Towards sustainable socially-aware mobile crowdsensing : leveraging hierarchical game for incentive mechanisms

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**Towards Sustainable Socially-Aware Mobile Crowdsensing:
Leveraging Hierarchical Game for Incentive Mechanisms**

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Towards Sustainable Socially-Aware Mobile Crowdsensing: Leveraging Hierarchical Game for Incentive Mechanisms

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A thesis submitted to the Nanyang Technological University in partial fulfillment
of the requirement for the degree of
Doctor of Philosophy

2020

Statement of Originality

I hereby certify that the work embodied in this thesis is the result of original research, is free of plagiarised materials, and has not been submitted for a higher degree to any other University or Institution.

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Authorship Attribution Statement

This thesis contains material from FOUR paper(s) published in the following peer-reviewed journal(s) where I was the first and/or corresponding author.

Chapter 3 is published as

Jiangtian Nie, Jun Luo, Zehui Xiong, Dusit Niyato and Ping Wang, A stackelberg game approach toward socially-aware incentive mechanisms for mobile crowdsensing, *IEEE Transactions on Wireless Communications*, vol. 18, no. 1, pp. 724–738, 2018,

The contributions of the co-authors are as follows:

- Prof Luo provided the initial research direction.
- I prepared the manuscript drafts. The manuscript was revised by Prof Luo, Prof Niyato and Prof Wang.
- I proposed the system model, formulated the optimization problem and performed the game theory analysis.
- Dr Xiong assisted in the implementation of game simulation.

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- I prepared the manuscript drafts. The manuscript was revised by Dr Xiong, Prof Luo, Prof Niyato and Prof Wang.
- I designed the system model, algorithm, and implemented all the relevant simulation coding to conduct the performance evaluation. I obtained and analyzed the engineering insights from the numerical results.

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The contributions of the co-authors are as follows:

- Prof. Luo provided the initial project direction.
- I prepared the manuscript drafts. The manuscript was revised by Dr Xiong, Prof Luo, Prof Niyato, Prof Wang and Prof Poor.
- I designed the system model, completed the mathematical derivations, implemented the simulation coding and conducted the performance evaluation.
- Dr Xiong assisted in the real-word data simulation.

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- Prof. Luo and Prof. Niyato provided the initial project direction.
- I performed the survey of literature review and designed the system framework. I implemented the relevant simulation coding and conducted the performance evaluation. I analyzed the engineering insights from the numerical results.
- I wrote the drafts of the manuscript. The manuscript was modified together with Prof Luo, Dr Xiong, Prof Niyato, Prof Wang and Prof Guizani. All authors contributed to the revision.

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Abstract

Traditional mobile crowdsensing has shown a great potential to address large-scale data sensing problems by allocating sensing tasks to pervasive mobile users with smart devices. As crowdsensing service provider involves data collection from mobile users, the issue of providing rewards to incentivize mobile users is fundamentally important to ensure the sustainability of crowdsensing system. Recently, socially-aware crowdsensing services have been introduced as the integration of social networks and crowdsensing platforms. For example, in health-related crowdsensing applications, a mobile user benefits from information regarding food, exercise, medicine and medical treatment collected and shared by her socially-connected friends and family members. In this thesis, incentive mechanism design is revisited in the context of socially-aware crowdsensing, where the game theory tool is used to study the interactions between crowdsensing service provider and mobile users.

In the first part of the thesis, incentive mechanism is designed by considering the underlying social network effects amid mobile social networks, for motivating the participants. Namely, one MU will obtain additional benefits from information contributed or shared by local neighbors in social networks. The process of rewarding and participating is modeled as a two-stage game, and backward induction is used to analyze the mobile users' participation level and the crowdsensing service provider's optimal reward mechanism. The analytical expressions are derived for the discriminatory incentive as well as the uniform incentive mechanisms.

In the second part of the thesis, information asymmetry challenges are investigated. A Bayesian Stackelberg game with incomplete information is formulated to analyze the interaction between the crowdsensing service provider and mobile users, where the social structure information, i.e., the social network effects, among mobile users is uncertain.

The existence and uniqueness of the Bayesian Stackelberg equilibrium is analytically validated by identifying the best response strategies of the mobile users.

To be more general and practical, different with the former two parts, incentive mechanism in presence of multiple crowdsensing service providers is studied in the third part of the thesis. Understanding the behaviors of mobile users and service providers in socially-aware crowdsensing is of paramount importance for incentive mechanisms. With this focus, a multi-leader and multi-follower Stackelberg game approach is proposed to model the strategic interactions among service providers and mobile users, where the social influence of mobile users and the strategic interconnections of service providers are jointly and formally integrated into the game modeling. Through backward induction methods, the existence and uniqueness of the Stackelberg equilibrium are theoretically proved.

In summary, this thesis addresses a few urgent challenging problems with the tools of game theory in the real implementation of incentive mechanism design in the context of socially-aware crowdsensing. Extensive numerical simulations are also conducted to illustrate some important properties of the equilibrium. Finally, several promising research directions are outlined for the future work.

Chapter 1

Introduction

In this chapter, the research scope of the thesis is presented , i.e., the overview of incentive mechanisms in crowdsensing, particularly in socially-aware crowdsensing. The research challenges and motivations are then elaborated. The key research contributions in this thesis and the thesis organization are finally summarized and provided.

1.1 Research Scope

In the past decade, we have been witnessing a fast proliferation of mobile users and devices in daily life. The ubiquitous mobile devices with various embedded functional sensors have remarkably promoted the information generation process. These advances stimulate the rapid development of mobile sensing technologies, and mobile crowdsensing [1], or crowdsensing¹ for short, becomes one of the most attractive and popular sensing paradigms. Mobile crowdsensing leverages the sensing capacity of worldwide available smart phones, e.g., GPS, camera and digital compass, to collect distributed sensory data. Mobile crowdsensing has been recognized as a emerging data collection system to facilitate a wide range of sensing applications and services, e.g., healthcare, intelligent transportation, and environmental monitoring. Instead of deploying massive

¹In the thesis, terms “mobile crowdsensing” and “crowdsensing” are used interchangeably.

Figure 1.1: One example on crowdsensing platform: the crowdsensing-based road traffic information sharing platform.

sensors in traditional sensing system, mobile crowdsensing leverages the existing pervasive personal mobile devices to outsource the sensing tasks. As such, mobile crowdsensing has offered some advantages such as high sensing scalability, great data diversity, and low deployment cost [2, 3]. Realizing the great business potential, lots of crowdsensing-based applications have been designed and introduced in a number of areas. Sensorly [4] is dedicated for WiFi coverage information, Waze [5] and GreenGPS [6] are to collect road traffic information, DietSensor [7] is proposed to share and track users' diet and nutrition, and Noisetube [8] is for monitoring noise pollution.

A basic mobile crowdsensing platform typically includes a Crowdsensing Service Provider (CSP) and a collection of smart phones or Mobile Users (or users for short). The CSP can post a set of sensing tasks with different purposes, and users are actively involved to perform the corresponding tasks, then the CSP offers services to users accordingly. Take a realistic crowdsensing-based road traffic information sharing platform (such as Waze [5]) for example, the company Waze acting as the CSP, posts transportation-based sensing tasks. Those drivers who are interested and then enrolled acting as users

sense and share their data e.g., driving speed or real time locations. The CSP is then able to aggregate the data and provide drivers different crowdsensing services, such as offering live traffic map and providing the driving navigation services, as shown in the Fig. 1.1.

Nevertheless, the implementation of crowdsensing still faces several challenges, one of which is that the voluntary participation in the crowdsensing platform may not be sustainable. This is from the fact that the users need to spend their own resources, e.g., smart phone battery, CPU computing power, storage memory, to accomplish the sensing tasks. Another major concern that discourages the mobile users from participation comes from the potential privacy issues. Therefore, individuals are reluctant to participate and share their collected information due to the lack of sufficient motivation and incentive. Nevertheless, the crowdsensing platforms depend on total users participation level to a great extent. To stimulate and recruit users with mobile devices to join in, CSPs usually provide a reward as a monetary incentive to compensate users' costs or risks. How to design incentive mechanism properly to motivate users by a reward to execute crowdsensing tasks is worth thorough investigations. When the reward is high, more users want to participate and contribute. However, the high reward may lead to an exorbitant cost and redundant information. Conversely, when the reward is small, the collected sensing information from mobile participants is insufficient. Incentive mechanisms in mobile crowdsensing has attracted numerous research attentions, however, most of these studies failed to consider social network among users.

Recently, socially-aware mobile crowdsensing, as Fig. 1.2 shows, has been introduced as an integration of mobile crowdsensing and social networks, rapidly gaining in popularity in the fields of healthcare, entertainment, travel and so on. For example, in wellness and healthcare domains, the applications Runkeeper [9] allows users to use portable or wearable devices to sense and share their fitness information/data with their friends

Figure 1.2: The illustrations of socially-aware crowdsensing services.

from online social networks (e.g., Facebook and Twitter), thereby tracking their exercise. It is shown that the users can benefit from such socially-aware crowdsensing services. For example, a user will reap more benefits, like enjoying the fun of celebrating fitness achievements or comparing with others, if more her friends and family members join the services and contribute their information. Furthermore, it is reported that the users' engagement in physical activities can be significantly improved due to a high sense of relatedness [10, 11]. As such, social influence and couplings among socially-connected users have played a remarkable role in socially-aware crowdsensing. In this case, incentive mechanisms design in socially-aware crowdsensing becomes the research scope and major focus of this thesis.

Moreover, the CSP and users can be self-interested, and make rational decisions towards their individual objectives. This makes a game-theoretical approach naturally suitable to study their strategic decisions. Game theory is able to provide a formal analytical structure with a series of mathematical methods to study interdependent interactions

among rational entities [12]. Among different game theoretic approaches/models, Stackelberg game is one of the approaches ideal to depict the hierarchical interactions between CSPs and users. Stackelberg game [12] models a hierarchical, sequential decision making among players, i.e., a leader choosing its strategy before followers. In crowdsensing, a CSP, i.e., a leader, determines the total reward for users, i.e., followers. Given the reward, the users decide whether to perform sensing tasks to obtain the reward or not. In [13], the authors designed a uniform incentive mechanism for the situation in which all users receive the same reward. The uniqueness of equilibrium is validated, where the profit of the CSP is maximized, and no users could increase its utility from performing sensing tasks by unilaterally deviating from its current strategy. In [14], the authors proposed a similar Stackelberg game model, but a discriminatory incentive mechanism is adopted that different users may receive different rewards.

Nevertheless, there still exist a few urgent challenges in incentive mechanisms for socially-aware crowdsensing, which have not been well addressed in the literature. This will be further elaborated in the next section.

1.2 Research Challenges and Motivations

1.2.1 Social Network Effects

Most of the existing studies have addressed the incentive mechanisms for mobile crowdsensing without considering the interdependent behaviors of mobile users from social domain. This interdependency originates from the network effects. Traditionally, *network effects* refer to the phenomenon that public goods or service is more valuable if it is adopted by more users. In crowdsensing platforms, the participation behavior of mobile users can be deemed as buying “public goods”, which means that the mobile users are more willing to participate and obtain more benefits if the number of other users is

greater. For example, in a crowdsensing-based road traffic information sharing application, a user can receive a better and accurate traffic report if more users join and share their road information. Consequently, the complex and interdependent user behaviors post a big challenge to crowdsensing systems. In fact, network effects frequently exist in densely connected social relationship, playing an important role in promoting the wisdom of crowds [15, 16].

Nevertheless, only a few studies [17, 18] have studied the incentive mechanisms for crowdsensing and exploited the network effects at the same time. The authors in [17, 18] studied the behaviors of mobile users considering the global network effects², which is not appropriate for the structure of an underlying social domain. By contrast, social (local) network effects refer to the case where each user is only influenced directly by the decisions of other densely socially-connected users [20, 21]. For example, in a traffic sharing crowdsensing platform, a user (driver) could obtain a more precise traffic information nearby if more neighbourhood users (users in the same or nearby road) of this user join and contribute their traffic data. On the contrary, this user cannot obtain much benefits if the users in other distant roads join and share their traffic data. This fact motivates us to explore the role of social (local) network effects in designing incentive mechanisms of crowdsensing service.

In Chapter 3, the above challenging problem will be addressed. Therein, the social interactions among users will be studied and a Stackelberg game is formulated to model the rewarding interactions among the CSP and users.

1.2.2 Incomplete Information

Again, most of the prior studies typically adopt a game-theoretic modeling with complete information to investigate incentive mechanisms in crowdsensing. Therein, mobile users

²Global network effects refer to as the phenomenon that a user will obtain higher value when its behavior aligns with any other users [19].

are assumed to upload their private information or personal type to the CSP truthfully. This situation can happen when there is a supervising third party institution in the market.

However, information is rarely complete and known by all players, for example, without the supervising entity, a user does not report private information (type) to the CSP because of the concern on privacy leakage or selfish behaviors. In this case, CSPs do not know the exact information of users, such as sensing preferences, data quality or potential users' malicious behaviors. This information is crucial in determining incentive mechanisms to reach providers' best strategies. Consequently, the uncertain behaviors from users may lead to inefficiency of incentive mechanisms. Therefore, the incomplete information scenario is more suitable and applicable to the real-world crowdsensing applications.

Some studies adopt Bayesian game-theoretic methods that incorporate the probability theory to analyze the random behaviors with uncertain factors such as the participation cost [22]. However, the model for incomplete information about social tie/influence in socially-aware crowdsensing needs to be developed. Motivated by this, Chapter 4 extends the analysis to the scenario where the social structure information, i.e., the social network effects, is not exactly known by the CSP and users. Thus, the incentive mechanism is formulated as a Bayesian Stackelberg game [23, 24], and evaluate the game equilibrium by defining and optimizing the expected utility of users and the expected revenue of the CSP.

1.2.3 Strategic Interactions among Multiple CSPs

From the literature, a large number of existing studies on crowdsensing merely focused on designing incentive mechanisms for a single CSP, which are hence not applicable to the real-world applications. To be more general and practical, it is imperative to study crowdsensing platforms consisting of multiple CSPs and multiple users.

Some studies have considered the multiple CSPs issues such as [25, 26, 27]. Nevertheless, these studies on multiple CSPs neglect the incorporation of social influence among users. This consideration is limited in the sense that it fails to realistically characterize the impacts of social couplings in socially-aware crowdsensing. Moreover, these studies fail to consider the interconnections of difference services of different CSPs, which can be described as substitutability and complementarity. If two services are substitutable, then a user having more of one service causes herself to desire less of the other service. For example, if a user wants to track her running data, she may only select one of the CSPs that provide similar running partner services. By contrast, if two services are complementary, using more of one service requires more usage of another service. For example, a user wants to monitor her health state, she may select both one CSP providing exercise track services and one providing nutrition track services.

Therefore, the users can benefit more from having complementary crowdsensing services together. Specifically, to achieve the profit maximization, how can each CSP strategically design the reward to different users by taking into account both the social influence and the competition from other CSPs in an integrated manner? However, this question has not been answered in the existing literature. Chapter 5 aims to solve this problem by jointly considering the social influence and multiple CSPs while studying the incentive mechanisms for crowdsensing.

1.3 Summary of Contributions and Thesis Organization

Chapter 1 briefly presents the research scope of this thesis. Specifically, the overview of incentive mechanisms for socially-aware crowdsensing is introduced, and its three potential challenges are presented as the research motivations.

Chapter 2 provides the literature review of prior studies that relate to this research. The novel contributions of this thesis and its significance compared with other existing work in the literature are discussed and highlighted.

Chapter 3 investigates the role of social network effects on incentive mechanisms in socially-aware crowdsensing using a hierarchical Stackelberge game approach. Specifically, the interaction between a CSP and mobile users is modeled as a two-stage game and analyze each stage systematically through backward induction. In addition, the social (local) network effects in the model is exploited, and the heterogeneity of the mobile participants are fully characterized. Moreover, Chapter 3 proposes the optimal incentive mechanism in terms of discriminatory reward and uniform reward with complete information.

Chapter 4 develops the Bayesian Stackelberg game to resolve the information asymmetry from incentive mechanisms in socially-aware crowdsensing. Moreover, Chapter 4 investigates incentive mechanism for the crowdsensing platform with incomplete information on social network effects. In the Bayesian Stackelberg game based incentive mechanism, the specific information on social network effects is under uncertainty. Lastly, a unique Bayesian Nash equilibrium adopted by the mobile users is obtained in closed-form. Thereafter, the existence and uniqueness of the Bayesian Stackelberg equilibrium is proved.

