

The optimal effort a^* and opening reward t^*, respectively, have the form of

$$a^* = C^{-1}\beta \quad \text{and} \tag{3.41}$$

$$t^* = \overline{w} + \frac{1}{2}a^T C a = \overline{w} + \frac{1}{2}(C^{-1})^T \beta^T \beta. \tag{3.42}$$

3.4.2.4 Comparisons

In Fig. 3.5, we compare the principal's utility from the six incentive mechanisms as we vary the task-specific operation cost coefficient c_{ii}. From the simulation results we see that, as the cost coefficient c_{ii} increases, the principal's utility is decreasing as well. The reason for this phenomenon is that larger cost coefficient c_{ii} means more operation cost when implying an effort. Therefore, the user is less likely to exert effort in the crowdsourcing activity. With less data are collected from the users, the principal's utility will certainly decrease. In addition, from Fig. 3.5, we see that the principal obtains the largest utility in the *Independent* case. Followed by the *Opening Reward*, *Stochastic Independent*, and *Technologically Independent*, the *General* case proposed by us brings the fifth highest utility to the principal, while the *Single Bonus* gives the least utility.

In Fig. 3.6, we analyze the impact of user's risk averse degree η on the principal's utility. As the principal's utility $V = a - t$ in the *Opening Reward* is independent of the risk averse degree η, we cannot see any change in the principal's utility. For the other five mechanisms, we

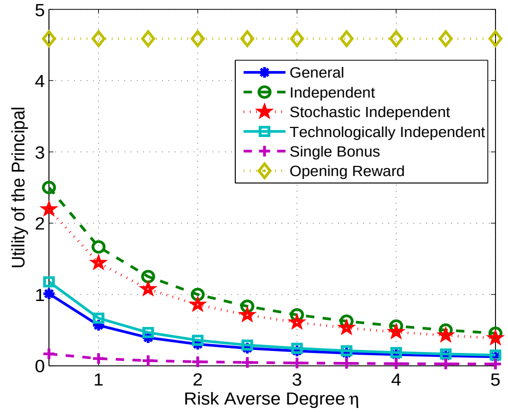


Figure 3.6: The principal's utility as risk averse degree η varies.

see that the principal's utility is decreasing as the user's risk averse degree η increases. This result is intuitive as a larger η means the user becomes more conservative and sensitive to risk, thus less likely to participate in. With less effort obtained from the user, the principal's utility will certainly decrease. From Fig. 3.6 we also obtains the similar ranking of the principal's utility as in the previous figure: the *Independent* case brings higher utility than the *Stochastic Independent*, *Technologically Independent*, and *General* one, and the *Single Bonus* one brings the smallest utility for the principal.

In Fig. 3.7, we increase the variance σ_i^2 to see how the principal's utility varies. Similar to the previous case, the principal's utility $V = a - t$ in the *Opening Reward* is independent of the covariance matrix. Thus, we cannot see any change of the principal's utility. For the other mechanisms, the principal's utility is decreasing with the variance, which is in accordance with our conclusion in the previous section. The variance σ_i^2 of measurement error denotes the relationship between effort levels exerted by the user and the performance observed by the principal. As σ_i^2 increases, it indicates a weaker relationship between effort levels and the expected reward achieved. As a result, the users are likely to exert lower levels of effort with increases in uncertainty, and thus a lower cost of participation. With the decrease of optimal effort, less data is obtained from the user, the principal's utility will certainly decrease. From Fig. 3.7 we also obtain the similar ranking of the principal's utility as in the previous figure: the *Independent* case brings higher utility

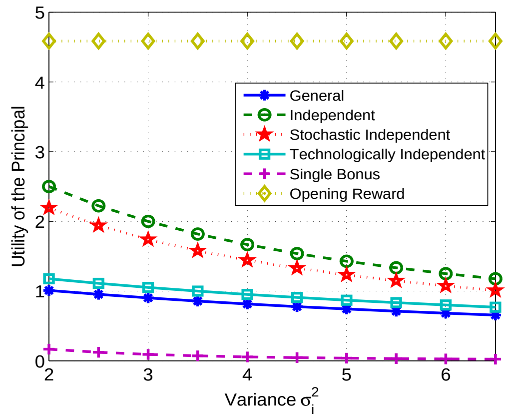


Figure 3.7: The principal's utility as measurement error variance σ_i^2 varies.

than *Stochastic Independent*, followed by *Technologically Independent* and *General* one, the *Single Bonus* one brings the lowest utility for the principal.

The reason for the performance ranking of the six mechanisms in Fig. 3.5, Fig. 3.6, and Fig. 3.7 is as follows. The *Independent* mechanism is the ideal case of the *General* multi-dimension case. As less measurement cost is occurred when predicting the outcome and less operation cost is encountered due to effort substitution, a higher utility is obtained than the other mechanisms. The *Stochastic Independent* and *Technologically Independent* are partial independent cases of the *General* multi-dimension one, thus, the principal's utility lies between the *Independent* and *General* mechanisms. But as we have assigned larger values for the covariance matrix of the the measurement error than the operation cost coefficient matrix, more effort will be exerted in the *Stochastic Independent* than in the *Technologically Independent* mechanism. Therefore, the principal's utility is higher in the *Stochastic Independent* than in the *Technologically Independent* case, while the *Single Bonus* only reward user with only one dimension evaluation. As a result, the users have less incentive to exert more effort in other tasks. In return, less utility is obtained by the principal. For the result of the *Opening Reward* case, it seems unreasonable at the first sight, as it brings the principal the highest utility than the other three mechanisms. While we notice that *Opening Reward* is a "once-for-all" deal which does not provide continuous incentives for the users, i.e., after the users have fulfilled their duty and receive the reward, they are more likely to stop participating in crowdsourcing.

3.5 Conclusions

In this paper, we have investigated the problem of providing incentives for users to participate in the crowdsourcing by rewarding user from multi-dimension evaluations. We solve the principal's utility maximization problem in both one-dimension and multi-dimension cases. Furthermore, we give analysis of special scenario of the multi-dimension model. Finally, we use the numerical results to analyze the optimal reward package by varying different parameters. In addition, we compare the principals' utility under the six different incentive mechanisms, and show that the principal's utility deteriorates with large operation cost coefficient, higher risk aversion of users, and large measurement error variance.

Chapter 4

Tournament Based Incentive Mechanism Designs for Mobile Crowdsourcing

4.1 Introduction

Nowadays, people can access various sophisticated location based services (e.g., Google Maps with traffic information) using their smartphones through wireless access networks. With the drastic growth in the location based service market, as well as the rapid development of big data technologies, more data as well as user participation are required to support more sophisticated services. There are mobile applications available that can detect WiFi hotpots within a certain distance of the user's current location. Smartphone users help collect the WiFi hotpot information which includes the location, router name, password, etc. for the service provider which is denoted as principal here after. However, when participating in such crowdsourcing, users consume their resources such as battery and computing capacity [2]. Therefore, many users hesitate to participate which is a major impediment to the growth of mobile crowdsourcing [38]. Thus, incentive mechanism designs are in critical need to motivate the users to participate.

In the literature, it has already been noticed that there is an urgent need to alleviate the conflict by introducing incentive mechanism for users. Inspired by the effort based reward from the labor market, several works have been proposed to address this problem by providing users with the reward that is consistent with their performance. Examples are the works in [6] and [11], as well as one of our previous work [41]. The previous mentioned works capture the fundamental aspect of providing necessary incentive for user to participate in crowdsourcing. Yet, they mainly assume that the principal employs only one user and rewards it on the basis of the absolute performance.