Chapter 5 proposes the incentive mechanism in socially-aware crowdsensing taking social influence and multiple CSPs into account jointly. A multi-leader multi-follower based game-theoretic framework is developed to model the hierarchical two-stage interactions between CSPs and users. Essentially, the social influence of users and the strategic interconnections of CSPs are formally incorporated in the payoff modeling of game in an integrated manner. A multi-leader multi-follower Stackelberg game is formulated. The Stackelberg game model optimizes the decisions of players to achieve their individual

objectives, thereby jointly achieving the profit maximization of CSPs and utility maximization of users. For comparison, Chapter 5 also studies the cooperation scenario for CSPs where all the CSPs jointly determine the collusive reward strategies in order to maximize their aggregate profits.

Finally, Chapter 6 provides the conclusion of the thesis, and sheds light on a number of promising open directions for the future work.

Chapter 2

Literature Review

In this chapter, an overview of state-of-the-art research studies on mobile crowdsensing and incentive mechanisms in mobile crowdsensing is presented. Then the related works on socially-aware crowdsensing are reviewed and a series of major challenges of the real implementation of incentive mechanisms in socially-aware crowdsensing are listed: 1) Social network effects among mobile users; 2) Incomplete information between users and Crowdsensing Service Providers (CSPs); and 3) Strategic interactions among multiple CSPs. This chapter also provides and discusses the significant contributions of each chapter in this thesis and their major differences compared with other studies in the literature.

2.1 Mobile Crowdsensing

The formal concept of mobile crowdsensing was firstly proposed in [1], and it is often called as crowdsensing by researchers for short. In [1], crowdsensing is described as a new sensing paradigm where individuals equipped with mobile devices collectively sense and share data regarding to a certain phenomenon of interest. The authors in [1] described the unique characteristics of crowdsensing and introduced some real-life crowdsensing applications. Before the emergence of crowdsensing, there had been several similar concepts including crowd wisdom and participatory sensing. The authors in [28] clarified the

differences among these similar concepts and addressed the fusion of human and machine intelligence as the technical foundation of crowdsensing.

In [1, 28], several challenges of operating crowdsensing platforms were discussed, such as system reliability, resource limitation, privacy preservation, and incentive schemes. Among these challenges, the incentive mechanism design is critical to ensure the enrollment of users and sufficient sensing data. Next, this chapter will provide a literature review about incentive mechanisms in crowdsensing.

2.2 Incentive Mechanisms in Mobile Crowdsensing

Incentive mechanisms play an important role in sustainable crowdsensing, and hence have attracted lots of research attentions [29, 30]. In the following, the studies of incentive mechanisms are divided into four categories based on different objectives.

2.2.1 Participation Level Maximization

The most primary objective of designing incentive mechanisms is to enroll sufficient users to perform sensing tasks such that the CSPs can obtain the corresponding profit gains. Studies on how to maximize the users' participation level, the utilities of users, and profit gains of CSPs are reviewed as follows. In [13, 31], the authors proposed a reward-based mechanism, where the CSP announces a total reward, then the task and reward are allocated if sufficient number of users are willing to collaborate, and the total will be shared among users. In [32], the authors formulated a Stackelberg game to model the interactions among a CSP and users, where the CSP determines the reward and the users decide on the working time. The game equilibrium analysis is provided to optimize the reward. Therein, the authors also devised a reverse auction-based incentive mechanism to maximize the data utility of the CSP. The auction properties for assuring the feasibility of the incentive mechanism are verified. In [33], the authors presented a mechanism for

participation level determination and reward allocation using optimal reverse auction, in which the CSP receives service queries and initiates an auction for user participation. The authors in [34] presented a novel Vickrey-Clarke-Groves game based incentive mechanism for sensing resource sharing by the encouraged participants. The task allocation and resource sharing algorithm is developed to achieve the social fairness and efficiency trade off. In [35], the authors proposed a reverse auction framework, where the users bid their expected reward for their participation, and the CSP selects a subset of bidders (users) to maximize the total participation levels subject to the limited budget. The authors in [36] took the fairness of users into account and presented a reward allocation scheme to promote users' participation and the total utilities of users accordingly.

2.2.2 Quality Aware Incentive Mechanism

Data quality is also a significant consideration while designing incentive mechanisms. A crowdsensing system may still fail to work well even if it owns numerous users as some or even most of the studies upload fake or low-quality data.

Continuous low quality sensing information negatively affects the preciseness of crowdsensing services. Thus, Quality of Information (QoI) that each individual participant and the whole crowd collect is also a critical metric to justify the efficiency of incentive mechanisms. In [37], the authors focused on the issue of data quality of sensing information, and rewarded the participant depending on the quality of its collected data. The authors in [38] explored the truthful mechanism with strong requirements of data integrity where the tasks are time window dependent. A reverse auction framework is adopted to derive the optimal incentive, which is computationally efficient and individually rational. In [14], the authors considered the user-centric model where each user can ask for reserve price, and designed the truthful and scalable auction mechanism for the CSP to achieve revenue maximization. The authors in [39] developed mathematical models

to characterize the quality of recruited users in different sensing applications, aiming to minimize the total cost while satisfying the quality requirements. The authors in [40] studied incentivizing user participation and assigning location dependent tasks with capacity budget. A truthful one-round auction with approximation algorithm is designed to obtain the optimal reward offered to the participants. [41] proposed quality-aware incentive mechanism, in which the CSP pays the participants according to the quality of their sensing information. In [42], the authors proposed a long-term dynamic incentive mechanism to capture the dynamic nature of long-term data quality of participants, where a truthful, quality-aware and budget feasible algorithm is designed for task allocation with polynomial-time computational complexity. In [43], the authors proposed a user selection algorithm using reinforcement learning, where the users are selected according to the historical information on data quality which will be updated by evaluating the status of task accomplishment. The authors in [44] designed an incentive mechanism consisting of two phases to guarantee the data truthfulness of users. Specifically, the former part of the reward is given to users before performing a sensing task based on their historical performance. After the task is done, the users will get the latter part of reward depending on his/her current performance.

2.2.3 Privacy-Aware Incentive Mechanism

Without privacy-preserving mechanisms, users can be reluctant to participate because of the privacy concern on disclosure of personal information. Therefore, privacy protection becomes a significant concern or objective when designing incentive mechanisms. The authors in [45] investigated the auction based incentive mechanism considering social cost minimization and privacy preservation. The participants are selected based on predefined score functions by the CSP, and the individual rationality and differential privacy are guaranteed. The authors in [46] formulated the one-to-many Nash bargaining game to model the interaction between the CSP and participants. The distributed

algorithm that ensures the participators' privacy and reduces the computation load of the CSP is provided. The authors in [47] utilized the blockchain and smart contracts to privacy-preserving incentive mechanism to select users with high-quality of data and avoid malicious behaviors. In [48], the authors studied a privacy-preserving information collection problem with the consideration of information correlation and social relationship. The authors in [49] proposed a privacy mechanism that reduced users' privacy leakage by combining designed noises to the original processed results. In [50], the authors quantified the privacy compensation for data sensing and leveraged contract theory to offer different contracts to users with different privacy preferences. In [51], the authors employed image fuzzy processing to protect users' privacy when the users take and upload photos. In [52], the authors devised an incentive mechanism by leveraging obfuscation function to protect users' personal information from being divulged as some sensing data may contain some sensitive information, such as users' preference or location.

2.2.4 Coverage Maximization

When it comes to location-based crowdsensing services, it is of vital importance to evaluate data coverage issues. For example, if we want to monitor the air quality in a city, the quality of air data uploaded from users are expected to spread across an area of interest, instead of concentrating at only one point. Some of the existing studies have taken the considerations of data coverage in the incentive schemes. The authors in [53] proposed an incentive assignment algorithm to maximize the coverage of area of interest while satisfying a limited resource budget. The algorithm is validated to ensure the representative data samples collection. The authors developed a new framework called Steered Crowdsensing in [54], which controls incentives by introducing gamifications with monetary reward to location-based services. The authors in [55] addressed how to maximize the utility of the coverage of sensing with limited budget for strategy-proof mobile

crowdsensing. To avoid the spatial correlation of sensing data, the authors in [56] proposed the incentive algorithms ensuring that any two users within a limited geographical distance cannot obtain reward concurrently.

2.2.5 Time-sensitive Incentive Mechanism

Sometimes the tasks in crowdsensing systems are not static and will vary with time. Therefore a few of research works focused on modeling dynamic incentive mechanism. In [57], the authors investigated incentive mechanisms in terms of temporal aspect, where sensing tasks are scheduled based on users' sensing costs and available time periods. The authors in [58] considered that the sensing information has an attached time-sensitive value that decreases over time and focused on the incentive design for cooperative data collection of participants. The authors in [59] designed a time-dependent incentive mechanism where the reward dynamically changes based on the real-time priority of sensing tasks and location of users.

2.3 Incentive Mechanism in Socially-Aware Crowdsensing: Principles and Challenges

Recently, socially-aware crowdsensing has been introduced as the integration of social networks and crowdsensing platforms. In a socially-aware crowdsensing system, social ties among users appear to be an important concern as users are allowed to share information with other socially-connected users. As such, incentive mechanism designs for socially-aware crowdsensing are of great importance and require a thorough investigation. This section lists and highlights a series of major research challenges of incentive mechanism designs in socially-aware crowdsensing, which are also the focuses for each chapter in this thesis.

2.3.1 Social Network Effects in Incentive Mechanisms

The first challenge of implementing incentive mechanism in real-world applications is the interdependent behaviors of users. There are two factors resulting in such interdependent behaviors: social networks and network effects. First, it is noted that social networks play an vital role in incentive mechanism for crowdsensing and have been studied in some prior studies. For example, the authors in [60] introduced the social influence among users and demonstrated its significant role in crowdsensing. The users are encouraged to cooperatively perform sensing tasks through social ties, which significantly improves the system efficacy [61]. The authors in [62] leveraged the social relationships among users to promote global cooperation, where they assumed that the quality of sensing tasks are not dependent.

The second factor originates from network effects. Network effects describe the phenomenon that the participation of one user will attract his/her socially-connected users to participate in the same services. In fact, network effects exist in plenty real-world data communication scenarios, e.g., mobile data trading [63] and traffic offloading [64]. However, in the area of crowdsensing, only a few earlier studies have attempted to study the incentive mechanisms with network effects. One pioneering work [17] studied the incentive mechanism for crowdsensing and exploited the network effects at the same time. However, the authors in [17] investigated the behaviors of mobile users under the global network effects, which is not appropriate for the structure of an underlying social network.

The combination of social networks and network effects leads to social network effects. Social (local) network effects refer to the case where each user is only influenced directly by the decisions of other densely socially-connected users [21, 65]. Therefore, this motivates us to explore the role of social network effects on the incentive mechanism of crowdsensing service in this thesis. Along with this direction, Chapter 3 provides

the analysis on incentive mechanisms with social network effects. Therein, the social interactions among users are studied and a Stackelberg game is formulated to model the rewarding interactions among the CSP and users. Chapter 3 also theoretically analyzes the impacts of social influence on incentive mechanisms by addressing the Stackelberg equilibrium.

2.3.2 Incomplete Information in Incentive Mechanisms

Meanwhile, most of the existing studies adopt game-theoretic modeling with complete information to investigate the incentive mechanism in crowdsensing. However, information is rarely complete and known by all players. For example, CSPs do not know the exact preferences, information quality or some personal sensitive data. This information is crucial in determining incentive mechanisms to reach CSPs' best strategies. Consequently, the limited/incomplete information of CSPs may lead to inefficiency of incentive mechanisms. The incomplete information situation can also be referred as the information asymmetry. Information asymmetry is widespread in communication and wireless networks in the fields of traffic offloading in cellular networks [66, 67] and incentive framework in WiFi network [68]. There have been some studies exploring the impacts of incomplete information in crowdsensing incentive schemes. For example, the authors in [22] adopted Bayesian game-theoretic methods that incorporate the probability theory to analyze the random behaviors with uncertain participation cost. In [69], the authors considered a sealed market for the CSP, where the users have imperfect information on other users behavior. The iterative game framework is introduced and the incentive mechanism is obtained by best response dynamics with several iterations. In [50], the authors studied the incomplete information scenario where the CSP does not know each user's exact privacy preference type, but know each type's distribution. In this case, CSP cannot tailor a precise contract item to every certain user, but need to decide a menu of optimal contracts for every type of users.

However, the model for incomplete information about social tie/influence in socially-aware crowdsensing is unexplored and needs to be developed. Chapter 4 develops a Bayesian game model to study the incomplete information of social influence in socially-aware crowdsensing. The optimal reward under uncertainty of social influence was analytically obtained and the interdependence of user behaviors were investigated.

2.3.3 Incentive Mechanisms Design with Multiple CSPs

Moreover, most of the above mentioned studies merely considered the task allocation in crowdsensing platform with a single CSP, which is infeasible in real crowdsensing scenarios. Some of the existing studies have considered a more practical scenario where there are multiple CSPs in crowdsensing platform such as [25, 16, 70, 71, 26, 27]. In [25], the authors formulated the reward competition as a dynamic non-cooperative game. A distributed learning algorithm was proposed where different CSP learns from its historic information to obtain the final incentive policy and each CSP independently designs the reward to maximize its profit and each user decides which CSP. In [70], the authors developed a Markov game to model the CSPs' competitive rewarding strategies with dynamically arriving users, aiming to minimize the social cost by obtaining the Markov correlated equilibrium as the solutions. Likewise, the authors in [16] explored the incentive mechanism with multiple CSPs, where the incentive mechanism is modeled as a noncooperative game. In [71], the authors studied the cooperative task assignments of multiple CSPs, and adopted a clustering method by utilizing the neural networks for user grouping. Besides the competition, the authors in [26] also analyzed the benefits of cooperative among all CSPs by employing bargaining game. The authors in [27] adopted the deep reinforcement learning scheme enabling each CSP to study the reward policy from the interaction history, requiring none of users' privacy information. In [72, 73], the authors studied the insufficient participation problem without a preassumed large user

pool, by first selecting a small set of users and then leveraging the social influence to encourage more users.

Nevertheless, these studies on multiple CSPs neglect the incorporation of social influence among users and the interconnections of service providers . Considering this, Chapter 5 models the interactions among the CSPs and the socially-connected users as a multi-leader multi-follower Stackelberg game, where the social influence of users and the strategic interconnections of service providers are jointly and formally integrated into the game modeling.

Chapter 3

A Hierarchical Game for Incentive Mechanisms with Social Network Effects

This chapter¹ studies the optimal strategies of Crowdsensing Service Providers(CSPs) and Mobile Users(MUs²) in the incentive mechanisms in crowdsensing platform, where for the first time, the influences of the social network effects are considered.

The rest of this paper is organized as follows. Section 3.1 describes the system model and the game formulation. Section 3.2 analyzes the MUs participation level and optimal reward using backward induction under complete information scenarios. Section 3.3 presents the performance evaluation. Section 3.4 summarizes the paper.

3.1 System Model and Game Formulation

This section first presents the system model of incentive mechanisms under consideration. Next the hierarchical Stackelberg formulation is proposed for modeling the interactions among the CSP and MUs.

¹The work in this chapter has been published in [74].

²For ease of explanation, instead of “users”, “MUs” are used to represent “Mobile Users” in the technical parts in this thesis.

3.1.1 System Model

The interaction between a CSP and MUs is modeled as a simultaneous one-shot game, as Fig. 3.1 shows, where the MUs' actions are to choose the participation level and the CSP provides the payment as a reward to incentivize the MUs.

3.1.1.1 Mobile Users' Utility

In the system, the set of MUs are defined as $\mathcal{N} \triangleq \{1, \dots, N\}$. MU $i \in \mathcal{N}$ decide its participation level, i.e., the effort level in participation (e.g., sensing data transmission frequency or sensing resolution), denoted by x_i where $x_i \in (0, +\infty)$.

Let $\mathbf{x} \triangleq (x_1, \dots, x_N)$ represents for all MUs' participation levels, and $\mathbf{x}_{-i}$ for the participation levels of all other MUs except MU i . The reward per effort unit provided to the MUs is given as: $\mathbf{r} = [r_1, \dots, r_i, \dots, r_N]^\top$. In summary, the utility function of MU i is:

$$u_i(x_i, \mathbf{x}_{-i}) = f_i(x_i) + \Phi(x_i, \mathbf{x}_{-i}) + r(x_i) - c(x_i). \quad (3.1)$$

The first term $f_i(x)$ represents the private utility that MU i obtained through the participation, and can be formulated as $f_i(x_i) = a_i x_i - b_i x_i^2$, where $a_i > 0$ and $b_i > 0$ are the coefficients that capture the intrinsic value of the participation to different MUs with heterogeneity [20, 21, 63]. For example, in a crowdsensing application of traffic

Figure 3.1: A Mobile Crowdsensing Market with Social Network Effects.

information sharing, the accuracy of traffic condition on a particular location becomes higher if there exists a user reporting information on that location more frequently [5], i.e., larger x_i . The linear-quadratic function captures the decreasing marginal returns from participation.

The second term, $\Phi(x_i, \mathbf{x}_{-i})$ is denoted as the external benefits gained from the network effects, which is the key component from Eq. (3.1). In social networks, an MU can enjoy an additional benefit from information contributed or shared by the others [19]. The existing work in crowdsensing explored the network effects of global nature, where the additional benefits due to new coming MUs are the same for all the existing MUs [17]. However, due to the structural properties of the underlying social network, it is more appropriate to consider the network effects locally in Crowdsensing service, i.e., the social network effects. Then, the adjacency matrix $\mathcal{G} = [g_{ij}]_{i,j \in \mathcal{N}}$ is introduced. The elements in matrix g_{ij} indicates the influence which MU j has on MU i , which can be unidirectional or bidirectional. This paper considers the case where $g_{ij} = g_{ji}$, i.e., the social tie is reciprocal. Nevertheless, the proposed model can be applied to asymmetric social ties straightforwardly, which is discussed in Section 3.2.3. Specifically, $\sum_{j \in \mathcal{N}} g_{ij} x_i x_j$ represents the additional benefits obtained from the network effects, similar to that in [20, 21, 65].

The third term, $r(x_i)$, is the reward from CSP to the MU i , which is equal to $r_i x_i$ with the participation level based reward mechanism. The last term $c(x_i)$ denotes the cost associated to the participation level of the MU, e.g., energy consumption and network bandwidth consumed. Similar to [17], it is assumed that the cost is equal to $c x_i$, where c is the MU's unit cost. It is noted that, the same approach can be applied to the model with the heterogeneous unit cost (e.g., $c_i x_i^2$) straightforwardly, which will be discussed in Section 3.2.4. The utility function of MU i is expressed by:

$$u_i(x_i, \mathbf{x}_{-i}, \mathbf{r}) = a_i x_i - b_i x_i^2 + \sum_{j=1}^N g_{ij} x_i x_j + r_i x_i - c x_i.$$

3.1.1.2 CSP's Utility

The monopoly CSP is assumed to operate and maintain the platform with a fixed cost, which is ignored for the simplicity of the analysis later. Then, the formulation of revenue for the CSP is given by the profit from total aggregated contribution of all MUs minus the total reward paid to MUs:

$$\Pi = \mu \sum_{i=1}^N (sx_i - tx_i^2) - \sum_{i=1}^N r_i x_i. \quad (3.2)$$

Similar to [65], the linear-quadratic function is also used to transfer an MUs' participation level to the revenue of CSP, which features the law of diminishing return: an MU's contribution increases with the MU's effort level but the marginal return decreases. If all the MUs do not contribute any effort, the utility received by the CSP is $s0 - t0^2 = 0$. μ is a changeable coefficient indicating the value of MUs' participation level. $s, t > 0$ are parameters representing the concavity of MUs' utility.

3.1.2 Hierarchical Stackelberg Game Formulation

The interaction between the CSP and the MUs is modeled as a two-stage single-leader-multiple-follower Stackelberg game as follows.

Definition 3.1 *Two-stage reward-participation game:*

- *Stage I (Reward): The CSP determines the reward, aiming at the highest revenue:*

$$\mathbf{r}^* = \arg \max_{\mathbf{r}} \left\{ \mu \sum_{i=1}^N (sx_i - tx_i^2) - \sum_{i=1}^N r_i x_i \right\};$$

- *Stage II (Participation): Each MU $i \in \mathcal{N}$ chooses the participation level x_i , given the observed reward $\mathbf{r}$ and the participation levels of other MUs $\mathbf{x}_{-i}$, with the goal to maximize its individual utility:*

$$x_i^* = \arg \max_{x_i} u_i(x_i, \mathbf{x}_{-i}, \mathbf{r}).$$

The players in a Stackelberg game consist of one leader and a collection of followers. The leader (CSP) moves first and the followers (MUs) take actions accordingly. In the Stackelberg game, the MUs and the CSP are rational and self-interested, taking strategies to maximize their individual payoffs.

The hierarchical Stackelberg game is solved by finding a subgame perfect equilibrium for discriminatory reward mechanism and uniform reward mechanism for all MUs. The Stackelberg equilibrium is defined as a stable point where the payoff of the CSP (leader) is maximized given that the MUs (followers) adopt their best responses [12].

3.2 Hierarchical Stackelberg Game Equilibrium Analysis

3.2.1 Stage II: MUs' Participation Equilibrium

Based on the definition of the Nash equilibrium, each MU chooses its participation level that is the best response. By setting the first-order derivative $\frac{\partial u_i(x_i, \mathbf{x}_{-i})}{\partial x_i}$ to 0, the best response of MU i can be obtained as follows:

$$x_i^* = \max \left\{ 0, \frac{r_i - c + a_i}{2b_i} + \sum_{j=1}^N \frac{g_{ij}}{2b_i} x_j \right\}, \forall i. \quad (3.3)$$

Each MU's best response includes two parts: $\frac{r_i - c + a_i}{2b_i}$ is independent from the strategies of the other MUs, and $\sum_{j=1}^N \frac{g_{ij}}{2b_i} x_j$ is dependent on the other MUs' participation levels due to underlying social network effects. Although the participation level strategy of each MU is obtained as in Eq. (3.3), the Nash equilibrium cannot be ensured to be unique or even exist since each MU may unboundedly increase its participation level if the other MUs' participation levels are large enough. Then, an sufficient assumption is presented, under which there exists a unique Nash equilibrium as described in Theorem 3.1. Without Assumption 3.1, some players may choose infinite participation levels regarding one task when positive effects are very strong. Note that an MU has the limitation on participation

level due to the battery capacity of a mobile device, and thus the Assumption 3.1 is reasonable.

Assumption 3.1 $\sum_{j=1}^N \frac{g_{ij}}{2b_i} < 1, \forall i$.

Theorem 3.1 *Under Assumption 3.1, the existence and uniqueness of MU participation equilibrium, i.e., the Nash equilibrium of Stage II in this Stackelberg game can be guaranteed.*

Proof. **Existence of MU participation equilibrium:** Let $\mathbf{x}^*$ denote the strategy profile in this MU participation sub-game, and $x_i^\dagger$ as the largest participation level in $\mathbf{x}^*$. Then,

$$\begin{aligned} x_i^\dagger &= \left(\frac{r_i - c + a_i}{2b_i} + \sum_{j=1}^N \frac{g_{ij}}{2b_i} x_j \right)^+ \\ &\leq \frac{r_i - c + a_i}{2b_i} + \sum_{j=1}^N x_i^\dagger \frac{g_{ij}}{2b_i} \\ &\leq \frac{|r_i - c + a_i|}{2b_i} + \sum_{j=1}^N x_i^\dagger \frac{|g_{ij}|}{2b_i}. \end{aligned} \quad (3.4)$$

Thus, under Assumption 3.1,

$$x_i^\dagger \leq \frac{|r_i - c + a_i|}{2b_i - \sum_{j=1}^N |g_{ij}|} = \hat{x}. \quad (3.5)$$

As a result, the strategy space $[0, \hat{x}]$ is convex and compact and the utility function $u_i(x_i, \mathbf{x}_{-i})$ is continuous in x_i and $\mathbf{x}_{-i}$. The second-order derivative of MU's objective function will be obtained as

$$\frac{\partial^2 u_i}{\partial x_i^2} = -2b_i < 0. \quad (3.6)$$

Thus, the MU participation sub-game is a concave game which admits the Nash equilibrium.

Uniqueness of MU participation equilibrium: Firstly, $-\frac{\partial^2 u_i}{\partial x_i^2} = -(-2b_i + g_{ii}) = 2b_i$. Then, based on Assumption 3.1,

$$-\frac{\partial^2 u_i}{\partial x_i^2} > \sum_{j=1}^N g_{ij} = \sum_{j=1}^N |g_{ij}| = \sum_{j=1}^N \left| -\frac{\partial^2 u_i}{\partial x_i \partial x_j} \right|,$$

which satisfies the dominance solvability condition, i.e., Moulin's Theorem [75]. As a result, the uniqueness of MU participation equilibrium is guaranteed under Assumption 3.1. $\square$

Next the best response dynamic algorithm is proposed to obtain the Nash equilibrium with respect to MUs' participation level, as shown in Algorithm 1.

Algorithm 3.1 Simultaneous best-response updating for finding Nash equilibrium of MU participation sub-game

```

1: Input:
   Precision threshold  $\varepsilon$ ,  $x_i^{[0]} \leftarrow 0$ ,  $x_i^{[1]} \leftarrow 1 + \varepsilon$ ,  $k \leftarrow 1$ ;
2: while  $\left\|x_i^{[k]} - x_i^{[k-1]}\right\|_1 > \varepsilon$  do
3:   for all  $i \in \mathcal{N}$  do
4:      $x_i^{[k+1]} = \left(\frac{r_i - c + a_i}{2b_i} + \sum_{j=1}^N x_j^{[k]} \frac{g_{ij}}{2b_i}\right)^+$ ;
5:   end for
6:    $k \leftarrow k + 1$ ;
7: end while
8: Return  $\mathbf{x}_i^{[k]}$ ;

```

Proposition 3.1 *Algorithm 3.1 achieves the Nash equilibrium of MU participation sub-game.*

Proof. Let $\kappa_{ij} = \frac{g_{ij}}{2b_i}$ and $\Delta x_i^{[k]} = x_i^{[k]} - x_i^*$, for all $i \in \mathcal{N}$. From step 4 of Algorithm 3.1,

$$\begin{aligned}
\left|\Delta x_i^{[k]}\right| &\leq \left|\sum_{j=1}^N \kappa_{ij} \Delta x_j^{[k]}\right| \\
&\leq \sum_{j=1}^N \kappa_{ij} \left|\Delta x_j^{[k]}\right|.
\end{aligned} \tag{3.7}$$

It can be also obtained that

$$\|\Delta \mathbf{x}^{[k]}\|_\infty = \max_i \left|\Delta x_i^{[k]}\right|. \tag{3.8}$$

Accordingly, it is concluded that

$$\begin{aligned}
\|\Delta \mathbf{x}^{[k]}\|_\infty &\leq \max_i \left(\left|\sum_{j=1}^N \kappa_{ij} \Delta x_j^{[k]}\right|\right) \\
&\leq \max_i \sum_{j=1}^N \kappa_{ij} \max_i \left(\left|\Delta x_j^{[k]}\right|\right) \\
&= \max_i \sum_{j=1}^N \kappa_{ij} \|\Delta \mathbf{x}^{[k]}\|_\infty.
\end{aligned} \tag{3.9}$$

Under Assumption 3.1, $\sum_{j=1}^N \kappa_{ij} < 1, \forall i$. Thus, $\|\Delta x^{[k]}\|_\infty \leq \|\Delta x^{[k-1]}\|_\infty$, and the algorithm leads to a contraction mapping of $\|\Delta x^{[k-1]}\|_\infty$. The proof is completed. $\square$

For the ease of presentation, the following definitions are listed:

$$\mathbf{B} := \text{diag}(2b_1, 2b_2, \dots, 2b_N),$$

$$\mathbf{a} := [a_i]_{N \times 1},$$

$$\mathbf{1} := [1]_{N \times 1},$$

$$\mathbf{G} := [g_{ij}]_{N \times N},$$

$$\mathbf{r} := [r_i]_{N \times 1},$$

$$\mathbf{I} := \text{diag}(1, 1, \dots, 1)_{N \times N}.$$

For the rest of the paper, similar to [21, 76], an ideal assumption that each MU will have a positive participation level is considered, which is a special case of Eq. (3.3). Then, with Lemma 3.1, Eq. (3.3) can be rewritten in a matrix form as follows:

$$\mathbf{x} = \mathbf{K}(\mathbf{a} + \mathbf{r} - c\mathbf{1}), \quad (3.10)$$

where $\mathbf{K} = (\mathbf{B} - \mathbf{G})^{-1}$.

Lemma 3.1 $\mathbf{B} - \mathbf{G}$ is positive definite matrix, which is invertible.

Proof. If Assumption 3.1 holds,

$$\begin{aligned} (\mathbf{B} - \mathbf{G})_{ii} &= 2b_i - g_{ii} = 2b_i > \sum_{j=1, j \neq i}^N g_{ij} = \sum_{j=1}^N g_{ij} \\ &= -\sum_{j=1}^N (\mathbf{B} - \mathbf{G})_{ij} = -\sum_{j=1}^N |(\mathbf{B} - \mathbf{G})_{ij}|. \end{aligned}$$

Accordingly, $\mathbf{B} - \mathbf{G}$ is strictly diagonal dominant and all the diagonal elements, i.e., $2b_i$ are larger than 0. Based on Gershgorin circle theorem [77], every eigenvalue λ of $\mathbf{B} - \mathbf{G}$ satisfies

$$|(\mathbf{B} - \mathbf{G})_{ii} - \lambda| < \sum_{j=1}^N |(\mathbf{B} - \mathbf{G})_{ij}|. \quad (3.11)$$

Accordingly, it can be known that $\lambda > 0$, and thus $\mathbf{B} - \mathbf{G}$ is a positive definite matrix, from which its invertibility follows. The proof is completed. $\square$

3.2.2 Stage I: Optimal Reward Mechanism

In this stage, the monopoly CSP determines the reward to be paid to the MUs, the objective of which is to maximize its overall revenue. The discriminatory reward mechanism and uniform reward mechanism with the full information scenario are firstly studied.