However, when rewarding users based on absolute performance, the principal has a strong incentive to cheat by claiming that users had poor performances that deserve low rewards, so that the principal can pay less [3]. This will result in a decrease of all users' utilities. Another example is that

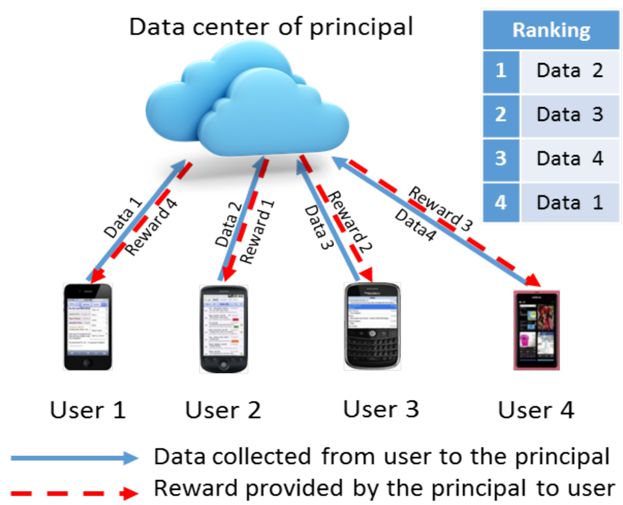


Figure 4.1: Crowdsourcing incentive mechanism by tournament.

when there is a positive mean measurement error at user's performance, every user's performance will result in an increase at the principal's observation. Thus, users are rewarded more than they should, but the principal encounters a loss of utility since it has to pay more. We name this case that affects both sides as *common shock*, which can be either positive or negative to user performance and reward. If both users and principal are aware of this *common shock*, we can regard the trading between them as trading with *full information*. However, in the general case, this *common shock* is unobservable to either or both sides. While incentive mechanism based on absolute performance can be easily affected, the tournament design can filter out this *common shock* problem.

One obvious advantage of rank order tournament over absolute performance rewards is that ordinal ranking is easy to measure and hard to manipulate [3]. In a tournament, the principal has to offer the fixed amount of rewards no matter who wins. In this paper, we will propose a a multi-user design that rewards users' performance in crowdsourcing by a tournament reward structure based on the rank order. A brief illustration of crowdsourcing tournament rewarding mechanism is shown by Fig. 4.1. After obtaining the data from the users, the principal will generate an ascending list regarding user's performance. Here, User 1 achieves the highest performance and will be rewarded the highest amount Reward 4, while User 2 performs worst with the smallest amount of Reward 1.

The main contributions of this paper are first we consider a tournament structure incentive mechanism that rewards users by their rank orders which can tackle the *common shock* problem. Second, we propose the solution for the tournament by approximating the absolute performance based optimal contract with *full information* by step functions. Third, in the simulation part, we introduce another well known tournament mechanism for comparison purposes in order to demonstrate the effectiveness of tournament mechanisms to improve the principal's utility. The proposed mechanisms allow the principal to successfully maximize the utilities and the users to obtain continuous incentives to participate in mobile crowdsourcing.

The remainder of this paper is organized as follows. First, we will introduce the network model in Section 4.2. Then, the design of tournament is described in Section 4.3, in which we also give the analysis of the optimal contract with full information. The performance evaluation is conducted in Section 4.4. Finally, conclusions are drawn in Section 4.5.

4.2 System Model

We refer to the model in [60] and consider a crowdsourcing network in which one risk neutral principal employs a fixed group of identical risk averse users, $i = 1, \ldots, n$, to collect data. The principal rewards users based on their relative performances which can be referred to the quality of the received data (e.g., quantity, correctness, and importance). In a n-user tournament, the users' performances are sorted in an ascending order, and the fixed prizes $(W_1, W_2, \ldots, W_n)$ are rewarded. We use the numbering conventional in the study of order statistics: "first place" is the lowest performance and W_1 is the prize received by the user with the lowest performance.

4.2.1 Common Shock Problem

When users help to collect data for the principal, the user exerts an effort a. Note that the user's effort a is a hidden information, since the principal can only observe the performance level q of the users, i.e., the quality of the received data. Therefore, the performance of user i, q_i, depends stochastically on the user's effort level, a_i. In particular,

$$q_i = z_i + \varepsilon, \tag{4.1}$$

where ε is a random variable representing the *common shock* that affects all of the users and z_i is a random variable whose distribution depends on a_i. Due to the *common shock*, such as the measurement error at the principal as mentioned previously, the quality of received data q_i cannot reflect the user's actual performance or effort exactly. Therefore, the performance of the user is a noisy signal of its effort.

Let G denote the distribution function for the *common shock* (μ, σ), where σ is the variance. We assume that ε has zero mean when no *common shock* presents

$$\int \varepsilon dG(\mu, \sigma) = 0. \tag{4.2}$$

By this assumption, regardless of its assessment of ε, every user believes that its performance and that of every other user have the same mean if they take the same effort.

4.2.2 Rank Order Statistic

Let $F(z_i; a_i)$ denote the cumulative distribution function (CDF) for z_i, given a_i. $F(z_i; a_i)$ has a continuous probability distribution function (PDF) $f(z_i; a_i)$ which is positive everywhere and continuously differentiable in a_i. Since the users are identical ex-ante, F does not depend on i. The value of z_i is not known to the user until its choice of a_i is made. We assume that z_i and (ε, σ) independent, since the term z_i is independently and identically distributed for every common value of a_i and q_i.

Assume that the principal observes only the performance levels of the users, $q = (q_1, q_2, \ldots, q_n)$, but cannot directly observe the users' effort levels. Under the tournament, user i's reward depends only on the rank order of q_i in q, instead of the performance level q_i. Since each user's performance is given by $q_i = z_i + \varepsilon$, we can easily obtain $z_i \geq z_j$ from $q_i \geq q_j$. That is, the rank order of the performances depends only on z_i and not on ε. Therefore, the realization of (μ, σ) does not affect the game played by the users, and the equilibrium effort level will be independent of σ. Hence, we can analyze the game in terms of just z_i. In a n-user tournament, user i wins prize W_j if and only if z_i, is the jth-order statistic of $(z_1, \dots, z_n)$. The density function $\phi_{jn}(z;a)$ for the jth-order statistic in a sample of size n drawn from the distribution $F(z;a)$ is [8]

$$\frac{(n-1)!}{(n-j)!(j-1)!} f(z;a) F^{j-1}(z;a)[1-F(z;a)]^{n-j}. \tag{4.3}$$

This density function denotes that the user i's performance outperforms $j-1$ number of users, and falls behind $n-j$ number of users.

4.2.3 Utility of the Users

The realized performance of each user then is a stochastic function of its effort and the value of the *common shock*. Here, we consider the user's reward from the principal's prize in terms of utility. It is also convenient to think of the cost of exerting effort in terms of utility. The preferences of each user i over the prize, W_i, and the exerted effort, a_i, are represented by the utility function

$$U_t(W_i, a_i) = u(W_i) - \gamma(a_i), \quad W_i \geq 0, \quad a_i \geq 0, \quad i = 1, \dots, n, \tag{4.4}$$

where u is a strictly increasing and strictly concave function of W_i, and γ is strictly increasing and strictly convex with a_i. The user's utility is obtained from the prize minus the exerting effort.

For convenience, the principal can construct the user's reward function in terms of utility $w = (w_1, w_2, \dots, w_n)$ by defining $w_i = u(W_i)$, $\forall i$. We have the user's expected utility is the expected value of rewards minus the cost,

$$U_t(w, a) = \sum_{j=1}^{n} w_j P(\text{rank} = j) - \gamma(a), \tag{4.5}$$

where $P(\text{rank} = j)$ is the probability that the user is in the jth place among all n users at the measured performance level $q = z + \varepsilon$. Given the density function $\phi_{jn}(z;a)$, the probability can be obtained by an integration of the density function $\phi_{jn}(z;a)$. Thus, the user's utility function can be written as

$$U_t(w, a) = \sum_{j=1}^{n} w_j \int \phi_{jn}(z;a) dz - \gamma(a). \tag{4.6}$$

In the symmetric equilibrium all users spend the same amount of effort $\bar{a}$ and expect an equal probability $1/n$ of reaching any of the n ranks. Given the effort choice of $\bar{a}$, we can derive the users' expected utility from (4.6) as

$$U_t(w, \bar{a}) = \frac{1}{n}\sum_{j=1}^{n} w_j - \gamma(\bar{a}). \tag{4.7}$$

4.2.4 Utility of the Principal

The principal's problem is to design a reward structure for the n users. We assume that the principal is constrained to offer a fixed minimum level of expected utility to each user, so that we can judge the relative performance of tournaments by examining the expected utility of the principal. The risk neutral principal's objective is to maximize the summation of all the users' performances minus the total prizes to the users

$$V_t(W_i, a_i) = E\left[\sum_{i=1}^{n}(q_i - W_i)\right]. \tag{4.8}$$

Given that the performance q follows a conditional distribution $f(q - \varepsilon, a)$ and under a common shock, the principal's expected utility can be written as

$$\begin{aligned} V_t(w, a) &= \int\int qf(q - \varepsilon, a)dG(\mu, \sigma)dq - \sum_{j=1}^{n} W_j \qquad (4.9)\\ &= \int zf(z, a)dz - \sum_{j=1}^{n} W_j, \end{aligned}$$

where (9) is result from our previous conclusion that z is independent from the common shock (μ, σ), and thus we can simply replace q with z.