3.2.2.1 Discriminatory Reward Mechanism

Under reward discrimination, the CSP is able to provide different levels of reward for MUs to maximize its revenue. The revenue maximization problem can be formulated as follows:

$$\begin{aligned} \underset{\mathbf{r}}{\text{maximize}} \quad & \Pi = \mu \sum_{i=1}^N (sx_i - tx_i^2) - \sum_{i=1}^N r_i x_i \\ & = \mu(s\mathbf{1}^\top \mathbf{x} - \mathbf{x}^\top t\mathbf{x}) - \mathbf{r}^\top \mathbf{x} \\ \text{subject to} \quad & \mathbf{x} = \mathbf{K}(\mathbf{a} + \mathbf{r} - c\mathbf{1}). \end{aligned} \quad (3.12)$$

By plugging $\mathbf{x}$ into the objective function in Eq. (5.32),

$$\Pi = \mu \left(s\mathbf{1}^\top \mathbf{K}(\mathbf{a} + \mathbf{r} - c\mathbf{1}) - t(\mathbf{a} + \mathbf{r} - c\mathbf{1})^\top \mathbf{K}^2(\mathbf{a} + \mathbf{r} - c\mathbf{1}) \right) - \mathbf{r}^\top \mathbf{K}(\mathbf{a} + \mathbf{r} - c\mathbf{1}). \quad (3.13)$$

Setting the first-order condition of objective function in Eq. (5.32) with respect to $\mathbf{r}$ to zero, i.e., $\frac{\partial \Pi}{\partial \mathbf{r}} = 0$, it can be obtained that

$$\mu(s\mathbf{K}\mathbf{1} - 2t\mathbf{K}^2(\mathbf{a} + \mathbf{r} - c\mathbf{1})) - \mathbf{K}(\mathbf{a} + \mathbf{r} - c\mathbf{1}) - \mathbf{K}\mathbf{r} = 0. \quad (3.14)$$

Then,

$$\mu(s\mathbf{K}\mathbf{1} - 2t\mathbf{K}^2(\mathbf{a} - c\mathbf{1})) - \mathbf{K}(\mathbf{a} - c\mathbf{1}) = (2\mathbf{K} + 2\mu t\mathbf{K}^2)\mathbf{r}. \quad (3.15)$$

Finally, the optimal value $\mathbf{r}^*$ is represented as follows:

$$\mathbf{r}^* = (2\mathbf{I} + 2\mu t\mathbf{K})^{-1} \{ \mu[s\mathbf{1} - 2t\mathbf{K}(\mathbf{a} - c\mathbf{1})] - (\mathbf{a} - c\mathbf{1}) \}. \quad (3.16)$$

3.2.2.2 Uniform Reward Mechanism

In this case, the CSP can only choose a single uniform reward to be paid to all the MUs, i.e., $r_i = r$, for all i . Then, the optimization problem is given by

$$\begin{aligned} \underset{r}{\text{maximize}} \quad & \Pi = \mu \sum_{i=1}^N (sx_i - tx_i^2) - r \sum_{i=1}^N x_i \\ & = \mu(s\mathbf{1}^\top \mathbf{x} - \mathbf{x}^\top t\mathbf{x}) - r\mathbf{1}^\top \mathbf{x} \\ \text{subject to} \quad & \mathbf{x} = \mathbf{K}[\mathbf{a} + (r - c)\mathbf{1}]. \end{aligned} \quad (3.17)$$

Similarly, $\mathbf{x}$ from objective function is eliminated in Eq. (3.17), then

$$\Pi = \mu \left(s\mathbf{1}^\top \mathbf{K}[\mathbf{a} + (r - c)\mathbf{1}] - t[\mathbf{a} + (r - c)\mathbf{1}]^\top \mathbf{K}^2[\mathbf{a} + (r - c)\mathbf{1}] \right) - r\mathbf{1}^\top \mathbf{K}[\mathbf{a} + (r - c)\mathbf{1}]. \quad (3.18)$$

Then, its first-order optimality condition with respect to the reward r is evaluated, which yields that

$$\frac{\partial \Pi}{\partial r} = \mu \{ (s\mathbf{1}^\top \mathbf{K}\mathbf{1} - 2t[\mathbf{a} + (r - c)\mathbf{1}]^\top \mathbf{K}^2\mathbf{1}) - \mathbf{1}^\top \mathbf{K}[\mathbf{a} + (r - c)\mathbf{1}] - r\mathbf{1}^\top \mathbf{K}\mathbf{1} \} = 0. \quad (3.19)$$

As a result, the optimal value of the uniform reward is represented by

$$r^* = (2\mu t\mathbf{1}^\top \mathbf{K}^2\mathbf{1} + 2\mathbf{1}^\top \mathbf{K})^{-1} \left\{ \mu [s\mathbf{1}^\top \mathbf{K}\mathbf{1} - 2t(\mathbf{a} - c\mathbf{1})^\top \times \mathbf{K}^2\mathbf{1}] - \mathbf{1}^\top \mathbf{K}(\mathbf{a} - c\mathbf{1}) \right\}. \quad (3.20)$$

3.2.3 Discussions on Asymmetric Social Influence

It is noted that the proposed approach is not restricted to the symmetry assumption that $g_{ij} = g_{ji}$. This subsection will illustrate the model with asymmetric social influence in the complete information.

In Lemma 3.1, it can be proved that $\mathbf{B} - \mathbf{G}$ is invertible by proving it is a positive definite matrix, and evidently the positive definite matrix is symmetric. Nevertheless, $\mathbf{B} - \mathbf{G}$ is strictly diagonally dominant even when $g_{ij} = g_{ji}$ does not hold. According to

Levy–Desplanques theorem [78], a strictly diagonally dominant matrix is non-singular. Thus, $\mathbf{B} - \mathbf{G}$ is still invertible. Therefore, without the symmetry assumption of g_{ij} , the Lemma 3.1 still holds.

Recall that $\mathbf{K} = (\mathbf{B} - \mathbf{G})^{-1}$ is symmetric, since $g_{ij} = g_{ji}$. Thus, $\mathbf{K}^\top + \mathbf{K}$ can be simplified as $2\mathbf{K}$. However, when $g_{ij} \neq g_{ji}$, $\mathbf{K} = (\mathbf{B} - \mathbf{G})^{-1}$ is not symmetric, and $\mathbf{K}^\top + \mathbf{K}$ cannot be simplified, which will complicate the mathematical calculation process. Nevertheless, the analytical solution for the profit maximization of the CSP is still structurally the same as that in Section 3.2.2.

For the discriminatory incentive mechanism: When $g_{ij} \neq g_{ji}$, the objective function of the CSP and the optimal value of $\mathbf{x}^*$ keep unchanged. By plugging $\mathbf{x}$ into the objective function of the CSP,

$$\Pi = \mu \left(s\mathbf{1}^\top \mathbf{K} (\mathbf{a} + \mathbf{r} - c\mathbf{1}) - t(\mathbf{a} + \mathbf{r} - c\mathbf{1})^\top \mathbf{K}^2 (\mathbf{a} + \mathbf{r} - c\mathbf{1}) \right) - \mathbf{r}^\top \mathbf{K} (\mathbf{a} + \mathbf{r} - c\mathbf{1}). \quad (3.21)$$

Next the partial derivative of the objective function of the CSP with respect to the decision vector $\mathbf{r}$ is set to zero, i.e., $\frac{\partial \Pi}{\partial \mathbf{r}} = 0$,

$$\frac{\partial \Pi}{\partial \mathbf{r}} = \mu \left(s\mathbf{K}\mathbf{1} - t \left(\mathbf{K}^2 + (\mathbf{K}^2)^\top \right) (\mathbf{a} + \mathbf{r} - c\mathbf{1}) \right) - \mathbf{K} (\mathbf{a} + \mathbf{r} - c\mathbf{1}) - \mathbf{K}\mathbf{r} = 0. \quad (3.22)$$

Then,

$$\mu \left(s\mathbf{K}\mathbf{1} - t(\mathbf{K}^2 + (\mathbf{K}^2)^\top) (\mathbf{a} - c\mathbf{1}) \right) - \mathbf{K} (\mathbf{a} - c\mathbf{1}) = \left(2\mathbf{K} + \mu t(\mathbf{K}^2 + (\mathbf{K}^2)^\top) \right) \mathbf{r}. \quad (3.23)$$

The optimal value $\mathbf{r}^*$ is represented as follows:

$$\mathbf{r}^* = \left(2\mathbf{K} + \mu t(\mathbf{K}^2 + (\mathbf{K}^2)^\top) \right)^{-1} \left(\mu \left(s\mathbf{K}\mathbf{1} - t(\mathbf{K}^2 + (\mathbf{K}^2)^\top) (\mathbf{a} - c\mathbf{1}) \right) - \mathbf{K} (\mathbf{a} - c\mathbf{1}) \right). \quad (3.24)$$

For uniform incentive mechanism, $\mathbf{x} = \mathbf{K} [\mathbf{a} + (r - c)\mathbf{1}]$. Therefore,

$$\Pi = \mu \left(s\mathbf{1}^\top \mathbf{K} (\mathbf{a} + r\mathbf{1}) - t(\mathbf{a} + r\mathbf{1})^\top \mathbf{K}^2 (\mathbf{a} + r\mathbf{1}) \right) - r\mathbf{1}^\top \mathbf{K} (\mathbf{a} + r\mathbf{1}). \quad (3.25)$$

Then, for its first-order optimality condition with respect to the reward r ,

$$\frac{\partial \Pi}{\partial r} = \mu \left(s \mathbf{1}^\top \mathbf{K} \mathbf{1} - 2t(\mathbf{a} + r \mathbf{1})^\top \mathbf{K}^2 \mathbf{1} \right) - \mathbf{1}^\top \mathbf{K} (\mathbf{a} + r \mathbf{1}) - r \mathbf{1}^\top \mathbf{K} \mathbf{1} = 0. \quad (3.26)$$

As a result, with simple steps, the optimal value of the uniform reward is represented by

$$r^* = \left(\mu t \mathbf{1}^\top (\mathbf{K}^2 + \mathbf{K}^{2^\top}) + 2 \mathbf{1}^\top \mathbf{K} \mathbf{1} \right)^{-1} \times \left(\mu \left(s \mathbf{1}^\top \mathbf{K} \mathbf{1} - t(\mathbf{a} - c \mathbf{1})^\top (\mathbf{K}^2 + \mathbf{K}^{2^\top}) \mathbf{1} \right) - \mathbf{1}^\top \mathbf{K} (\mathbf{a} - c \mathbf{1}) \right). \quad (3.27)$$

3.2.4 Discussion on Heterogenous Cost Function

Note that the model can be straightforwardly extended to a more generalized heterogeneous unit cost and nonlinear cost function here, and an example when the cost function becomes $c_i x_i^2$ is studied. This function is chosen since it can represent the condition that the incurred cost increases when the MU keeps increasing its participation level, and the marginal increase is increasing (instead of keeping unchanged for linear cost function).

In the following, how the approach can be applied to the model with heterogeneous non-linear cost function in the complete information scenarios will be illustrated.

Firstly, the utility of MU i is reformulated as follows:

$$u_i(x_i, \mathbf{x}_{-i}, \mathbf{r}) = a_i x_i - b_i x_i^2 + \sum_{j=1}^N g_{ij} x_i x_j + r_i x_i - c_i x_i^2. \quad (3.28)$$

The best response of MU i becomes:

$$x_i^* = \max \left\{ 0, \frac{r_i + a_i}{2b_i + 2c_i} + \sum_{j=1}^N \frac{g_{ij}}{2b_i + 2c_i} x_j \right\}, \forall i. \quad (3.29)$$

Then, an assumption is made for sufficient condition similar to that in Assumption 3.1, i.e., Assumption R3.1: $\sum_{j=1}^N \frac{g_{ij}}{2b_i + c_i} < 1, \forall i$. Under such assumption, the MU has the upper bound on participation level, e.g., due to the battery capacity of a mobile device, and thus this assumption is reasonable. Provided that Assumption R3.1 holds, the existence

and uniqueness of Nash equilibrium in MU participation game can still be proved in the way that is structurally the same as the proof of Theorem 3.1.

Next the closed-form solution for the unique Nash equilibrium is written in matrix form as follows:

$$\mathbf{x} = \mathbf{K}'(\mathbf{a} + \mathbf{r}), \quad (3.30)$$

where $\mathbf{K}' := (\mathbf{B} + \mathbf{C} - \mathbf{G})^{-1}$, $\mathbf{C} := \text{diag}(2c_1, 2c_2, \dots, 2c_N)$, $\mathbf{B} := \text{diag}(2b_1, 2b_2, \dots, 2b_N)$ and $\mathbf{G} := [g_{ij}]_{N \times N}$.

Under Assumption R3.1, $\mathbf{B} + \mathbf{C} - \mathbf{G}$ is invertible similar to the proof in Lemma 3.1. Next, the incentive mechanism with heterogenous non-linear cost function is derived.

First, for the discriminatory incentive mechanism, the CSP's revenue is formulated as follows:

$$\Pi = \mu \left(s\mathbf{1}^\top \mathbf{K}'(\mathbf{a} + \mathbf{r}) - t(\mathbf{a} + \mathbf{r})^\top \mathbf{K}'^2(\mathbf{a} + \mathbf{r}) \right) - \mathbf{r}^\top \mathbf{K}'(\mathbf{a} + \mathbf{r}). \quad (3.31)$$

Taking the partial derivative of the above objective function with respect to the decision vector $\mathbf{r}$ to zero,

$$\frac{\partial \Pi}{\partial \mathbf{r}} = \mu \left(s\mathbf{K}'\mathbf{1} - 2t\mathbf{K}'^2(\mathbf{a} + \mathbf{r} - c\mathbf{1}) \right) - \mathbf{K}'(\mathbf{a} + \mathbf{r} - c\mathbf{1}) - \mathbf{K}'\mathbf{r} = 0. \quad (3.32)$$

Then,

$$\mu \left(s\mathbf{K}'\mathbf{1} - 2t\mathbf{K}'^2\mathbf{a} \right) - \mathbf{K}'\mathbf{a} = \left(2\mathbf{K}' + 2\mu t\mathbf{K}'^2 \right) \mathbf{r}. \quad (3.33)$$

Finally, the optimal value of $\mathbf{r}^*$ is represented as follows:

$$\mathbf{r}^* = (2\mathbf{I} + 2\mu t\mathbf{K}')^{-1} (\mu(s\mathbf{1} - 2t\mathbf{K}'\mathbf{a}) - \mathbf{a}). \quad (3.34)$$

Likewise, for uniform incentive mechanism,

$$\Pi = \mu \left(s\mathbf{1}^\top \mathbf{K}'(\mathbf{a} + r\mathbf{1}) - t(\mathbf{a} + r\mathbf{1})^\top \mathbf{K}'^2(\mathbf{a} + r\mathbf{1}) \right) - r\mathbf{1}^\top \mathbf{K}'(\mathbf{a} + r\mathbf{1}). \quad (3.35)$$

Then, evaluating its first-order optimality condition with respect to the uniform reward r yields

$$\frac{\partial \Pi}{\partial r} = \mu \left(s \mathbf{1}^\top \mathbf{K}' \mathbf{1} - 2t(\mathbf{a} + r\mathbf{1})^\top \mathbf{K}'^2 \mathbf{1} \right) - \mathbf{1}^\top \mathbf{K}' (\mathbf{a} + r\mathbf{1}) - r \mathbf{1}^\top \mathbf{K}' \mathbf{1} = 0. \quad (3.36)$$

As a result, with simple steps, the optimal value of the uniform reward is represented by

$$r^* = \left(2\mu t \mathbf{1}^\top \mathbf{K}'^2 \mathbf{1} + 2 \mathbf{1}^\top \mathbf{K}' \mathbf{1} \right)^{-1} \left(\mu \left(s \mathbf{1}^\top \mathbf{K}' \mathbf{1} - 2t \mathbf{a}^\top \mathbf{K}'^2 \mathbf{1} \right) - \mathbf{1}^\top \mathbf{K}' \mathbf{a} \right). \quad (3.37)$$

3.3 Performance Evaluation

This section investigates the performance of the incentive mechanism of CSP, and evaluate the impacts of different parameters of mobile social networks in this section. Assume there are N MUs and related parameters are set as follows. a_i and b_i both follow normal distribution $\mathcal{N}(\mu_a, 2)$ and $\mathcal{N}(\mu_b, 2)$. In addition, the social tie g_{ij} follows $\mathcal{N}(\mu_g, 1)$. Other parameters are set as: $c = 15$, $\mu = 0.1$, $s = 20$, $t = 0.05$, $\mu_a = \mu_b = 15$, $\mu_g = 0.05$ and $N = 50$. As expected and verified in Fig. 3.2 and Fig. 3.3, the discriminatory incentive yields the larger revenue for the CSP, compared with the uniform incentive. Intuitively, the reason is that the CSP can adjust the reward according to individual MU's effort and contribution, which is proven by Fig. 3.4.

Impacts of the total number of MUs on the proposed incentive mechanisms are studied next, as illustrated in Fig. 3.2. As the number of MUs increases, the total utilities of participants and the revenue of the CSP also increase under both mechanisms. The reason is that when the total number of MUs increases, the number of social neighboring MUs also increases. Owing to the underlying social network effects, the MUs are motivated by their social neighbours to have higher participation levels, and the revenue of the CSP is improved accordingly. In addition, with the increase of total number of participants, the total offered reward increases since the CSP tends to encourage more MUs to participate,

Figure 3.2: The impact of total number of MUs on the Crowdsensing service provider and mobile participants.

in order to attain a greater revenue gain. In particular, the discriminatory and uniform incentive mechanisms enable the CSP to reduce the reward paid to the MUs, i.e., the cost, and therefore achieve a greater revenue gain in turn. Figure 3.3 depicts the impact of average value of social network effects on MUs and CSPs. It can be observed that when the social network effects becomes stronger, the total utilities of participants and the revenue of the CSP also increase. Since when the strength of social tie is stronger, the external benefits gained from social network effects are greater. In other words, the socially-aware MUs are motivated by each other and have higher participation levels consequently. When the participation levels are high enough, the CSP would offer less reward to save money. In turn, the total utilities of participants and the revenue of the

Figure 3.3: The impact of average value of social network effects on the Crowdsensing service provider and mobile participants.

CSP are improved. Furthermore, it shows that the total offered reward under the uniform incentive mechanism and the discriminatory incentive mechanism have no big difference from both Figs. 3.2 and 3.3. The reason is that the CSP under the discriminatory incentive mechanism is able to achieve a balanced reward allocation with the similar cost. For example, the CSP can offer more reward to some MUs and less reward to some other MUs, which leads to a greater overall participation level. This intuition is demonstrated in Fig. 3.4. From the third sub-figure in Fig. 3, it can be found that the uniform reward curve has several fluctuations suffering from the randomness of the social tie g_{ij} when network effects become stronger. Nevertheless, the uniform reward still remains largely unchanged (around 50). This is different from the third sub-figure in Fig. 2, where the fluctuations cannot be observed. The reason is that Fig. 2 illustrates

Figure 3.4: A case illustration of distribution of normalized reward and participation level.

the impacts of the number of MUs on total offered reward from the CSP. Intuitively, the total reward increases when the number of participants increases. Thus, the slight fluctuations cannot be observed in Fig. 2 since the reward keeps increasing.

To evaluate the influence of social network effects on individual MU, the optimal reward and MUs' participation level with the number of 50 MUs is studied, and the similar default parameters setting to that in above discussions is adopted. The adjacency matrix G is generated as follows:

$$\begin{cases} g_{i,i+1} = 0.2 \times \left(0.5 - \left(0.5 - \frac{i-1}{N}\right)^2\right), & i \in [1, N-1]; \\ g_{i+1,i} = 0.2 \times \left(0.5 - \left(0.5 - \frac{i-1}{N}\right)^2\right), & i \in [1, N-1]; \\ g_{i,j} = 0, & \text{otherwise.} \end{cases} \quad (3.38)$$

From Eq. (3.38), only participants who are adjacent in participant indexes (neighbours) can affect each other. From Fig. 3.4, it can be observed that the CSP offers each

participant the same reward when it has no information about the value of matrix $\mathbf{G}$. Given the reward from the CSP, the MUs have different participation level equilibrium as shown in Fig. 3.4, where the participation levels of the MUs are socially related to each other. In particular, the 27th MU is the most susceptible or influenced one in this network because it has the highest participation level given the same reward. On the contrary, the 1st and the 51st MUs are the most influential ones. Therefore, with the knowledge about the value of matrix $\mathbf{G}$, the CSP is likely to offer more reward to the 1st and the 51st MUs and less to the 27th MU, under the discriminatory incentive mechanism. The reason is that the CSP tends to have the highest participation level from the participant with the lowest cost and thus have a greater revenue gain. However, under the uniform incentive mechanism, the CSP can offer only the same reward to the participants. As such, the CSP usually offers more reward and promotes the participants to attain higher participation level, but the incurred extra cost is also very high, which decreases the revenue of the CSP consequently.

3.4 Summary

This work develops a two-stage game theoretic model, and analyzed each stage using backward induction. The Crowdsensing Service Provider (CSP) sets the incentive mechanism in the first stage, and the Mobile Users (MUs) decide their participation level given the observed reward in the second stage. Taking the social (local) network effects among the MUs into account, the optimal incentive mechanism is proposed, i.e., discriminatory reward and uniform reward under complete information scenario, where the closed-form expression for optimal reward is obtained. Moreover, the approximations for reward incentive under incomplete information scenario are derived. Performance evaluations have verified that network effects significantly promote the participation level and the CSP's

revenue. Further, it has been validated that the discriminatory reward mechanism helps the CSP to achieve greater revenue gain.

Chapter 4

A Hierarchical Game for Incentive Mechanisms with Incomplete Information

The goal of this chapter¹ is to study the interactions between Crowdsensing Service Providers(CSPs) and Mobile Users(MUs²) in the incentive mechanisms in crowdsensing platform the with the presence of private information (type) of mobile users.

The rest of the chapter is organized as follows. Section 4.1 describes the system model and the game formulation. Section 4.2 formulates a Bayesian Stackelberg game where the social structure information is uncertain, and study the Bayesian game equilibrium. Section 4.3 presents the performance evaluation and Section 4.4 concludes the paper.

4.1 System Model and Game Formulation

A Bayesian Stackelberg game [23] is employed to model the interactions among the Crowdsensing Service Provider (CSP) and the socially-aware participants, i.e., Mobile Users (MUs). The MUs' actions are to decide their individual participation level and the CSP offers the payment as a reward to stimulate the MUs. To fit the proposed model into

¹The work in this chapter has been published in [79].

²For ease of explanation, instead of “users”, “MUs” are used to represent “Mobile Users” in the technical parts in this thesis.

real-world crowdsensing applications, an incomplete information scenario is considered, where the social structure information (the social network effects) is uncertain, i.e., not known by the CSP and MUs. Thereafter, the expected utility of MUs and the expected revenue of the CSP are defined.

A group of N MUs are considered in the mobile network, denoted as a set $\mathcal{N} \triangleq \{1, \dots, N\}$. Each MU $i \in \mathcal{N}$ decides an individual participation level denoted by $x_i \in (0, +\infty)$, which denotes the effort level of participation (e.g., sensing data transmission frequency or sensing resolution). $\mathbf{x} \triangleq (x_1, \dots, x_N)$ and $\mathbf{x}_{-i}$ represent the participation levels of all MUs and all other MUs except the MU i , respectively. The reward per effort unit offered to the MUs is denoted as: $\mathbf{r} = [r_1, \dots, r_i, \dots, r_N]^\top$. With the aforementioned notations, the utility of MU i can be defined as:

$$u_i(x_i, \mathbf{x}_{-i}) = f_i(x_i) + \Phi(x_i, \mathbf{x}_{-i}) + r(x_i) - c(x_i). \quad (4.1)$$

The internal benefits that MU i receives from the participation is denoted as $f_i(x_i) = a_i x_i - b_i x_i^2$, where $a_i, b_i > 0$ have the same definition as Chapter 3. In order to focus on the networking structure uncertainty only, $a_i = 1$ and $b_i = 1/2$ are set in the following analysis. $\Phi(x_i, \mathbf{x}_{-i})$ represents the additional benefits obtained from the network effects. From the perspective of social domain, external benefits can be obtained by an MU from information contributed by other participants [19]. Due to the structural properties from underlying social domain, an adjacency matrix $G = [g_{ij}]_{i,j \in \mathcal{N}}$ is introduced to assist the analysis, where each element g_{ij} indicates the influence of MU j on MU i . In this paper, $g_{ij} = g_{ji}$, i.e., the social tie is reciprocal. Nevertheless, the proposed model can be applied to asymmetric social ties straightforwardly (Please refer to Section 4.2.4). Specifically, $\sum_{j \in \mathcal{N}_i} g_{ij} x_i x_j$ represents the additional benefits obtained from the network effects, similar to that in [20, 21], where $\mathcal{N}_i$ denotes the social neighbours of the MU i .

Lastly, $r(x_i) = r_i x_i$ represents the reward from the CSP to the MU i . $c(x_i)$ indicates the cost associated to the participation level of the MU, e.g., energy consumption. Without loss of generality, the cost is assumed to equal $c(x_i) = c x_i$, where c is the MU's unit cost. The same approach can also be applied to the model with heterogeneous unit cost (like $c_i x_i^2$) straightforwardly (Please refer to Section 4.2.5) Note that the important social structure information may be unknown by the decision makers, i.e., the CSP and MUs. Accordingly, the proposed game can be modeled as a Bayesian game with incomplete information where the Bayesian analysis is adopted to predict the game outcome. In particular, the social degree of each MU is treated as private information and is considered as the type of the followers and only its probability distribution is commonly known. As aforementioned, the mobile social networking structure is represented by an interaction matrix, i.e., the adjacency matrix G . If the adjacency matrix G is common knowledge, the utility of MU i is given as follows:

$$u_i(x_i, \mathbf{x}_{-i}, \mathbf{r}) = x_i - \frac{1}{2}x_i^2 + \sum_{j=1}^N g_{ij}x_i x_j + r_i x_i - c x_i. \quad (4.2)$$

Note that we set $a_i = 1$ and $b_i = 1/2$ in order to concentrate on the social structure uncertainty. Moreover, without loss of generality, for all the social neighbours of MU i , i.e., $j \in \mathcal{N}_i$, $g_{ij} = \gamma > 0$, and γ is a given social network effect coefficient. Thus, the above equation is rewritten as follows:

$$u_i(x_i, \mathbf{x}_{-i}, \mathbf{r}) = x_i - \frac{1}{2}x_i^2 + \gamma x_i \sum_{j \in \mathcal{N}_i} x_j + r_i x_i - c x_i. \quad (4.3)$$

Therefore, the expected utility is expressed as follows:

$$U_i(x_i, \mathbf{x}_{-i}, \mathbf{r}) = \mathbb{E}[u_i(x_i, \mathbf{x}_{-i}, \mathbf{r})] = x_i - \frac{1}{2}x_i^2 + \gamma x_i \mathbb{E}\left[\sum_{j \in \mathcal{N}_i} x_j\right] + r_i x_i - c x_i. \quad (4.4)$$

The social structure leads to different in-degrees and out-degrees of MUs. The in-degree denotes the number of other MUs that a certain MU influences, the out-degree

denotes the number of other MUs influencing this MU. Thus, the in-degree represents its influence and the out-degree represents its susceptibility. The distribution³ of in-degree and out-degree captures the social network effects from the network interaction patterns [20, 80, 81, 82, 83]. Note that the proposed model can still be applied to the asymmetric social ties, since both the in-degree and out-degree distributions of each MU are considered instead of the degree distribution. For example, an MU Alice has the social influence on MU Bob, but Bob may not have the social influence on Alice. The reason is that Alice may have different in-degree and out-degree.

The in-degree $l \in D$ and out-degree $k \in D$, where $D = \{0, 1, \dots, k^{max}\}$ and k^{max} denotes the maximum possible value. $P : D \rightarrow [0, 1]$ and $H : D \rightarrow [0, 1]$ as the probability distributions of out-degree and in-degree, respectively, and $\sum_{k \in D} P(k) = \sum_{l \in D} H(l) = 1$. Furthermore, it is assumed that two probability distributions are independent and their variances are denoted as σ_k^2 and σ_l^2 , respectively. Due to consistency theory, $\sum_{k \in D} P(k)k = \sum_{l \in D} H(l)l = \bar{k}$, and thus $\bar{k}$ is referred to as the mean value of social network effects. Moreover,

$$\mathbb{E} \left[\sum_{j \in \mathcal{N}_i} x_j \right] = k_i \times \text{Avg}(\mathbf{x}_{-i}), \quad (4.5)$$

where $\text{Avg}(\mathbf{x}_{-i}) = \mathbb{E}[x_j | j \in \mathcal{N}_i]$ denotes the average participation level of social neighbours of MU i .

In order to obtain the expression of $\text{Avg}(\mathbf{x}_{-i})$, the concept of “*Configuration Model*” in *Network Science* [84] is employed to model the random networks generated with only in-degree distribution. According to Configuration Model’s property (See Chapter 12.2 in [84]), to a user, the degree distribution of its randomly chosen neighbor is $\bar{H}(l) =$

³Since the social ties/links are constructed by the in/out-degree information of MUs, the social ties/links are also treated as random variables in some sense. Note that γ in the model is a given social network effect coefficient, which captures the strength of social ties/links. Although the value of γ is given, the social ties/links follow certain probability distribution instead of being a constant value. It is also noteworthy that γ can be treated as an approximate term instead of an exact value. Nevertheless, the impacts of uncertainty of γ can still be absorbed into the distribution of in/out-degree since these impacts are interdependent.

$\frac{H(l)l}{\sum_{l' \in D} H(l')l'}$. In other words, a randomly selected social neighbours of MU i has the in-degree distribution as $\bar{H}(l)$ and out-degree distribution as $P(k)$. Thus, by denoting the participation level of the MU with out-degree k and in-degree l as $x(k, l)$ [82, 83],

$$\text{Avg}(\mathbf{x}_{-i}) = \sum_{l \in D} \bar{H}(l) \left(\sum_{k \in D} P(k) x(k, l) \right), \quad (4.6)$$

where $\bar{H}(l) = \frac{H(l)l}{\sum_{l' \in D} H(l')l'}$. Note that given $\text{Avg}(\mathbf{x}_{-i})$, the participation level of MU i only depends on the reward and its out-degree k . Thus, the final expected utility of MU i is expressed as follows:

$$U_i(x_i, \mathbf{x}_{-i}, \mathbf{r}, k_i) = (1 + r_i - c)x_i - \frac{1}{2}x_i^2 + \gamma k_i x_i \text{Avg}(\mathbf{x}_{-i}), \quad (4.7)$$

and the type of the MU is its in-degree and out-degree, which is denoted as (l, k) .

Since only the distribution of the in-degree and out-degree information is known, instead of maximizing the revenue as defined in Eq. (3.2), the objective of the leader, i.e., the CSP, is to maximize its expected revenue, which is given as follows:

$$\Pi = \sum_{l \in D} \left(\sum_{k \in D} H(l) P(k) ((\mu s - r(k, l)) x(k, l) - \mu t(x(k, l))^2) \right), \quad (4.8)$$

where $r(k, l)$ is the reward offered to the MU with out-degree k and in-degree l .

4.2 Bayesian Stackelberg Game Equilibrium Analysis

This section adopts the backward induction to analyze the Bayesian Stackelberg game.

4.2.1 Stage II: Follower Game:

For the given incentive or the reward determined by the CSP, the Bayesian Nash equilibrium in the follower game is examined, which is characterized by the following theorem.

Theorem 4.1 *The existence and uniqueness of the Bayesian Nash equilibrium of the follower game can be guaranteed, provided that the following condition*

$$\gamma k^{\max} < 1 \quad (4.9)$$

holds.

Proof. The existence of Bayesain follower game: The following condition needs to be ensured to prove the existence of Nash equilibrium in the follower game (Proposition 1 in [85])

$$\frac{\partial U_i(\bar{x}, \mathbf{x}_{-i}, \mathbf{r}, k_i)}{\partial x_i} \leq 0, \forall i \in \mathcal{N}, k \in Z^+, r \in \mathbb{R}^+, \exists \bar{x} \geq 0, \forall x \leq \bar{x} \quad (4.10)$$

holds, where $\bar{x} = \text{Avg}(\mathbf{x}_{-i})$. Since

$$\begin{aligned} \frac{\partial U_i(\bar{x}, \mathbf{x}_{-i}, \mathbf{r}, k_i)}{\partial x_i} &= (1 + r_i - c) - \bar{x} + \gamma k_i \text{Avg}(\mathbf{x}_{-i}) \\ &\leq (1 + r_i - c) - \bar{x} + \gamma k^{\max} \bar{x} \\ &= 1 + r_i - c + (\gamma k^{\max} - 1) \bar{x}, \end{aligned} \quad (4.11)$$

the condition in Eq. (4.10) holds provided that $\gamma k^{\max} < 1$ is satisfied.