4.3 Problem Formulation

4.3.1 Optimization Problem

Given the number of users n that participate in this crowdsourcing, the principal's problem is to design $(w, \bar{a})$ to maximize (4.9) subject to the two constraints that $\bar{a}$ is an optimal decision rule for the user given w and that the expected utility of the user is at least $\bar{u}$, i.e.,

$$\max_{(w,\bar{a})} \int zf(z,a)dz - \sum_{j=1}^{n} W_j, \tag{4.10}$$

$$s.t.$$

$$(a) \quad \bar{a} = \arg\max_{a} \sum_{j=1}^{n} w_j \int \phi_{jn}(z;a)dz - \gamma(a),$$

$$(b) \quad \frac{1}{n}\sum_{j=1}^{n} w_j - \gamma(\bar{a}) \geq \bar{u}.$$

(a) is the incentive compatible (IC) constraint; it represents that given any reward structure, the problem facing each user is to choose a level of effort that maximizes own utility. We can solve the optimal effort by taking the first derivative of the IC constraint, which is given by

$$\sum_{j=1}^{n} w_j \frac{\partial P(\text{rank} = j)}{\partial a} - \gamma'(a) = 0. \tag{4.11}$$

(b) is the individual rationality (IR) constraint; it provides the necessary incentive for users to participate. We must have the utility no less than the reservation utility when a user is not taking any effort ($a = 0$). Here, we define $S_t(n)$ as the set of feasible n-user tournaments that satisfy the IC and IR constraints. The set of feasible tournaments is always nonempty, since it always contains the "no incentive" tournament, $[(\bar{u}, \bar{u}, \ldots, \bar{u}), 0] \in S_t(n)$, for all n. The utility per user to the principal under this tournament is $\bar{V}$.

From the problem formulation we see that the optimal tournament depends on the number of users n, the distribution function F, but not on the distribution function G. In other words, tournament approach is robust against lack of information or lack of agreement about G.

4.3.2 Tournament Design

To obtain the tournament, we can derive from the optimal contract which reward user based on the absolute performance with full information. First, we will formulate the optimal contract problem with full information. Then, we will show that we can design the tournament by step-functions to approximate the optimal contract.

4.3.2.1 Optimal Contract under Full Information

In the optimal contract, the principal rewards users based on the absolute performance. We define the reward $R(q)$ as a linear and increasing function of q. Thus, the utility user obtained from the reward is $u(R(q))$, and denoted as $v(q)$ for simplicity. The contract the principal offered to user is (v, A), where A is the effort. In this full information case, G is given by $\varepsilon = 0$ with probability 1, i.e., the principal knows ε.

Thus, the user i's utility under contract is represented by

$$U_c(v, a) = v(q_i) - \gamma(a_i), \quad q_i \geq 0, \quad a_i \geq 0, \quad i = 1, \dots, n, \tag{4.12}$$

where v is also a strictly increasing and concave function as u. As we can see, $v(q_i)$ is a piecewise continuous utility function which related to the quantity of q_i instead of its rank. As noted above, $F(z; a)$ denotes the conditional distribution function for z given a, and $f(z; a)$ is the continuous density function of $F(z; a)$. As $\varepsilon = 0$ with probability 1, we can rewrite the user's expected utility function as

$$U_c(v, a) = \int v(z) f(z; a) dz - \gamma(a), \tag{4.13}$$

which is positive everywhere and continuously differentiable in a.

Followed by user's expected utility function in contract, the principal's expected utility can be written as

$$V_c(v, a) = E\left[\sum_{i=1}^{n} (q_i - R(q_i))\right], \tag{4.14}$$

where $\gamma[v(q_i)]$ is the cost utility function which is also a strictly increasing and strictly convex function of the utility provided to user, as in the tournament. Similarly, the expected utility of the principal from the contract (v, a) is

$$V_c(v, a) = \int \{z - R(z)\} f(z; a) dz. \tag{4.15}$$

With the user and principal's utility functions, we can formulate the contract which rewards user by their absolute performance as

$$\max_{(v,A)} \int \{z - R(z)\} f(z;a) dz, \tag{4.16}$$

$$s.t.$$

$$(a) \quad A = \arg\max_{a} \int v(z) f(z;a) dz - \gamma(a),$$

$$(b) \quad \int v(z) f(z;A) dz - \gamma(A) \geq \bar{u}.$$

Similar to the tournament, (a) is the IC constraint and (b) is the IR constraint. The principal's problem is to choose (v, A) to maximize its expected utility subject to the two constraints that A is the optimal decision rule for the user given v, and that the expected utility of the user is at least $\bar{u}$. Here, we define S_c as the set of feasible contracts that satisfy the IC and IR constraints. From [8], the piecewise continuous utility function and the user's optimal effort can be approximated arbitrarily closely by a step function, if there are enough steps. The sequence represented by the step functions is the unique solution of this optimal contract with full information, and the principal's utility is maximized. In addition, each of these step function represented contracts can be approximated arbitrarily close by a tournament if there are sufficient number of users.

4.3.2.2 Tournament by Approximation

Next, we will show that given a feasible contract $(v, A) \in S_c$, we can approximate the optimal contract by constructing a sequence of contracts $(w_{ni}, \bar{a}_n)$, where w_{ni} is a step function with n steps, $\bar{a}_n$ is a constant function.

The first thing we need to do is approximate the continuous utility function $v(z)$ by a step function. We notice that, the probability that a user achieves a specific rank is equal to the probability that the user's performance level falls into a corresponding interval of the CDF. Thus, given a specific rank, we can find the effort value q_{ni} by the inverse CDF of $F(q_{ni}; A) = i/(n+1)$ [8].

Then, we can define $\hat{w}_{ni}$, by

$$\hat{w}_{ni} = v(q_{ni}), \quad i = 1, \ldots, n. \tag{4.17}$$

Thus, we can replace the w_j in (4.10) with this approximation $\hat{w}_{ni}$. The optimal effort under tournament can be solved by

$$\bar{a}_n = \arg\max_{a} \sum_{i=1}^{n} \hat{w}_{ni} \int \phi_{in}(z; A) dz - \gamma(A). \tag{4.18}$$

Again, we calculate the error term $\bar{e}_n$ in this tournament design, and have

$$\bar{e}_n = \bar{u} + \gamma(\bar{a}_n) - \frac{1}{n} \sum_{i=1}^{n} \hat{w}_{ni}. \tag{4.19}$$

Finally, the utility in tournament is obtained by adding up the approximated $\hat{w}_{ni}$ and error $\bar{e}_n$

$$w_{ni} = \hat{w}_{ni} + \bar{e}_n, \quad i = 1, \ldots, n. \tag{4.20}$$

By now, we have the tournament $(w_{ni}, \bar{a}_n)$ that is close to the optimal contract with full information.

Each of these step-function contracts can be approximated arbitrarily close by a tournament with a sufficiently large number of users. Hence, the principal's expected utility is approximately unchanged. Moreover, the tournament's efficiency is unaffected by changes in G (the distribution of ε and the user's information about ε), so that the same tournament's utility remains arbitrarily close to the full information utility for any G as well as if the users can observe ε directly.

4.4 Simulation Results and Analysis

In this section, we will give numerical simulations to illustrate our results. First, we will give the specific form of the utility and cost functions we have defined in the system model. Then, we will show the tournament we obtained by the step function. Finally, we will analyze the system performance by varying different parameters, and do a comparison with other incentive mechanisms.

4.4.1 Simulation Setup

We assume that the conditional distribution follows the logistic distribution as [61]. The logistic distribution is a symmetric and bell shaped distribution, like the frequently used normal distribution. The PDF of a logistical distribution is

$$f(z;a) = \frac{\exp(-\frac{z-a}{\beta})}{\beta[1+\exp(-\frac{z-a}{\beta})]^2}, \tag{4.21}$$

and the CDF is

$$F(z;a) = \frac{1}{1+\exp(-\frac{z-a}{\beta})}, \tag{4.22}$$

where β is the coefficient related to the variance of logistic distribution, which is $\pi^2\beta^2/3$. As β is positively correlated with the variance, we will use β to denote the variance in the sequel. With the PDF and CDF of logistic distribution, we can derive the partial derivative of the probability for the jth-order statistic with respect to effort a, as

$$\frac{\partial P(\text{rank}=j)}{\partial a} = \frac{2j-n-1}{\beta[n(n+1)]}. \tag{4.23}$$

According to (4.11), we must have $2j-n-1>0$. Thus, the maximum number of reward recipients will not be more than half of the participate users. The reward recipients should be the users whose rank is higher than $(n+1)/2$. While the users whose rank is lower than $(n+1)/2$, will only receive a zero reward.