The uniqueness of Bayesain follower game: The proof of the uniqueness of the pure Bayesian Nash equilibrium can be directly derived from [85]. In particular, the sufficient condition that implies there exists at most one Bayesian Nash equilibrium is given as follows (Proposition 3 in [85]):

$$\left| \frac{\partial^2 U_i(\bar{x}, \mathbf{x}_{-i}, \mathbf{r}, k_i)}{\partial x_i \partial \text{Avg}(\mathbf{x}_{-i})} \right| / \left| \frac{\partial^2 U_i(\bar{x}, \mathbf{x}_{-i}, \mathbf{r}, k_i)}{\partial x_i \partial x_i} \right| < 1, \forall i \in \mathcal{N}. \quad (4.12)$$

With simple steps, $\left| \frac{\partial^2 U_i(\bar{x}, \mathbf{x}_{-i}, \mathbf{r}, k_i)}{\partial x_i \partial \text{Avg}(\mathbf{x}_{-i})} \right| / \left| \frac{\partial^2 U_i(\bar{x}, \mathbf{x}_{-i}, \mathbf{r}, k_i)}{\partial x_i \partial x_i} \right| = |\gamma k_i| \leq |\gamma k^{\max}|$. Thus, if $\gamma k^{\max} < 1$ holds, the condition given in Eq. (4.12) is guaranteed. The proof is then completed. $\square$

To obtain the closed-form expression of the unique Bayesian Nash equilibrium point in the follower game, the partial derivative of the expected utility given in Eq. (4.7) is firstly applied, i.e., $\frac{\partial U_i(\bar{x}, \mathbf{x}_{-i}, \mathbf{r}, k_i)}{\partial x_i} = 0$, as shown as follows:

$$x_i^* = 1 + r_i - c + \gamma k_i \mathbb{E}[x_j | j \in \mathcal{N}_i]. \quad (4.13)$$

Thus,

$$x(k, l) = 1 + r(k, l) - c + \gamma k \mathbb{E}[x(k, l) | (k, l) \in D^2]. \quad (4.14)$$

From Eq. (4.6),

$$\begin{aligned} \mathbb{E}[x(k', l') | (k', l') \in D^2] &= \sum_{l' \in D} \bar{H}(l') \sum_{k' \in D} P(k') x(k', l') \\ &= \sum_{l' \in D} \left(\bar{H}(l') \sum_{k' \in D} (P(k') (1 + r(k', l') - c + \gamma k' \mathbb{E}[x(k'', l'') | (k'', l'') \in D^2])) \right) \\ &= 1 + \bar{r} - c + \gamma \bar{k} \mathbb{E}[x(k'', l'') | (k'', l'') \in D^2], \end{aligned} \quad (4.15)$$

where $\bar{r} = \sum_{l \in D} \bar{H}(l) \sum_{k \in D} P(k) r(k, l)$ and $\bar{k} = \sum_{l \in D} \bar{H}(l) \sum_{k \in D} P(k) k = \sum_{k \in D} P(k) k$. Since

$$\mathbb{E}[x(k', l') | (k', l') \in D^2] = \mathbb{E}[x(k'', l'') | (k'', l'') \in D^2], \quad (4.16)$$

it can be concluded from Eq. (4.15) with the following expression

$$\text{Avg}(\mathbf{x}_{-i}) = \mathbb{E}[x_j | j \in \mathcal{N}_i] = \frac{1 + \bar{r} - c}{1 - \gamma \bar{k}}. \quad (4.17)$$

Therefore, the closed-form expression of the participation level of the MU with type (k, l) in the Bayesian follower game is given as follows:

$$x^*(k, l) = 1 + r(k, l) - c + \gamma k \frac{1 + \bar{r} - c}{1 - \gamma \bar{k}}. \quad (4.18)$$

4.2.2 Stage I: Leader Game

As the CSP has the information on the degree distributions of MUs but has no information on MUs' type, and thus can offer only a uniform reward⁴, i.e., $r(k, l) = r$ for all MUs. The optimal incentive mechanism obtained from the leader game is characterized by the following theorem.

Theorem 4.2 *The optimal reward offered by the CSP in the Bayesian Stackelberg game is unique, which is given as follows:*

$$r^* = c - 1 + \frac{(\mu s + 1 - c)(1 - \gamma \bar{k})}{2(1 - \gamma \bar{k} + \mu t + \mu t \gamma^2 \sigma_k^2)}. \quad (4.19)$$

Proof. The unique Bayesian follower game point given in Eq. (4.18) is plugged into the objective function given in Eq. (4.8). Since the unique participation level of the MU only depends on its out-degree k from Eq. (4.18), i.e., $x^*(k, l) = x^*(k)$, the expected revenue of the CSP given in (4.8) is then formulated as

$$\Pi = \sum_{k \in D} P(k) ((\mu s - r) x^*(k) - \mu t (x^*(k))^2). \quad (4.20)$$

⁴Note that the uniform incentive mechanism is more applicable in incomplete information scenario, where the CSP has no information on the specific type of each individual MU. However, the in/out-degree distributions of MUs can be obtained through, e.g., historical information or long-term learning, which makes the uniform incentive mechanism feasible. This can also be confirmed by the closed-form solution for the optimal uniform reward, since the expression of the optimal reward only includes the mean and variance of the in/out-degree distributions instead of the type of individual MU.

Particularly, the following mathematical transformations can be obtained,

$$\begin{aligned}
\Pi &= (\mu s - r) \left(1 + r - c + \gamma \bar{k} \frac{1 + r - c}{1 - \gamma \bar{k}} \right) - \mu t \sum_{k \in D} P(k) \left(1 + r - c + \gamma \bar{k} \frac{1 + r - c}{1 - \gamma \bar{k}} \right)^2 \\
&= (\mu s - r) \frac{1 + r - c}{1 - \gamma \bar{k}} - \mu t (1 + r - c) - 2\mu t (1 + r - c) \gamma \bar{k} \frac{1 + r - c}{1 - \gamma \bar{k}} \\
&\quad - \mu t \sum_{k \in D} P(k) k^2 \left(\gamma \frac{1 + r - c}{1 - \gamma \bar{k}} \right)^2 \\
&= (\mu s - r) \frac{1 + r - c}{1 - \gamma \bar{k}} - \mu t (1 + r - c) - 2\mu t (1 + r - c) \gamma \bar{k} \frac{1 + r - c}{1 - \gamma \bar{k}} \\
&\quad - \mu t \left(\bar{k}^2 + \sigma_k^2 \right) \left(\gamma \frac{1 + r - c}{1 - \gamma \bar{k}} \right)^2 \\
&= (\mu s - r) \frac{1 + r - c}{1 - \gamma \bar{k}} - \mu t \gamma^2 \sigma_k^2 \left(\gamma \frac{1 + r - c}{1 - \gamma \bar{k}} \right)^2 - \left(\mu t (1 + r - c) \right. \\
&\quad \left. + 2\mu t (1 + r - c) \gamma \bar{k} \frac{1 + r - c}{1 - \gamma \bar{k}} + \mu t \bar{k}^2 \left(\gamma \frac{1 + r - c}{1 - \gamma \bar{k}} \right)^2 \right) \\
&= (\mu s - r) \frac{1 + r - c}{1 - \gamma \bar{k}} - \mu t \gamma^2 \sigma_k^2 \left(\frac{1 + r - c}{1 - \gamma \bar{k}} \right)^2 - \mu t \left(1 + r - c + \gamma \bar{k} \frac{1 + r - c}{1 - \gamma \bar{k}} \right)^2 \\
&= (\mu s - r) \frac{1 + r - c}{1 - \gamma \bar{k}} - \mu t \gamma^2 \sigma_k^2 \left(\frac{1 + r - c}{1 - \gamma \bar{k}} \right)^2 - \mu t \left(\frac{1 + r - c}{1 - \gamma \bar{k}} \right)^2 \\
&= (\mu s + 1 - c - (1 + r - c)) \frac{1 + r - c}{1 - \gamma \bar{k}} - \mu t \gamma^2 \sigma_k^2 \left(\frac{1 + r - c}{1 - \gamma \bar{k}} \right)^2 - \mu t \left(\frac{1 + r - c}{1 - \gamma \bar{k}} \right)^2 \\
&= (\mu s + 1 - c) \frac{1 + r - c}{1 - \gamma \bar{k}} - (1 - \gamma \bar{k} + \mu t + \mu t \gamma^2 \sigma_k^2) \left(\frac{1 + r - c}{1 - \gamma \bar{k}} \right)^2. \tag{4.21}
\end{aligned}$$

Then, its first-order optimality condition with respect to the reward is evaluate, and

$\frac{\partial \Pi}{\partial r} = \frac{\partial \Pi}{\partial \frac{1+r-c}{1-\gamma \bar{k}}} \frac{\partial \frac{1+r-c}{1-\gamma \bar{k}}}{\partial r}$, which yields that

$$\left((\mu s + 1 - c) - 2(1 - \gamma \bar{k} + \mu t + \mu t \gamma^2 \sigma_k^2) \left(\frac{1 + r^* - c}{1 - \gamma \bar{k}} \right) \right) \frac{1}{1 - \gamma \bar{k}} = 0. \tag{4.22}$$

Thus, it can concluded that

$$1 + r^* - c = \frac{(\mu s + 1 - c)(1 - \gamma \bar{k})}{2(1 - \gamma \bar{k} + \mu t + \mu t \gamma^2 \sigma_k^2)}. \tag{4.23}$$

Therefore, the optimal uniform reward under Bayesian formulation is uniquely determined, which is given as

$$r^* = c - 1 + \frac{(\mu s + 1 - c)(1 - \gamma \bar{k})}{2(1 - \gamma \bar{k} + \mu t + \mu t \gamma^2 \sigma_k^2)}. \quad (4.24)$$

□

Furthermore, the benchmark case is studied where the CSP knows both the in-degree and out-degree of any individual follower. In such a situation, the CSP is able to offer discriminatory reward as incentive, $r(k, l)$ for the MU with out-degree k and in-degree l .

Theorem 4.3 *Provided that the CSP clearly knows the type of each individual MU, the optimal discriminatory reward $r(k, l)$ offered to the MU with out-degree k and in-degree l , is unique.*

Proof. The CSP determines $r(k, l)$ for the MU with out-degree k and in-degree l to maximize its expected revenue.

$$\begin{aligned} \Pi = \sum_{l \in D} \left(\sum_{k \in D} H(l) P(k) \left((\mu s - r(k, l)) \left(1 + r(k, l) - c + \gamma k \frac{1 + \bar{r} - c}{1 - \gamma \bar{k}} \right) - \right. \right. \\ \left. \left. \mu t \left(1 + r(k, l) - c + \gamma k \frac{1 + \bar{r} - c}{1 - \gamma \bar{k}} \right)^2 \right) \right). \end{aligned} \quad (4.25)$$

By taking the first derivative with respect to r with any out-degree $m \in D$ and in-degree $n \in D$,

$$\begin{aligned} \frac{\partial \Pi}{\partial r(m, n)} &= \frac{\partial}{\partial r(m, n)} H(n) P(m) \left((\mu s - r(m, n)) \left(1 + r(m, n) - c + \gamma m \frac{1 + \bar{r} - c}{1 - \gamma \bar{k}} \right) - \right. \\ &- \left. \mu t \left(1 + r(m, n) - c + \gamma m \frac{1 + \bar{r} - c}{1 - \gamma \bar{k}} \right)^2 \right) + \frac{\partial}{\partial r(m, n)} \sum_{l \neq n} \sum_{k \neq m} H(l) P(k) \\ &\times \left((\mu s - r(k, l)) \left(1 + r(k, l) - c + \gamma k \frac{1 + \bar{r} - c}{1 - \gamma \bar{k}} \right) - \right. \\ &- \left. \mu t \left(1 + r(k, l) - c + \gamma k \frac{1 + \bar{r} - c}{1 - \gamma \bar{k}} \right)^2 \right). \end{aligned} \quad (4.26)$$

Accordingly,

$$\frac{\partial \Pi}{\partial r(m, n)} = H(n)P(m) \left(- \left(1 + r(m, n) - c + \gamma m \frac{1 + \bar{r} - c}{1 - \gamma \bar{k}} \right) \right. \quad (4.27)$$

$$\begin{aligned} & + \left(1 + \gamma m \frac{\bar{H}(n)P(m)}{1 - \gamma \bar{k}} \right) (\mu s - r(m, n)) \\ & - 2\mu t \left(1 + r(m, n) - c + \gamma m \frac{1 + \bar{r} - c}{1 - \gamma \bar{k}} \right) \left(1 + \gamma m \frac{\bar{H}(n)P(m)}{1 - \gamma \bar{k}} \right) \\ & + \frac{\partial}{\partial r(m, n)} \sum_{k \neq m} \sum_{l \neq n} H(l)P(k) \left((\mu s - r(k, l)) \gamma k \frac{\bar{H}(n)P(m)}{1 - \gamma \bar{k}} \right. \\ & \left. - 2\mu t \gamma k \frac{\bar{H}(n)P(m)}{1 - \gamma \bar{k}} \left(1 + r(k, l) - c + \gamma m \frac{1 + \bar{r} - c}{1 - \gamma \bar{k}} \right) \right). \end{aligned} \quad (4.28)$$

Since $\frac{\partial \Pi}{\partial r(m, n)} = 0$,

$$\begin{aligned} 0 &= H(n)P(m) \left(- \left(1 + r(m, n) - c + \gamma m \frac{1 + \bar{r} - c}{1 - \gamma \bar{k}} \right) + \mu s - r(m, n) \right. \\ & \quad \left. - 2\mu t \left(1 + r(m, n) - c + \gamma m \frac{1 + \bar{r} - c}{1 - \gamma \bar{k}} \right) \right) + \gamma \frac{\bar{H}(n)P(m)}{1 - \gamma \bar{k}} \sum_{l \in D} \sum_{k \in D} H(l)P(k)k \\ & \quad \times \left(\mu s - r(k, l) - 2\mu t \left(1 + r(k, l) - c + \gamma k \frac{1 + \bar{r} - c}{1 - \gamma \bar{k}} \right) \right). \end{aligned} \quad (4.29)$$

With simple steps, the following expression is obtained

$$\begin{aligned} r^*(m, n) &= \frac{1}{2(1 + \mu t)} \left(c - 1 - \gamma m \frac{1 + \bar{r} - c}{1 - \gamma \bar{k}} + \mu s - 2\mu t \left(1 - c + \gamma m \frac{1 + \bar{r} - c}{1 - \gamma \bar{k}} \right) \right. \\ & \quad + \frac{\gamma n}{1 - \gamma \bar{k}} \left(\mu s - 2\mu t (1 - c) - \frac{2\mu t \gamma (1 + \bar{r} - c) (\sigma_k^2 + \bar{k}^2)}{(1 - \gamma \bar{k}) \bar{k}} \right. \\ & \quad \left. \left. - \gamma n \frac{1 + 2\mu t}{1 - \gamma \bar{k}} \psi \right) \right), \end{aligned} \quad (4.30)$$

where

$$\psi = \sum_{l \in D} \sum_{k \in D} \frac{1}{\bar{k}} k H(l) P(k) r(k, l). \quad (4.31)$$

Moreover, based on the definition of $\bar{r}$,

$$\begin{aligned}
 \bar{r} &= \sum_{m \in D} \sum_{n \in D} \bar{H}(n) P(m) r(m, n) \\
 &= \frac{1}{2(1 + \mu t)} \left(c - 1 - \gamma \bar{k} \frac{1 + \bar{r} - c}{1 - \gamma \bar{k}} + \mu s - 2\mu t \left(1 - c + \gamma \bar{k} \frac{1 + \bar{r} - c}{1 - \gamma \bar{k}} \right) + \frac{\gamma \bar{k}}{1 - \gamma \bar{k}} \right. \\
 &\quad \times \left(\mu s - 2\mu t (1 - c) - \frac{2\mu t \gamma (1 + \bar{r} - c) (\sigma_k^2 + \bar{k}^2)}{(1 - \gamma \bar{k}) \bar{k}} \right) - \gamma \bar{k} \frac{1 + 2\mu t}{1 - \gamma \bar{k}} \psi \Bigg). \quad (4.32)
 \end{aligned}$$

Thus,

$$\begin{aligned}
 \bar{r} &= \frac{1}{2(1 + \mu t)} \left(- \left(1 - c + \gamma \bar{k} \frac{1 + \bar{r} - c}{1 - \gamma \bar{k}} \right) \left(\frac{2\mu t}{1 - \gamma \bar{k}} + 1 \right) + \frac{\mu s}{1 - \gamma \bar{k}} \right. \\
 &\quad \left. - \frac{2\mu t \gamma^2 \sigma_k^2 (1 + \bar{r} - c)}{(1 - \gamma \bar{k})^2} \left(1 - c + \gamma \bar{k} \frac{1 + \bar{r} - c}{1 - \gamma \bar{k}} \right) - \gamma \bar{k} \frac{1 + 2\mu t}{1 - \gamma \bar{k}} \psi \right). \quad (4.33)
 \end{aligned}$$

Likewise, based on the definition of ψ given in Eq. (4.31),

$$\psi = \sum_{l \in D} \sum_{k \in D} \frac{1}{\bar{k}} k H(l) P(k) r(k, l). \quad (4.34)$$