In the system model, we have defined the evaluation function u as a concave function. Here, we set up the evaluation function u in a form of power function as

$$u(W) = \frac{W^\rho}{\rho}, \tag{4.24}$$

where ρ is the power coefficient and $0<\rho<1$. Here we further define the user's risk averse degree as

$$\eta = -\frac{u''}{u'} = \frac{W}{1-\rho}. \tag{4.25}$$

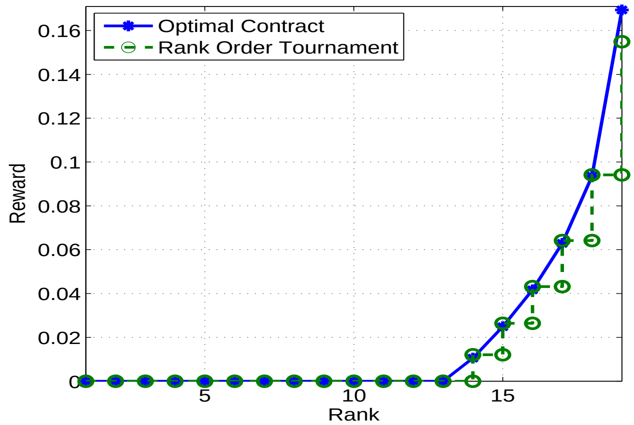


Figure 4.2: Approximation of optimal contract by tournament.

Under the same amount of reward, the larger of ρ and η, the more conservative and sensitive is user towards risk, and vice versa. When $\rho = 1$, the user is risk neutral. As ρ and η are positively correlated with each other, we will use ρ to denote the risk averse degree in the following part. For simplicity, we define the reward function as $R(q) = q$. Thus, the utility function in the optimal contract case becomes

$$v(q) = u[R(q)] = u(q) = \frac{q^\rho}{\rho}. \tag{4.26}$$

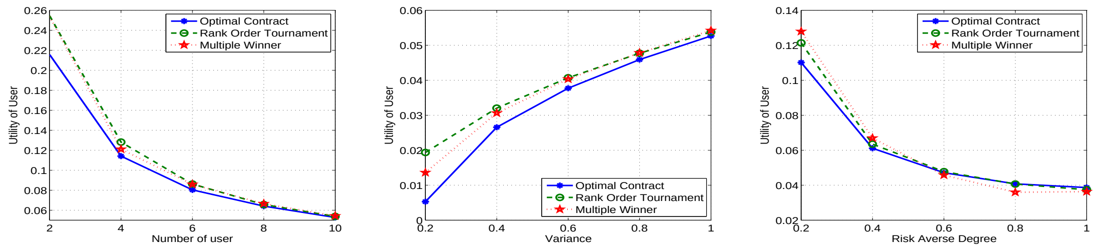
Furthermore, we have defined the cost function in the system model as a convex function. Thus, we set up the cost function γ in a quadratic form as

$$\gamma(a) = \frac{1}{2}a^2. \tag{4.27}$$

We assume that the reservation utility, when the user does not participate in the crowdsourcing, is $\bar{u} = 0$.

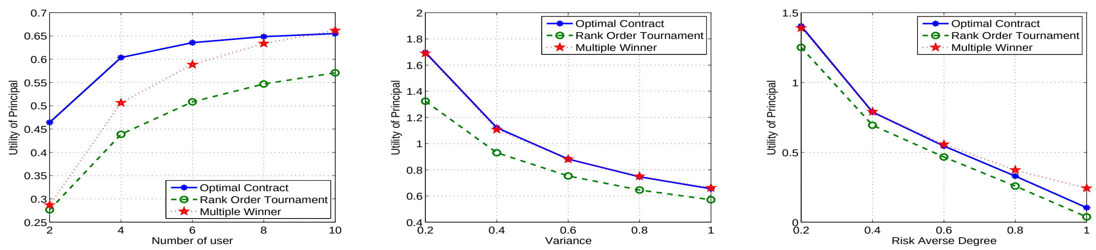
4.4.2 Reward by Tournament

In Fig. 4.2, we follow the steps in Section 4.3 to approximate the optimal contract by tournament with 19 users participate in, with x axis representing the rank of the users in an ascending order. As we can see, the reward obtained by the tournament is close to the reward from the optimal contract with full information. If we increase the number of user to infinity, the tournament can



(a) Number of users. (b) Variance. (c) Risk averse degree.

Figure 4.3: The utility per user as parameters vary.



(a) Number of users. (b) Variance. (c) Risk averse degree.

Figure 4.4: The utility of the principal as parameters vary.

approximate the optimal contract arbitrarily close. In addition, we see that, only users rank is larger or equal to 14 received a positive reward, which is consistent with our conclusion previously that no more than half of the users should be rewarded. be rewarded. Another observation from Fig. 4.2 is that, the higher the user rank, the larger the spread is, that is $W_j - W_{j-1} < W_{j+1} - W_j$. This result is due to the power function form of the evaluation function u. If we change the evaluation function u to a log function, the spread will be the same for all ranks. While if the evaluation function u follows the exponential form, the spread will become smaller for higher ranks.

4.4.3 Comparison

In this part, we are going to analyze user and principal's utilities by varying different parameters in the tournament. In the tournament we have proposed, there are many winners and the amount of reward is based on the relative rank achieved, with larger amounts rewarded to higher ranks. We refer to this as the Rank-Order Tournament (ROT). We will compare the results from the ROT with that from the optimal contract with full information, and another special cases of ROT:

the Multiple-Winners (MW) in which several top winners share the reward equally, and the optimal number of winners can be determined from (4.11).

In Fig. 4.3 we show the utility per user when varying different parameters, and in Fig. 4.4 we show the utility of the principal. The figures show that the factors impacting the design of the contest include the number of users for whom the contest is conducted, the degree of performance uncertainty in the environment (i.e., the strength of the relationship between effort and performance realized), and the user's risk averse degree towards the crowdsourcing activity.

4.4.3.1 Number of Users

When the number of users n increases, the marginal change in probability of achieving any rank decreases. Consequently, with increases in the pool of players, the user will be less likely to induce higher effort levels and less incentive to participate. Thus, we see the user's utility in Fig. 4.3a decreases with the increase of n. However, with more users participating in the crowdsourcing, even though the effort exerted from each user decreases, the summation of the data collected with more number of users increases. As a result, the principal's utility increases as we see from Fig. 4.4a.

4.4.3.2 Variance

The variance β denotes the relationship between effort levels exerted by the user and the performance observed by the principal. As β increases, it indicates a weaker relationship between effort levels and the expected rank achieved. As a result, the users are likely to exert lower levels of effort with the increase in uncertainty, and thus a lower cost of participation. While the optimal contract and tournament designs are independent of the uncertainty, greater uncertainty makes the users more likely to get enough incentives to participate. As we see from Fig. 4.3b that the user's utility is increasing as the variance increases. With the decrease of optimal effort, less data is obtained from the user, the principal's utility will certainly decrease. Therefore, from Fig. 4.4b indicates that the principal's utility is decreasing as the variance increases.

4.4.3.3 Risk Averse Degree

From the definition of risk averse degree we see that when ρ increases, users become more conservative and sensitive to risk, thus less likely to participate in. With less effort obtained from the user, the principal's utility will certainly decrease. Thus, we see from Fig. 4.3c and Fig. 4.4c that the user and principal's utilities decrease with the risk averse degree ρ.

Overall, we see that the optimal contract serves as the upper bound of the principal's utility, and the lower bound of the user's utility for the other two tournament mechanisms in most of the cases. This is intuitive since the optimal contract solves the optimal contract based on the absolute performance. While in tournament, we only have a limited number of users in the simulation. Thus, tournaments lose accuracy during the approximation. The optimal contract provides the principal with maximum utility while extracting as much utility from the users as possible.

From Fig. 4.3 and Fig. 4.4, we also see that the MW outperforms ROT in many cases. In addition, MW outperforms both the optimal contract and ROT when users are risk neutral in Fig. 4.3c and Fig. 4.4c. The reasons for both results can be inspired from the conclusions drawn in [61]. First, when the number of participating users is small, MW is a better mechanism rather than ROT, and is easier to implement. Second, when users are risk neutral, it is optimal to give the entire reward to the highest rank user, which is a special case of MW, rather than offering contract with positive spread in ROT and optimal contract.

4.5 Conclusions

In this paper, we have investigated the problem of providing incentives for users to participate in mobile crowdsourcing by applying the rank order tournament as the incentive mechanism. We have solved the rank order tournament by approximating the absolute performance based optimal contract with full information using step functions. Finally, we use the numerical results to show the tournament design, and compare the user's and principal's utilities under optimal contract and different tournament mechanisms. We have shown that by using the tournament, the principal successfully maximizes the utilities regardless of *common shock*. The principal's utility benefits from large number of users, but deteriorates with weaker relationship between exerted and observed effort levels, and higher risk aversion of users.

Chapter 5

Financing Contract with Adverse Selection and Moral Hazard for Spectrum Trading in Cognitive Radio Networks

5.1 Introduction

The recent popularity of hand-held mobile devices, such as smartphones, enables the inter-connectivity among mobile users without the support of Internet infrastructure. With the wide usage of such applications, the data outburst leads to a booming growth of various wireless networks and a dramatic increase in the demand for radio spectrum [62]. However, we are currently in the exhaustion of available spectrum. Thus, cognitive radio (CR) has emerged as a new design paradigm as its opportunistic access to the vacant licensed frequency bands, which releases the spectrum from shackles of authorized licenses, and at the same time improves the spectrum utilization efficiency [63].

Cognitive radio networks (CRNs) are designed based on the concept of dynamic spectrum sharing where CR users can opportunistically access the licensed spectrum. In a CRN, the primary users (PUs) are the licensed users to utilize the frequency band, while the secondary users (SUs) can only utilize those spectrum resources when the PUs are vacant. Whenever the PUs are back, the SUs must vacate the frequency band immediately to guarantee the PUs' quality of service (QoS) [64]. In other words, in a CRN, the PUs have higher priority to use the frequency bands than the SUs. The SU can be regarded as a radio which is capable of changing its transmitter parameters and transmitting/operating frequency based on its interaction with the environment [65].

In CRNs, the problems of spectrum sensing and resource allocation have been extensively studied in previous works such as [66]. In this work, we will focus on the economic aspect of spectrum trading between the PU and SU, which achieves SU's dynamic spectrum accessing/sharing and creates more economically benefits for the PU. The idea of the market-driven structure has

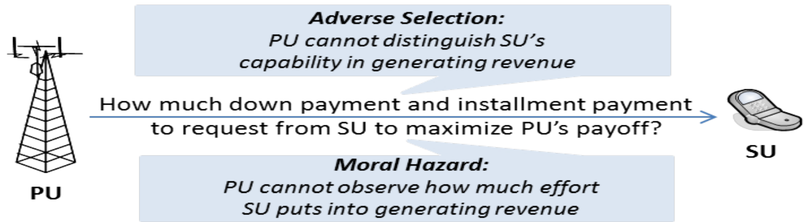


Figure 5.1: The problems of *adverse selection* and *moral hazard* in financing contract design.

initiated the spectrum trading model in CRNs, and promoted a lot of interesting researches on the design of trading mechanisms. Through spectrum trading, PUs can sell/lease their vacant spectrum for monetary gains, and SUs can purchase/rent the available licensed spectrum if they are in need of radio resources to support their traffic demands [9].

However, most mechanisms such as [67] are designed for the one-shot trading problem. Different from the previous studies, we consider offering a contract based mechanism that allows the SU to do a financing, as we do for a house or a car [68]. That is, the SU only needs to pay part of the total amount at the point of signing the contract, known as the down payment. Then the spectrum can be released to the SU by the PU. Successively, the SU can utilize the spectrum to transmit package and generate revenue. Afterwards, the SU pays the rest of the loan, known as the installment payment.

However, the PU may not have the full knowledge of the SU's financial status, i.e., how much cash the SU has in hand for the down payment, in which case the problem of *adverse selection* arises. Moreover, the PU neither knows the SU's capability in utilizing the spectrum, i.e., what is the SU's probability of successful generating revenue, where the problem of *moral hazard* arises [69]. Thus, we model the spectrum trading by a contract theoretical model which involves both *adverse selection* and *moral hazard* problems as shown in Fig. 5.1.

The main contributions of this paper are first we propose the spectrum trading mechanism as a financing contract, instead of a one-shot trading. Second, we propose the innovative model that involves both *adverse selection* and *moral hazard* problems, which is rooted in economics research. Third, we give detailed analysis of this model by considering three different scenarios, i.e., two extreme cases where only *adverse selection* or only *moral hazard* is present, and the general case where both of the two problems are present. Finally, through simulations, we analyze and compare the optimal contracts under the three scenarios, and provide a thorough study of the key parameters' influences on the PU's and SU's payoffs.

The remainder of this paper is organized as follows. First, we will introduce the system model in Section 5.2. Then, the problem formulation is described in Section 5.3, and we propose the solution of the three scenarios. The performance evaluation is conducted in Section 5.4. Finally, Section 5.5 draws the conclusion.

5.2 System Model

Based on the earliest model in [68], we consider the spectrum trading between one PU and one SU in one CRN. The contract can be extended to other SUs in the same CRN. Both the PU and SU are risk natural which means they have no preference between saving and consuming. The PU's spectrum is vacant, and the PU cannot generate any revenue from the vacant spectrum unless selling/leasing to the SU.

The PU offers a financing plan (t_i, r_i) to the SU to pay for utilizing the spectrum, where t_i is a down payment, and r_i is an installment payment to be paid from the future revenues generated. The problem that the PU needs to solve is to find the optimal contract that can maximize its expected return from the spectrum trading by deciding how much down payment, and how much installment payment the SU needs to pay.

The SU makes use of the spectrum to run its own "business", which can only result in a success (receive a revenue of $R \geq r_i \geq 0$) or failure (receive a revenue of 0), i.e., the revenue realizations: $X \in \{0, R\}$. The SU may be more or less able at utilizing this vacant spectrum, whose capability may belong to two different types $\theta \in \{\theta_L, \theta_H\}$ with $\theta_L < \theta_H$, which donate lower or higher capability to generate revenue, respectively. The PU may not be able to observe the SU's capability type, but with a priori that the SU has a high capability θ_H with probability $\beta \in [0, 1]$ and a low capability θ_L with probability $(1 - \beta)$.

The SU's capability θ can be translated into the probability of getting the high revenue R. Besides the capability, the SU can also increase its efforts e (e.g., transmission power) to raise probability of getting R. Thus, we define the SU's probability of generating high revenues R as $\theta e \in (0, 1)$. In addition, we assume that the SU's operation cost ψ on the spectrum is a convex function of effort e, which is

$$\psi(e) \equiv \frac{c}{2}e^2, \tag{5.1}$$

where c is the cost coefficient. To ensure that the probability $0 < \theta e < 1$, we take c to be large enough that the SU would never want to choose a level of effort e such that $\theta e \geq 1$.

We assume that there is no installment payment if the SU cannot generate revenue from utilizing the spectrum, i.e., $r_i = 0$ if $X = 0$. The installment payment r_i is made only when $X = R$. Thus, the expected payoff of SU with capability θ_i under contract (t_i, r_i) then takes the form of

$$U_{SU_i} = \theta_i e_i(R - r_i) - t_i - \frac{c}{2}e_i^2, \quad i \in \{L, H\}. \tag{5.2}$$

The revenue R minus installment payment r_i is the SU's income. The SU's expected payoff is the expected income minus the down payment and cost of operation.

Similarly, we define the expected payoff of the PU as

$$\begin{aligned} U_{PU} &= \sum_i \beta_i(t_i + \theta_i e_i r_i), \quad i \in \{L, H\} \\ &= \beta[t_H + \theta_H e_H r_H] + (1 - \beta)[t_L + \theta_L e_L r_L]. \end{aligned} \tag{5.3}$$

The PU's expected payoff is the summation of the down payment and expected installment payment.

Then, the PU's problem is

$$\begin{aligned} &\max_{(t_i, r_i)} \beta[t_H + \theta_H e_H r_H] + (1 - \beta)[t_L + \theta_L e_L r_L], \\ &\qquad s.t. \\ &(IC) \quad \theta_i e_i(R - r_i) - t_i - \frac{c}{2}e_i^2 \geq \theta_i e_i'(R - r_j) - t_j - \frac{c}{2}e_i'^2, \\ &(IR) \quad \theta_i e_i(R - r_i) - t_i - \frac{c}{2}e_i^2 \geq 0, \\ &\qquad \forall j \neq i, \quad i, j \in \{L, H\}, \end{aligned} \tag{5.4}$$

where e_i' is the effort of θ_i SU when selecting contract (t_j, r_j). The IC constraint stands for incentive compatibility, which means the SU can only maximize its expected payoff by selecting the financing contract that fits its own capability. The IR constraint stands for individual rationality, which provides the SU necessary incentives to sign the contract.