Thus,

$$\begin{aligned}
\psi &= \frac{1}{2(1+\mu t)\bar{k}} \left(-\bar{k}(1-c) - \frac{\gamma(1+\bar{r}-c)(\sigma_k^2 + \bar{k}^2)}{1-\gamma\bar{k}} + \mu s\bar{k} - 2\mu t \left((1-c)\bar{k} \right. \right. \\
&\quad \left. \left. + \frac{\gamma(1+\bar{r}-c)(\sigma_k^2 + \bar{k}^2)}{1-\gamma\bar{k}} \right) + \frac{\gamma\bar{k}^2}{1-\gamma\bar{k}} \left(\mu s - \frac{2\mu t\gamma(1+\bar{r}-c)(\sigma_k^2 + \bar{k}^2)}{(1-\gamma\bar{k})\bar{k}} \right. \right. \\
&\quad \left. \left. - 2\mu t(1-c) \right) - \gamma\bar{k}^2 \frac{1+2\mu t}{1-\gamma\bar{k}} \psi \right) \\
&= \frac{1}{2(1+\mu t)} \left(c-1 - \frac{\gamma\bar{k}(1+\bar{r}-c)(\sigma_k^2 + \bar{k}^2)}{1-\gamma\bar{k}} + \mu s - 2\mu t \left(1-c + \frac{\gamma\bar{k}(1+\bar{r}-c)}{1-\gamma\bar{k}} \right) \right. \\
&\quad \left. + \frac{\gamma\bar{k}}{1-\gamma\bar{k}} \left(\mu s - 2\mu t \left((1-c) + \frac{\gamma\bar{k}(1+\bar{r}-c)}{1-\gamma\bar{k}} \right) - \frac{2\mu t\gamma(1+\bar{r}-c)\sigma_k^2}{(1-\gamma\bar{k})\bar{k}} \right) \right. \\
&\quad \left. - \frac{\gamma\sigma_k^2(1+\bar{r}-c)}{(1-\gamma\bar{k})\bar{k}} - \frac{2\mu t\gamma\sigma_k^2(1+\bar{r}-c)}{(1-\gamma\bar{k})\bar{k}} - \gamma\bar{k} \frac{1+2\mu t}{1-\gamma\bar{k}} \psi \right) \\
&= \frac{1}{2(1+\mu t)} \left(- \left(1-c + \frac{\gamma\bar{k}(1+\bar{r}-c)}{1-\gamma\bar{k}} \right) \left(1 + \frac{2\mu t}{1-\gamma\bar{k}} \right) + \frac{\mu s}{1-\gamma\bar{k}} \right. \\
&\quad \left. - \frac{\gamma\sigma_k^2(1+\bar{r}-c)}{(1-\gamma\bar{k})\bar{k}} \left(1 + \frac{2\mu t}{1-\gamma\bar{k}} \right) - \gamma\bar{k} \frac{1+2\mu t}{1-\gamma\bar{k}} \psi \right). \tag{4.35}
\end{aligned}$$

The two expressions given in Eq. (4.33) and Eq. (4.35) together formulate a full rank linear equation system with two variables, i.e., $\bar{r}$ and ψ . Thus, the closed-form expression for both $\bar{r}$ and ψ can be obtained.

$$\begin{aligned}
\bar{r} &= \rho^{-1} \frac{\gamma\bar{k}}{2(1+\mu t) - \gamma\bar{k}} \left(- \left(1-c + \frac{\gamma\bar{k}(1-c)}{1-\gamma\bar{k}} \right) \left(1 + \frac{2\mu t}{1-\gamma\bar{k}} \right) + \frac{\mu s}{\gamma\bar{k}} \right) \\
&\quad - \frac{\mu t\gamma^2\sigma_k^2(1-c)}{(1-\gamma\bar{k})^2(1+\mu t)} + \frac{(1+2\mu t)\gamma^2\sigma_k^2(1-c)}{2(2+2\mu t - \gamma\bar{k})(1-\gamma\bar{k})(1+\mu t)} \left(1 + \frac{2\mu t}{\gamma\bar{k}} \right), \tag{4.36}
\end{aligned}$$

where

$$\begin{aligned}
\rho &= 1 + \frac{\gamma\bar{k}}{2(1+\mu t) - \gamma\bar{k}} \left(1 + \frac{2\mu t}{1-\gamma\bar{k}} \right) + \frac{\mu t\gamma^2\sigma_k^2(1+\bar{r}-c)}{(1-\gamma\bar{k})^2(1+\mu t)} \\
&\quad - \frac{(1+2\mu t)\gamma^2\sigma_k^2}{2(2+2\mu t - \gamma\bar{k})(1-\gamma\bar{k})(1+\mu t)} \left(1 + \frac{2\mu t}{\gamma\bar{k}} \right). \tag{4.37}
\end{aligned}$$

Likewise, the closed-form expression for the variable ψ can be derived through similar steps. Accordingly, $r(m, n)$ can be obtained after plugging these two closed-form expressions into Eq. (4.30), and thus the solution of $r(m, n)$ is unique. The proof is then completed. $\square$

4.2.3 Discussion on Incomplete Information of Internal Parameter

The incomplete information about social tie/influence of users has been discussed so far. However, there are other kinds of information which cannot be accessed by CSPs neither, such as the parameter a_i and b_i . The CSP has knowledge only about their expectations $\mathbb{E}[a]$ and $\mathbb{E}[b]$.

This subsection explores the uniform reward mechanism for the incomplete information scenario. To be more practical, the system model will be same as Chapter 3. Under the additional assumption as follows, the lower bound of single reward, i.e., single reward bound as in Theorem 4.4 is obtained.

Assumption 4.1 $c \geq \bar{a} + \mu s$, where $\bar{a} = \sum_{i=1}^N a_i/N$.

Theorem 4.4 *In the scenario of incomplete information, i.e., only the expectations of $\{a_i\}_{i=1}^n$ and $\{b_i\}_{i=1}^n$ are known and denoted by $\mathbb{E}[a]$ and $\mathbb{E}[b]$, the optimal uniform reward is bounded as shown in Eq. (4.42).*

Proof. Since the optimal value is

$$\mathbf{r}^* = (2\mathbf{I} + 2\mu t\mathbf{K})^{-1} \{ \mu [s\mathbf{1} - 2t\mathbf{K}(\mathbf{a} - c\mathbf{1})] - (\mathbf{a} - c\mathbf{1}) \}, \quad (4.38)$$

the average value of total offered reward can be easily obtained, i.e., $\bar{r} = \sum_i r_i/N$. Specifically, the expression of $\bar{r}$ is shown in Eq. (4.39). After taking the expectation with respect to the random variables $\{a_i\}_{i=1}^N$ and $\{b_i\}_{i=1}^N$, the analytical expression for

the optimal single reward bound with incomplete information is obtained in Eq. (4.42), where $E_b(\Xi)$ is to take the expected value for random variable b_i in the component of Ξ .

If $c \geq \bar{a} + \mu s$ holds,

$$\bar{r} = \frac{1}{N} \mathbf{1}^\top (2\mathbf{I} + 2\mu t \mathbf{K})^{-1} \{ \mu [s \mathbf{1} - 2t \mathbf{K} (\mathbf{a} - c \mathbf{1})] - (\mathbf{a} - c \mathbf{1}) \} \quad (4.39)$$

$$= \frac{-\mathbf{1}^\top (\mathbf{a} - c \mathbf{1})}{2N} + \frac{\mathbf{1}^\top}{N} (2\mathbf{I} + 2\mu t \mathbf{K})^{-1} [\mu s \mathbf{1} - \mu t \mathbf{K} (\mathbf{a} - c \mathbf{1})]. \quad (4.40)$$

$$\begin{aligned} r_u &= \frac{c - \bar{a}}{2} + E_b \left(\frac{1}{N} \mathbf{1}^\top [2(\mathbf{B} - \mathbf{G}) + 2\mu t \mathbf{I}]^{-1} [\mu s (\mathbf{B} - \mathbf{G}) - \mu t (\bar{a} - c) \mathbf{I}] \mathbf{1} \right) \\ &= \frac{c - \bar{a}}{2} \\ &\quad + E_b \left(\frac{1}{N} \mathbf{1}^\top [2(\mathbf{B} - \mathbf{G}) + 2\mu t \mathbf{I}]^{-1} [\mu s (\mathbf{B} - \mathbf{G}) + \mu s^2 t \mathbf{I} - \mu s^2 t \mathbf{I} - \mu t (\bar{a} - c) \mathbf{I}] \mathbf{1} \right) \\ &= \frac{c - \bar{a}}{2} + \frac{\mu s}{2N} \mathbf{1}^\top \mathbf{1} + E_b \left(\frac{1}{N} \mathbf{1}^\top [2(\mathbf{B} - \mathbf{G}) + 2\mu t \mathbf{I}]^{-1} [-\mu^2 s t - \mu t (\bar{a} - c)] \mathbf{1} \right) \\ &= \frac{c - \bar{a}}{2} + \frac{\mu s}{2} - \frac{\mu t}{N} (\mu s + \bar{a} - c) E_b (\mathbf{1}^\top [2(\mathbf{B} - \mathbf{G}) + 2\mu t \mathbf{I}]^{-1} \mathbf{1}) \end{aligned} \quad (4.41)$$

$$\Rightarrow r_u \geq \frac{c - \mathbb{E}[a]}{2} + \frac{\mu s}{2} - \frac{\mu t}{N} (\mu s + \mathbb{E}[a] - c) \mathbf{1}^\top [2\mathbb{E}_b[\mathbf{B}] - 2\mathbf{G} + 2\mu t \mathbf{I}]^{-1} \mathbf{1} \quad (4.42)$$

$$\mathbf{D} = 2\mathbf{B}_1 - 2\mathbf{G} + 2\mu t \mathbf{I} > 0$$

and

$$\mathbf{E} = 2\mathbf{B}_2 - 2\mathbf{G} + 2\mu t \mathbf{I} > 0,$$

and

$$\begin{aligned} &\underbrace{\beta \begin{bmatrix} \mathbf{1}^\top \mathbf{D} \mathbf{1} & \mathbf{1}^\top \\ \mathbf{1} & \mathbf{D} \end{bmatrix}}_{\geq 0} + (1 - \beta) \underbrace{\begin{bmatrix} \mathbf{1}^\top \mathbf{E} \mathbf{1} & \mathbf{1}^\top \\ \mathbf{1} & \mathbf{E} \end{bmatrix}}_{\geq 0} = \\ &\quad \begin{bmatrix} \beta \mathbf{1}^\top \mathbf{D}^{-1} \mathbf{1} + (1 - \beta) \mathbf{1}^\top \mathbf{E}^{-1} \mathbf{1} & \mathbf{1}^\top \\ \mathbf{1} & \beta \mathbf{D} + (1 - \beta) \mathbf{E} \end{bmatrix} \geq 0, \end{aligned}$$

where $\beta \in (0, 1)$. Using Schur decomposition,

$$\beta \mathbf{1}^\top \mathbf{D}^{-1} \mathbf{1} + (1 - \beta) \mathbf{1}^\top \mathbf{E}^{-1} \mathbf{1} \geq \mathbf{1}^\top [\beta \mathbf{D} + (1 - \beta) \mathbf{E}] \mathbf{1}. \quad (4.43)$$

Then, $f(\mathbf{X}) = \mathbf{1}^\top \mathbf{X}^{-1} \mathbf{1}$ is convex for all positive definite matrix $\mathbf{X}$. Based on Jensen's inequality in the multivariate case on random variable $\mathbf{X}$,

$$\mathbb{E}_Y [g(\mathbf{X})] \geq g[\mathbb{E}_Y (\mathbf{X})], \quad (4.44)$$

the lower bound of optimal reward with incomplete information, i.e., single reward bound is shown in Eq. (4.42). The proof is completed. $\square$

4.2.4 Discussions on Asymmetric Social Influence

It is noted that the proposed approach is not restricted to the symmetry assumption that $g_{ij} = g_{ji}$. In other words, social ties are not reciprocal under the consideration in incomplete information scenario. Instead, the adjacency matrix $\mathbf{G}$ leads to different in-degrees and out-degrees of MUs. The in-degree denotes the number of other MUs that a certain MU influences, the out-degree denotes the number of other MUs influencing this MU. Thus, the in-degree represents its influence and the out-degree represents its susceptibility. The distribution of in-degree and out-degree captures the social network effects from the network interaction patterns. Recall that since both the in-degree and out-degree distributions of each MU instead of the degree distribution, the proposed model can still be applied to the asymmetric social ties. For example, an MU Alice has the social influence on another MU, but the latter may not have the social influence on Alice. The reason is that Alice may have different in-degree and out-degree.

4.2.5 Discussion on Cost Function:

Note that the above model can be straightforwardly extended to a more generalized heterogenous unit cost and nonlinear cost function here, and an example when the cost

function becomes $c_i x_i^2$ is shown. This function can represent the condition that the incurred cost increases when the MU keeps increasing its participation level, and the marginal increase is increasing (instead of keeping unchanged for linear cost unction).

Recall that the expected utility of MU i in incomplete information scenario is reformulated as follows:

$$U_i(x_i, \mathbf{x}_{-i}, \mathbf{r}) = \mathbb{E}[u_i(x_i, \mathbf{x}_{-i}, \mathbf{r})] = x_i - \frac{1}{2}x_i^2 + \gamma x_i \mathbb{E}\left[\sum_{j \in \mathcal{N}_i} x_j\right] + r_i x_i - c_i x_i^2. \quad (4.45)$$

With the same deduction as Eq. 4.7, the expected utility can be expressed as follows:

$$U_i(x_i, \mathbf{x}_{-i}, \mathbf{r}, k_i) = (1 + r_i)x_i - \left(\frac{1}{2} + c_i\right)x_i^2 + \gamma k_i x_i \text{Avg}(\mathbf{x}_{-i}), \quad (4.46)$$

Similar to the proof of Theorem 4.1,

$$\begin{aligned} \frac{\partial U_i(\bar{x}, \mathbf{x}_{-i}, \mathbf{r}, k_i)}{\partial x_i} &= (1 + r_i) - c_i \bar{x} - \bar{x} + \gamma k_i \text{Avg}(\mathbf{x}_{-i}) \\ &\leq (1 + r_i) - c_i \bar{x} - \bar{x} + \gamma k^{\max} \bar{x} \\ &= 1 + r_i + (\gamma k^{\max} - 1 - c_i) \bar{x}. \end{aligned} \quad (4.47)$$

Due to the condition $\gamma k^{\max} < 1$, $\gamma k^{\max} - c_i < 1$ holds evidently. Thus, the existence of the Bayesian follower game can be still guaranteed. Moreover, it still holds that $\left| \frac{\partial^2 U_i(\bar{x}, \mathbf{x}_{-i}, \mathbf{r}, k_i)}{\partial x_i \partial \text{Avg}(\mathbf{x}_{-i})} / \frac{\partial^2 U_i(\bar{x}, \mathbf{x}_{-i}, \mathbf{r}, k_i)}{\partial x_i \partial x_i} \right| = |\gamma k_i| \leq |\gamma k^{\max}|$. Thus, the uniqueness of the Bayesian follower game is guaranteed even if changing the cost function of MUs. Based on the unique Bayesian Nash equilibrium, the CSP can still achieve the profit maximization through backward induction. The corresponding proof steps are structurally the same as the proof of Theorems 4.2 and 4.3 with the uniform cost.

4.3 Performance Evaluation

This section evaluates the performance of the proposed socially-aware incentive mechanisms of the CSP in crowdsensing applications, and investigate the impacts of different parameters of mobile networks on the performance.

Figure 4.1: The illustration of the optimal offered reward with respect to different in-degrees and out-degrees.

Similar to the above discussions, this section considers a group of N MUs. The in-degree and out-degree of MUs follow the normal distribution $\mathcal{N}(\bar{k}, \sigma_k^2)$ and $\mathcal{N}(\bar{k}, \sigma_l^2)$, respectively. The parameters are set as follows: $\gamma = 0.01$, $\bar{k} = 20$, $\sigma_k^2 = \sigma_l^2 = 10$, $\mu = 10$, $s = 20$, $t = 0.05$, $c = 15$, and $N = 100$.