Taking the first derivative of SU's expected payoff with respect to effort e, we have the SU's optimal choice of effort e^* under the contract (t, r) as

$$e_i^* = \frac{1}{c}\theta_i(R - r_i), \quad i \in \{L, H\}. \tag{5.5}$$

Similarly, we have $e_i' * = \frac{1}{c}\theta_i(R - r_j)$. As we can see from this equation, the SU's optimal choice of effort e_i^* is independent of t_i but is decreasing in r_i. In other words, the SU will have fewer incentives to put more effort in utilizing the spectrum, if it must share more of the generated revenue, regardless of the amount of the down payment t_i. The decrease of effort e directly affects the probability of successfully generating revenue R. Thus, it is critical to balance the trade off between providing necessary incentives for the SU and request more installment payment from the SU.

Replacing SU's choice of effort e_i and e_i' in (5.4), we have the PU's problem in the following form.

$$\max_{(t_i, r_i)} \beta[t_H + \frac{1}{c}\theta_H^2(R - r_H)r_H] + (1 - \beta)[t_L + \frac{1}{c}\theta_L^2(R - r_L)r_L], \tag{5.6}$$

$$\begin{aligned} s.t. \quad (IC) \quad & \frac{1}{2c}[\theta_i(R - r_i)]^2 - t_i \geq \frac{1}{2c}[\theta_i(R - r_j)]^2 - t_j, \\ (IR) \quad & \frac{1}{2c}[\theta_i(R - r_i)]^2 - t_i \geq 0, \\ & \forall j \neq i, \quad i, j \in \{L, H\}. \end{aligned}$$

In this problem, it is not possible to decide a priority which of the two incentive problems is the more important, i.e., to disentangle the *moral hazard* from the *adverse selection* dimension. In the following section, we will detail the respective roles of *moral hazard* and *adverse selection* and the implications of their simultaneous presence. As we shall see, the design of the optimal financing contract for this problem depends on whether only the *adverse selection* or the *moral hazard* (or both) are explicitly taken into account.

5.3 Problem Formulation

In this section, we will solve the PU's problem by giving detailed analysis of the proposed model by considering three different scenarios, i.e., two extreme cases where only *adverse selection* or *moral hazard* is present, and the general case where both are present.

5.3.1 Optimal Contract with Moral Hazard Only

Suppose that the PU is able to observe the SU's financial status. So that the *adverse selection* problem is removed, and the only remaining incentive problem is *moral hazard*. Then the PU's problem can be treated separately for different capability SU and reduces to

$$\max_{(t_i,r_i)} t_i + \frac{1}{c}\theta_i^2(R-r_i)r_i, \tag{5.7}$$

$$s.t. \quad (IR) \quad \frac{1}{2c}[\theta_i(R-r_i)]^2 - t_i \geq 0,$$

$$i \in \{L, H\}.$$

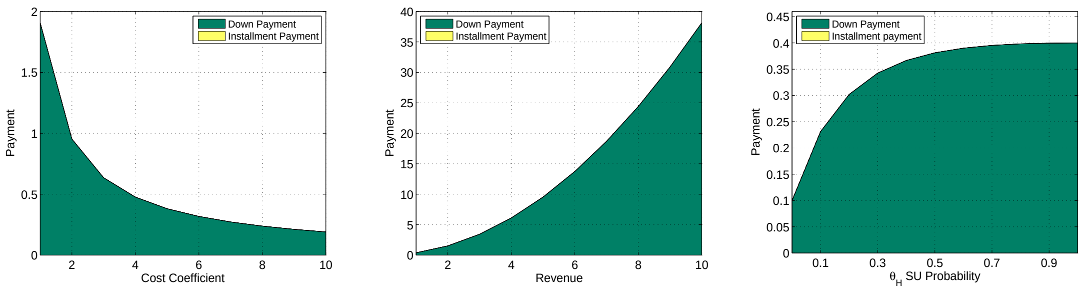
Since the IR constraint is binding, the problem becomes

$$\max_{r_i} \frac{1}{2c}[\theta_i(R-r_i)]^2 + \frac{1}{c}\theta_i^2(R-r_i)r_i. \tag{5.8}$$

After simplification, the problem is equivalent to

$$\max_{r_i} \frac{1}{2c}\theta_i^2(R^2-r_i^2). \tag{5.9}$$

The solution for this maximization problem is $r_H = r_L = 0$ and $t_i = \frac{1}{2c}\theta_i^2 R^2$. As there is no *adverse selection* present, the PU only need to minimize the negative effect of *moral hazard*. To avoid the *moral hazard* problem, it is optimal for the PU to sell the spectrum for cash only, and not keep any financing participation in. The only reason why the PU might want to keep some financing participation in this pure *moral hazard* case is that the SU may be financially constrained and may not have all the cash available for the down payment.



(a) Cost Coefficient c (b) Revenue R (c) θ_H SU Probability β

Figure 5.2: The financing contract for θ_H SU as parameters vary.

5.3.2 Optimal Contract with Adverse Selection Only

Suppose now that the SU's effort level is fixed at some level $\widehat{e}$, but the PU cannot observe the SU's financial status. The PU's problem then reduced to

$$\max_{(t_i,r_i)} \beta[t_H + \theta_H \widehat{e} r_H] + (1-\beta)[t_L + \theta_L \widehat{e} r_L], \tag{5.10}$$

$$s.t. \quad (IC) \;\; \theta_i \widehat{e}(R - r_i) - t_i \geq \theta_i \widehat{e}(R - r_j) - t_j,$$

$$(IR) \;\; \theta_i \widehat{e}(R - r_i) - t_i - \frac{c}{2}\widehat{e}^2 \geq 0,$$

$$\forall j \neq i, \quad i, j \in \{L, H\}.$$

This problem also has a simple solution: $r_H = r_L = R$ and $t_i = -\frac{1}{2}c\widehat{e}^2 < 0$. Intuitively, the down payment should be larger than or equal to 0. However, in this optimal contract, the SU has a negative down payment, i.e., the PU has to pay $\frac{1}{2}c\widehat{e}^2$ to the SU instead. This result is due to the fact that the PU asks for 100% of the future return from the SU. In order to hold the IR constraint, a down payment from the PU to the SU is necessary.

5.3.3 Optimal Contract with Adverse Selection and Moral Hazard

The simplicity of the preceding solutions is of course driven by the extreme nature of the setup. However, neither extreme formulation is an adequate representation of the basic problem in practice, and that it is necessary to allow for both types of incentive problems to have a plausible description of the spectrum trading in practice. Not surprisingly, the optimal menu of contracts where both types of incentive problems are present is some combination of the two extreme solutions that we have highlighted.

Solving the problem of the PU can be done by relying on the pure *adverse selection* methodology detailed in [21]. Specifically, the analysis shows that only the IR constraint of the θ_L SU and the IC constraint of the θ_H SU will be binding. Indeed, first, when the θ_L SU earns nonnegative rents, so will the θ_H SU, who can always mimic the θ_L SU. Second in the symmetric information scenario, that is, pure *moral hazard* optimum, the PU manages to leave the θ_H SU with no rents, but this outcome is what would induce the SU to mimic the θ_L SU. Therefore, the PU has to solve

$$\max_{(t_i,r_i)}\{\beta[t_H+\frac{1}{c}\theta_H^2(R-r_H)r_H]+(1-\beta)[t_L+\frac{1}{c}\theta_L^2(R-r_L)r_L]\}, \tag{5.11}$$

$$s.t.$$

$$(IC)\quad \frac{1}{2c}[\theta_H(R-r_H)]^2-t_H=\frac{1}{2c}[\theta_H(R-r_L)]^2-t_L,$$

$$(IR)\quad \frac{1}{2c}[\theta_L(R-r_L)]^2-t_L=0.$$

Using the two binding constraints to eliminate t_H and t_L from the objective function, we obtain the usual efficiency-at-the-top condition $r_H=0$ (as in the pure *moral hazard* case).

The first-order condition with respect to r_L involves the usual trade-off between surplus extraction from the θ_L SU and informational rent concession to the θ_H SU, and leads to

$$r_L=\frac{\beta(\theta_H^2-\theta_L^2)R}{\beta(\theta_H^2-\theta_L^2)+(1-\beta)\theta_L^2}, \tag{5.12}$$

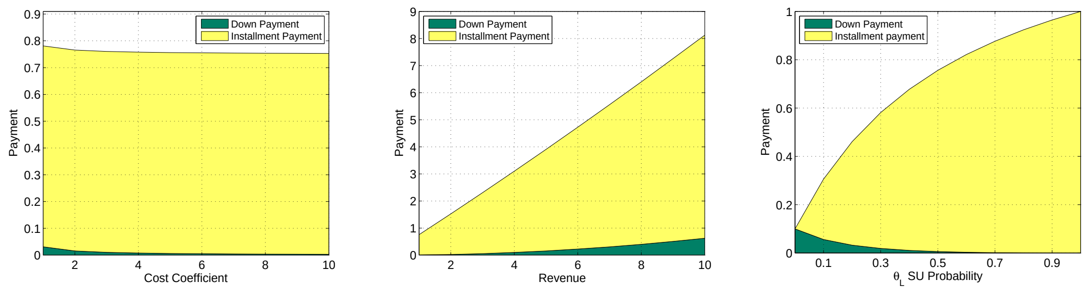
which is bigger than 0.

By taking r_L and r_H into the constraints IC and IR in (11), we obtain the down payments in this general case, which are:

$$t_L=\frac{1}{2c}[\theta_L(R-r_L)]^2 \quad \text{and} \tag{5.13}$$

$$t_H=t_L+\frac{1}{2c}\theta_H^2[(R-r_H)^2-(R-r_L)^2]. \tag{5.14}$$

The optimal menu of contracts is thus such that there is no effort-supply distortion for the high capability SU because it is a 100% residual claimant. But there is a downward effort distortion



(a) Cost Coefficient c (b) Revenue R (c) θ_L SU Probability β

Figure 5.3: The financing contract for θ_L SU as parameters vary.

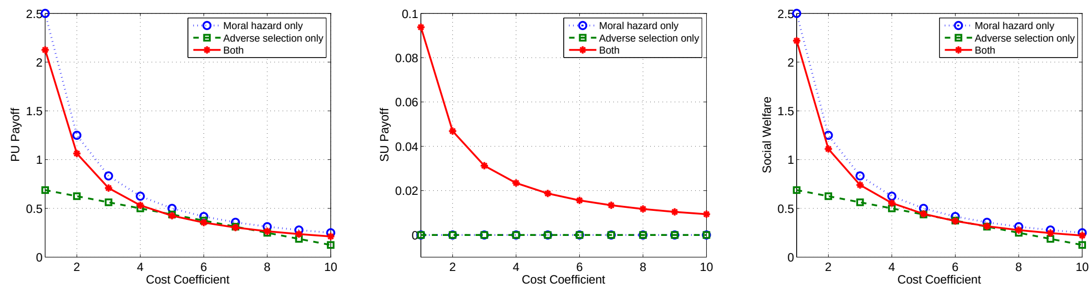
for the low capability SU that serves the purpose of reducing the informational rent of the high capability SU. The extent of the distortion, measured by the size of r_L, depends on the size of the ability differential $(\theta_H^2 - \theta_L^2)$ and on the PU's prior β: The more confident the PU is that it faces a high SU type, the larger is its stake r_L and the larger is the down payment t_H.

5.4 Simulation Results and Analysis

In this section, we will first give an analysis about the financing contract when both *adverse selection* and *moral hazard* are present by varying the parameters such as the cost coefficient, revenue, and the SU's probability of being θ_H. For the two extreme cases where only *adverse selection* or *moral hazard* is present, the results can be predicted from the general case. Then, we will conduct comparisons among the PU's and SU's payoffs, and social welfare among the three scenarios we have proposed. In the simulation set up, we assume that $\theta_H = 2$ and $\theta_L = 1$. We set $c = 10$ as a high value so that we can guarantee $\theta_H e < 1$ always holds.

5.4.1 Financing Contract Analysis

In Fig. 5.2, we show the financing contract for θ_H SU when both *adverse selection* and *moral hazard* are present. We see that, with the varying of the three parameters, the installment payment r_H remains 0, as we have stated in the previous section. When the PU knows it is facing a SU with enough cash in hand, it will ask the SU to pay the total amount money when signing the contract, but no installment payment afterwards.



(a) PU's payoff (b) SU's payoff (c) Social welfare

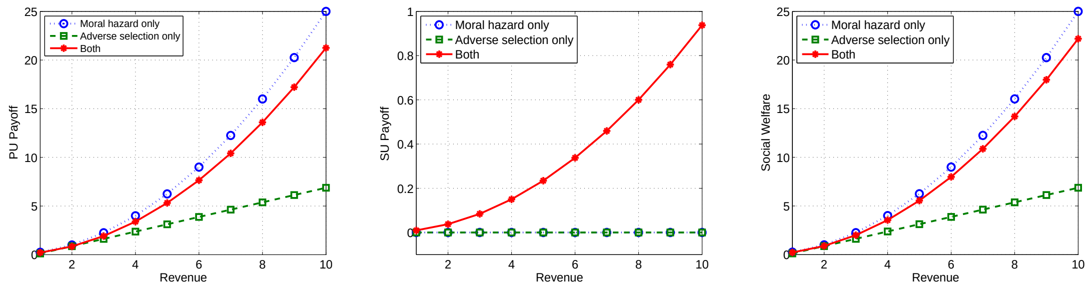
Figure 5.4: The system performance as the cost coefficient c varies.

From Fig. 5.2a we see that, as the cost coefficient c increases, the down payment (i.e., the price of the spectrum) decreases. This result is intuitive in the sense that, when the SU's cost of generating revenue by utilizing the spectrum increases, the SU will be less likely to participate. Thus, the PU must lower its price to attract SU's participation. Otherwise, the vacant spectrum is wasted and 0 payoff is obtained by the PU.

In Fig. 5.2b we see that, as the SU's revenue R by "running" on the PU's spectrum increases, the cash payment required from the PU increases. This result is also easy to see as if the spectrum can bring more revenue for the SU, the spectrum's value is higher. Thus, the PU would definitely assigned a higher price for the spectrum.

Fig. 5.2c shows when the PU's probability of trading with a θ_H SU increases, it will also rise the spectrum's price. As we have defined in the system model, the SU's successful probability of obtaining a revenue is θe. Therefore, under the same effort e, the high capable SU will bring larger expected revenue than low capable SU, as $\theta_H > \theta_L$. Thus, similar to Fig. 5.2b, the PU will rise the price as the value of spectrum increases.

Fig. 5.3 is similar to Fig. 5.2, as we are showing the financing contract for the θ_L SU. While different from Fig. 5.2 is that, the PU ask for both cash and installment payment from the low capable SU, instead of only down payment when the SU is high capable. This result is intuitive in the sense that, the low capable SU has limited cash at hand at the trading. Thus, the PU will only ask for a small amount of down payment first, while most of the money is paid after the SU has generated revenue from using the spectrum as we have stated in the previous section.



(a) PU's payoff (b) SU's payoff (c) Social welfare

Figure 5.5: The system performance as the revenue R varies.

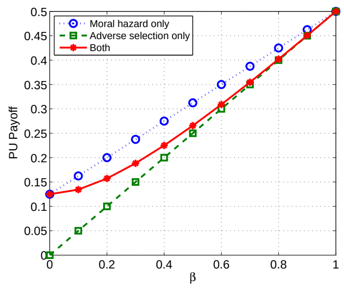
From Fig. 5.3a we see that, as the cost coefficient c increases, both the down and installment payments decrease. The reason for this result is the same as that in Fig. 5.2a that the PU must lower its price to attract SU's participation.

In Fig. 5.3b we see that, as the SU's revenue R by running on the PU's spectrum increases, both the down and installment payment asked from the PU increase. The reason for this result is the same as that in Fig. 5.2b that as the spectrum's value grows higher, the PU would definitely ask for a higher price.

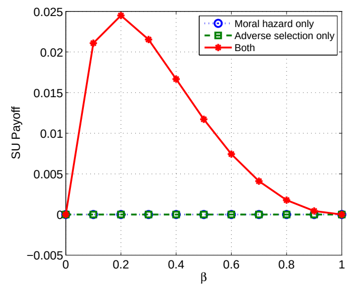
Fig. 5.3c shows the optimal contract when the PU's probability of trading with a θ_L SU increases. As the PU becomes more certain that it is trading with a low capable SU with less cash in hand, it will lower the cash payment first, but ask for more installment payment instead, which is the SU's price of paying less cash at first.

5.4.2 System Performance

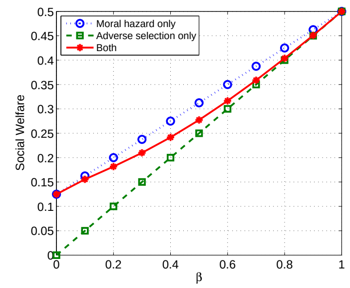
From Fig. 5.4 to Fig. 5.6, we compare the system performance under the three scenarios we have proposed: *moral hazard* only, *adverse selection* only, and when both are present. In the following part, we will give a detailed analysis of the cost coefficient c, revenue R, and distribution β's effects on the system performance.



(a) PU's payoff



(b) SU's payoff



(c) Social welfare

Figure 5.6: The system performance as the θ_H SU probability β varies.

5.4.2.1 Cost Coefficient

In Fig. 5.4, we vary the value of the cost coefficient c to see the effects on the PU's and SU's payoffs, and the social welfare in the three scenarios. As we can see, PU's and SU's payoffs and social welfare decrease as the cost coefficient increases, except the SU's payoff under *moral hazard* only and *adverse selection* only scenarios. Under those two extreme cases, the PU has the full acknowledgment of either the SU's cash in hand or the effort put into using the spectrum. Thus, the PU can extract as much revenue as possible from the SU, which leaves the SU with 0 payoff. The reason for the decreasing of payoffs and social welfare is similar to the analysis we gave for Fig. 5.2a and 5.3a that as the cost increasing, the price for the spectrum will decrease to attract SU. As a result, the payoffs of the PU and SU, together with social welfare, will decrease.

5.4.2.2 Revenue

In Fig. 5.5, we try to see the PU and SU's payoffs, and the social welfare when the revenue R can be generated from using the spectrum increases. We see that the payoffs and social welfare increase with the revenue except the SU's payoff under *moral hazard* only and *adverse selection* only scenarios. The increase of payoffs and social welfare with the revenue R is easy to understand as we have explained in the previous paragraph that the PU will extract all the information rent from the SU.

5.4.2.3 Distribution

In Fig. 5.6, we see that PU's payoff and the social welfare increase as β gets larger. The reason for this result is the same as we have explained for Fig. 5.2c and 5.3c, as the PU will ask for more money if it believes that it is facing a high capable SU. However, the increase of β has a negative effect on the SU's payoff as the PU is trying to extract revenue from the SU.

Overall, from Fig. 5.4-5.6,we see that, the two extreme cases serve as the upper and lower bounds, respectively. The PU's payoff in the general case where both *moral hazard* and *adverse selection* present lies between the two extreme cases.

5.5 Conclusions

In this paper, we have proposed a financing contract to address the problem of spectrum trading in a cognitive radio network. We have modeled the problem by considering both the *adverse selection* and *moral hazard* of the SU. In addition, we have analysed three different scenarios, i.e., two extreme cases where only *adverse selection* or *moral hazard* is present, and the general case where both are present. Through extensive simulations, we have given the analysis about the financing contract for all considered scenarios. We have also shown different parameters' effects on the system performance and that the two extreme cases serve as the upper and lower bound of the general case where both problems are present.

Chapter 6

Conclusion and Future Works

6.1 Conclusion Remarks

In this dissertation, we have provided the contract theory framework for wireless networking, which was nominated Nobel Prize in economics for 2014. Contract theory is highly evaluated due to its effectiveness in market power and regulation — specifically how to regulate oligopolies in situations with asymmetric information, i.e., when regulators do not know everything about how firms are operating. Meanwhile, contract theory itself is an efficient tool in dealing with asymmetric information between employer/seller(s) and employee/buyer(s) by introducing cooperation. Such a framework for designing regulations and has been applied to a number of industries, from banking to telecommunications. Given the properties of wireless networks, which encounters many situations of asymmetric information and the need of cooperation, contract theory is an excellent tool by modeling the employer/seller(s) and employee/buyer(s) as different roles depending on the scenario under consideration.

This dissertation provides a theoretical research between wireless communications, networking, and economics, in which different contract theory models have been applied in various wireless networks scenarios. We start with the fundamental concepts of contract theory, and introduced the potential applications for each class of the typical contract problems: *adverse selection*, *moral hazard* and the mixed of them two. Specially, we have investigated the design of reward, which is the most critical element in an incentive mechanism design. We have also provided a detailed description on the potential of using such contract-theoretic tools in several wireless applications, such as spectrum trading cognitive radio network, relay selection, distributed computing, D2D communication, and mobile crowdsourcing.

In the first application, the problem of pure *adverse selection* is studied to solved the incentive problem of encouraging cellular UEs to participate in D2D communication underlaid cellular network. Given the information asymmetry that the UEs' preferences are unobservable to the BS, we have proposed a self-revealing mechanism that forces UEs to select the contracts that are in consistent with their preferences. Simulation results have shown that the proposed approach out performs the *linear pricing* which does not try to retrieve any information at all, but lower than the optimal contract with *no information asymmetry*.

Next, the problem of pure *moral hazard* is studied to investigated the issue of providing incentives for smart device users to participate in the mobile crowdsourcing. Especially, we have solved the problem in two different situations: multi-dimension and multi-user. In the multi-dimension case, the principal offers multiple tasks for the user to complete, and rewards user from multi-dimension evaluations. The optimal contract is solved as a bundle of reward and effort (w, a). In the multi-user case, the principal rewards users based on the rank of their performance as in a tournament. The optimal contract is solved as a fixed list of prizes. In both applications, the numerical results showed the comparisons between the utilities in the optimal contracts and other different incentive mechanisms, and analyzed that the principal's utility varies with different parameters such as operation cost coefficient, risk aversion degree, and measurement error variance.

Finally, the mixed problem of both the *adverse selection* and *moral hazard* problems are studied to address the problem of spectrum trading in a cognitive radio network. The unobservable of SU's capability in generating revenue from utilizing the spectrum of modeled as *adverse selection* and the unobservable of SU's effort putting into utilizing the spectrum is modeled as *moral hazard*. The three different problems, i.e., two extreme cases where only *adverse selection* or *moral hazard* is present, and the general case where both are present are solved and analyzed. Through extensive simulations, we have also shown different parameters' effects on the system performance and showed that the two extreme cases serve as the upper and lower bound of the general case where both problems are present.

From those works, we have seen contract theory as a useful framework to design incentive mechanisms to motivate the third party's cooperation in emerging wireless networks, such as heterogeneous networks, D2D communication, mobile crowdsouring and cognitive radio networks. In a nutshell, this dissertation is expected to provide an accessible and holistic survey on the use of new techniques from contract theory to address the future of wireless networks network economics area, and have a long term effect on problems such as incentive mechanism and pricing schemes design, resource sharing and trading.

6.2 Future Work

Under the background of rapid development wireless networks and the proliferation of highly capable mobile devices, cooperations in wireless networks are and will be in highly demand in various areas. Incentive mechanism design to ensure cooperation falls into the emerging world-class high-impact theoretical research between wireless communications, networking, and economics. Thus, we see there is a great potential to do further research in incentive mechanism design and use contract theory to solve cooperation problems in wireless networks. The following are research directions that can be further explored in this area of research.

- *Exploring emerging wireless network applications*: There are many areas in wireless networks where the cooperation among different parties is extremely needed. Some interesting areas where cooperation is expected to play a key role include wireless network virtualization, cloud radio access networks, physical layer security, multimedia distribution in ultra-dense networks, and load management in wireless networks with machine-to-machine communications.

- *Exploring new contract theory models*: First, current applications in wireless networks do all belong to the static basic and extended models in multi-dimension and multi-lateral *adverse selection* and *moral hazard* models. In the future works, we can extend the static models into repeated contracting ones, which show great potential in modeling more sophisticated interplay between different parties. Second, contract theory can be used to address wireless networking problems other than cooperation incentives. There are other models in contract theory that provide potential techniques, e.g., using insurance design and audition in mobile cloud computing or using system hierarchy efficiency in infrastructure deployment.

- *Exploring the connection between wireless physical meanings and economic factors*: By applying this micro economic model into wireless networks, it is important to well model and define the economic parameters with appropriate wireless communication network physical meanings. Since the ultimate goal of using contract theory here is to address the technical problems in wireless networks. Without properly characterizing the wireless network system, the solution will be less meaningful and infeasible to apply.

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