The optimal offered reward in terms of different in-degrees and out-degrees is illustrated in Fig. 4.1. Interestingly, the optimal offered reward increases with the increase of in-degree, and increases with the decrease of out-degree. Recall that the MU's in-degree represents its influence and the out-degree represents its susceptibility. As the in-degree of the MU increases, this MU can encourage more other MUs due to the underlying social network effects. In a crowdsensing-based road traffic information sharing platform, the drivers in critical central paths can be treated as the MUs with higher in-degree, i.e., greater influence. The road information from these drivers plays a great role, i.e., the

Figure 4.2: The impacts of mean value of social network effects.

participation of these drivers can greatly promote the participation of others. Thus, in the presence of social network effects, the CSP tends to offer more reward to the MUs with the higher in-degree, since they potentially motivate more participation level of other MUs. On the contrary, for the MUs with the higher out-degree, the CSP has no incentive to offer more reward. The reason is that the MUs with the higher out-degree are more susceptible, and these MUs are potentially positively affected by others. Consequently, the CSP is able to offer less reward to save the cost.

Furthermore, Fig. 4.2 shows the impacts of mean value of social network effects on the players of Bayesian Stackelberg game. As expected, the optimal offered reward decreases when the mean value of social network effects increases. The reason is that as the mean value of social network effects become stronger, the MUs can motivate each other to have higher participation level due to the interdependent participation behaviors. The total utilities of MUs become greater, and thus the CSP tends to offer less reward to save the cost. Consequently, the CSP achieves the greater revenue gain. In addition, comparing different curves with different value of μ , when μ , i.e., the equivalent

Figure 4.3: The impacts of variance of the distribution of in/out-degree.

monetary worth of MUs' participation level increases, the CSP tends to offer more reward as the participation incentive. The reason is that the CSP is more inclined to arouse the enthusiasms of MUs when the CSP can transform the participation level of MUs to more monetary revenue efficiently. Therefore, to extract more surplus from MUs, the CSP offers more reward and thus achieves a greater revenue gain.

Figure 4.3 illustrates the impacts of variance of the distribution of social network effects on the players of Bayesian Stackelberg game. As the variance of social network effects decreases, the achieved revenue under uniform incentive mechanism is close to that under discriminatory incentive mechanism. The reason is that the heterogeneity of MUs is reduced when the value of variance decreases. An extreme case may be considered when the value of variance is zero, i.e., the MUs are homogeneous, the discriminatory incentive mechanism yields the same results as those of the uniform incentive mechanism. On the contrary, when the value of variance increases, the achieved revenue under the discriminatory incentive mechanism increases. The reason is that discriminatory incentive mechanism enables the CSP to exploit the different preference, i.e., parameters of

utility function, for each of MUs, which leads to the decrease of total utilities of MUs and the increases of the revenue. Moreover, when the participation cost of MUs increases, the utility of MUs from participation is discounted. As such, the CSP tends to offer more reward to compensate the participation cost for improving their motivation. Meanwhile, the total utilities of MUs still decrease due to the increasing participation cost. Similarly, the revenue of the CSP decreases.

Lastly, both Figs. 4.2 and 4.3 demonstrate the fact that the discriminatory incentive mechanism performs better in terms of the achieved revenue compared with uniform incentive mechanism. The intuition is that, with the certain social structure information, the CSP can set different reward for different MUs, as verified by the Fig. 4.1. As such, the CSP can significantly encourage the greater participation level of MUs. In particular, the social structure information guides the CSP to extract more surplus from the MUs' participation, which results in the greater revenue gain.

In summary, the following engineering insights are summarized:

- The network effects tremendously stimulate higher MU participation level, which leads to the greater total utilities of MUs as well as the greater revenue of the CSP.
- The discriminatory incentive mechanism yields the greater revenue of the CSP than that of the uniform incentive mechanism in both the complete and incomplete information scenarios.
- The revenue gap between the uniform and discriminatory incentive mechanisms depends on the variance of network effects.
- The CSP has an incentive to offer more reward to the influential MUs and less reward to the susceptible MUs, in order to promote a greater overall participation level.

4.4 Summary

In this chapter, a novel socially-aware incentive mechanism has been proposed by leveraging the underlying social network effects to attract participants to crowdsensing platform. This chapter focuses on designing incentive mechanism with the consideration of incomplete information on social network effects, which is commonly applicable to some of the real-world crowdsensing applications. Specifically, the Bayesian Stackelberg game is formulated to analyze and evaluate the impacts of uncertainty of social network effects, which utilizes the structural properties from the underlying social domain. The unique Bayesian Stackelberg equilibrium has been considered as the optimal solution. Performance evaluation of this game model has shown the impressive role of social network effects in crowdsensing incentivizing.

Chapter 5

A Hierarchical Game for Incentive Mechanisms with Multiple Crowdsensing Service Provider

This chapter¹ studies a socially-aware crowdsensing market consisting of multiple CSPs and multiple users. Motivated by the fact that the players including CSPs and users are relational in nature, a game-theoretic framework is developed to characterize the feature of distributed decision making of players. Specifically, this chapter investigates the incentive mechanisms by formulating the two-stage interactions among CSPs and users as a hierarchical multi-leader multi-follower Stackelberg game, where the CSPs are leaders and the users are followers.

5.1 Multi-Leader Multi-Follower Game Model

To effectively analyze the incentive mechanisms, Chapter 5 considers a general socially-aware MCS scenario with multiple CSPs and multiple MCS mobile users, as illustrated in Fig. 5.1. Specifically, there are K CSPs and N socially-connected mobile users, the set of which are denoted by $\mathcal{K} \triangleq \{1, \dots, K\}$ and $\mathcal{N} \triangleq \{1, \dots, N\}$, respectively. The interactions among the CSPs and the socially-connected participants, i.e., Mobile Users (MUs), are

¹The work in this chapter has been published in [86].

Figure 5.1: System model of socially-aware crowdsensing applications with multiple CSPs and multiple MUs.

modeled as a multi-leader multi-follower Stackelberg game. The CSPs acting as the leaders firstly announce the sensing task and corresponding reward as incentive. Based on the reward, the MUs acting as the followers determine their individual participation levels (sensing efforts) in different CSPs, e.g., the sensing time or the frequency of sensing.

In the following, the payoff modeling for the multi-leader multi-follower game formulation is specified.

5.1.1 Utility Modeling of MUs

Let $\mathbf{X} = [\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_N]^\top$ denote the participation level vector for all MUs, where $\mathbf{x}_i = [x_{i1}, x_{i2}, \dots, x_{iK}]$, $i \in \mathcal{N}$, represent the vector of participation levels of MU i in all CSPs. Let $\mathbf{X}_{-i}$ denote the vector of participation levels for all other MUs except MU i . Likewise, r_{ik} is denoted as reward offered to MU i for performing the sensing tasks by CSP k . The reward vector is defined as $\mathbf{R} = [\mathbf{r}_1, \mathbf{r}_2, \dots, \mathbf{r}_N]^\top$, where $\mathbf{r}_i = [r_{i1}, r_{i2}, \dots, r_{iK}]$, $i \in \mathcal{N}$. The vector $\mathbf{r}_i$ consists of the reward to MU i from all different CSPs. In practice, all

participation levels are positive, i.e., $x_{ik} \in (0, +\infty)$, $i \in \mathcal{N}$, $k \in \mathcal{K}$. The socially-aware utility of MU i is then defined as follows:

$$u_i = f(\mathbf{x}_i) + \Phi(\mathbf{x}_i, \mathbf{X}_{-i}) + \beta(\mathbf{x}_i) + r(\mathbf{x}_i) - c(\mathbf{x}_i). \quad (5.1)$$

The first term $f(\mathbf{x}_i)$ indicates the fact that each MU i can obtain the internal benefits from the participation in all CSPs. The internal benefits are formulated as a linear-quadratic function: $f_i(\mathbf{x}_i) = \sum_{k \in \mathcal{K}} (a_{ik}x_{ik} - b_{ik}x_{ik}^2)$. Specifically, $a_{ik} > 0$ and $b_{ik} > 0$ are the internal coefficients capturing the direct value to each MU i from the participation in CSP k [20, 79], where a_{ik} indicates the maximum internal willingness rate for participation, and b_{ik} represents the elasticity factor of willingness.

Due to the social influence/tie among MUs, the second term, $\Phi(\mathbf{x}_i, \mathbf{X}_{-i})$ is incorporated to represent the external benefits gained from the participation in socially-aware services in MCS. In socially-aware services, the social influence that one MU has on the other MUs can be termed as “social network effects”, and the MU can enjoy an additional benefit from information contributed or shared by the others because of such network effects [19]. To model the network effects, the adjacency matrix $\mathbf{g}^k = [g_{ij}^k]_{i,j \in \mathcal{N}, k \in \mathcal{K}}$ is introduced. The entry in the i th row and j th column of matrix $\mathbf{g}^k$, i.e., g_{ij}^k , denotes the social influence that MU j has on MU i in crowdsensing service provided by CSP k , $\forall i, j \in \mathcal{N}$, $\forall k \in \mathcal{K}$. As per [87, 88], the MU’s social influence to another is likely to imitate the latter’s influence to the former, and vice versa. That is, two socially-connected friends in networks incline to influence each other and then behave similarly. Consequently, the social influence from one MU to another MU, and vice versa tend to be the same. Motivated by this, it is assumed that $g_{ij}^k = g_{ji}^k$ in this work, i.e., the social influence/tie in the same service provided by CSP k is reciprocal, $\forall i, j \in \mathcal{N}$, $\forall k \in \mathcal{K}$. Following [20, 63, 89] in the social network settings, $\sum_{k \in \mathcal{K}} \sum_{j \in \mathcal{N}} g_{ij}^k x_{ik} x_{jk}$ represents the indirect benefits gained from the participation, originating from network effects. Taking

again the example of healthcare-based crowdsensing services, an MU can benefit from the accuracy of diet recommendation, and the accuracy can be promoted by exploiting the nutritional information contributed and shared by her socially-connected friends taking similar types of food. With a larger value of g_{ij}^k , i.e., more influence, the participation level of MU j can increase the external benefits of MU i faster.

Considering the fact that practically there exist multiple crowdsensing services for MUs, substitutability and complementarity are further incorporated to realistically describe the interconnections of different services. If two services are substitutable, then an MU having more of one service causes himself/herself to desire less of the other service. For example, if an MU wants to track her running data, she may only select one of the CSPs that provide similar running partner services. By contrast, if two services are complementary, using more of one service requires more usage of another service. For example, an MU wants to monitor her health state, she may select both one CSP providing exercise track services and one providing nutrition track services. Therefore, the MUs can benefit more from having complementary crowdsensing services together. In Fig. 5.1 with three CSPs, an MU may choose either Nike Run Club [90] or Runkeeper, since these two services are substitutable and any of them can satisfy the MU's needs of exercise. However, it is highly possible that an MU chooses MyPlate Calorie Tracker [91] and one of running services at the same time due to the complementarity. Following [92], the market demands are assumed to be symmetric, which means the marketing clout among different CSPs will be average and there is no CSP owning overwhelming market power compared with other CSPs. Therefore, the influence between any pair of CSPs will be mutually similar. In this work, the parameter ζ_i^{ks} is used to denote the interconnection, i.e., the substitutability or complementarity, between two crowdsensing services from CSPs k and s in terms of MU i , and $\zeta_i^{ks} = \zeta_i^{sk}, \forall i, j \in \mathcal{N}, \forall k \in \mathcal{K}$. As such, the third term $\beta(\mathbf{x}_i) = \sum_{k \in \mathcal{K}} \sum_{s \in \mathcal{K}} \zeta_i^{ks} x_{ik} x_{is}$ is used to incorporate substitutability and complementarity of services. When $\zeta_i^{ks} > 0$, a user choosing CSP s will have a positive impact

on its willingness of choosing CSP k , which indicates that the service from CSP k and that from CSP s are complementary. When $\zeta_i^{ks} < 0$, choosing CSP s will discourage the user from joining CSP k , meaning that the service from CSP k and that from CSP s are substitutable.

For the fourth term, the total reward offered to MU i from all CSPs is denoted by $r(\mathbf{x}_i) = \sum_{k \in \mathcal{K}} r_{ik}x_{ik}$, depending on the MU's participation level. The last term $c(\mathbf{x}_i)$ represents the associated cost of MU i incurred by its participation such as energy and network bandwidth consumption. Following the vast literature, e.g., [17, 32, 49], the cost function $c(\mathbf{x}_i)$ is formulated as $\sum_{k \in \mathcal{K}} c_{ik}x_{ik}$, where c_{ik} denotes the unit cost of MU i for the participation in CSP k .

To sum up, the utility of MU $i \in \mathcal{N}$ is formulated as follows:

$$u_i(\mathbf{x}_i, \mathbf{X}_{-i}, \mathbf{r}_i) = \sum_{k \in \mathcal{K}} \left(a_{ik}x_{ik} - b_{ik}x_{ik}^2 + \sum_{j \in \mathcal{N}} g_{ij}^k x_{ik}x_{jk} + \sum_{s \in \mathcal{K}} \zeta_i^{ks} x_{ik}x_{is} + r_{ik}x_{ik} - c_{ik}x_{ik} \right). \quad (5.2)$$

5.1.2 Profit Modeling of CSPs

The payoff function, i.e., the profit, of each CSP consists of two components: one is the revenue obtained from the total aggregated participation or contributions of all MUs, the other is the reward cost paid to its MUs. Therefore, the profit of CSP $k \in \mathcal{K}$ is given by

$$\Pi_k(\mathbf{r}^k, \mathbf{X}) = \mu \sum_{i \in \mathcal{N}} (s_{ik}x_{ik} - t_{ik}x_{ik}^2) - \sum_{i \in \mathcal{N}} r_{ik}x_{ik}, \quad (5.3)$$

where $\mathbf{r}^k = [r_{1k}, r_{2k}, \dots, r_{Nk}]$. $\mathbf{r}^k$ denotes the reward profile, i.e., the strategy of CSP k .

Following [79, 89], the linear-quadratic function is leveraged to convert the MUs' sensing contributions into the monetary revenue of CSPs. That is, the revenue obtained from MUs increases with the participation level of MUs, but with the decreasing marginal increase. μ is the revenue coefficient acting as an adjustable factor converting the MUs' sensing contributions into equivalent monetary revenue, and s_{ik} and t_{ik} are the positive

coefficients which indicate the internal valuation rate of CSP k induced by the contribution of MU i and corresponding elasticity factor, respectively.

5.1.3 Stackelberg Game Formulation

Game theory is powerful when studying the decentralized decision makings among strategic agents [12, 32]. This part models the interactions among the CSPs and the MUs as a two-stage hierarchical game, i.e., Stackelberg game. The players in a Stackelberg game consist of leaders and followers. The leaders move first and the followers take actions accordingly. In the Stackelberg game, all the players including the CSPs and the MUs aim to maximize their individual payoffs in the process of decision making, where the leader game in Stage I is the profit maximization of the CSPs and the follower game in Stage II is the utility maximization of the MUs. In particular, each CSP $k \in \mathcal{K}$ determines the reward $\mathbf{r}^k$ for one unit of participation level from all MUs, and each MU $i \in \mathcal{N}$ decides on the amounts of participation levels $\mathbf{x}_i$ for different CSPs under the social influences from other socially-connected MUs.

In the game model, the MUs and the CSPs are rational and self-interested, taking strategies to maximize their individual payoffs, whose objectives are to solve the following optimization problems. Given the reward profiles of all CSPs (i.e., $\mathbf{R}$) and the participation profiles of other MUs (i.e., $\mathbf{X}_{-i}$), each MU $i \in \mathcal{N}$ determines its participation levels $\mathbf{x}_i$ by solving the following problem:

$$\begin{aligned} \mathbf{Prob}_{MU_i} : \quad & \max \quad u_i(\mathbf{x}_i, \mathbf{X}_{-i}, \mathbf{R}) \\ & \text{s.t.} \quad Q_i, \end{aligned} \tag{5.4}$$

where $Q_i \in [0, +\infty)$ is the strategy space of MU i .

Considering all the participation profiles of MUs (i.e., $\mathbf{X}$), each CSP $k \in \mathcal{K}$ determines its reward profile $\mathbf{r}^k$ in order to maximize its profit. Therefore, the profit maximization

problem faced by each CSP $k \in \mathcal{K}$ is given by

$$\begin{aligned} \mathbf{Prob}_{CSP_k} : \quad & \max \quad \Pi_k(\mathbf{r}^k, \mathbf{X}) \\ & \text{s.t.} \quad Y_k, \end{aligned} \tag{5.5}$$

where $Y_k \in [0, +\infty)$ is the strategy space of CSP k .

One of the challenges in addressing the above game lies in the high dimensionality of the strategy space of each player. Also, the network effects among MUs, and the substitutability/complementarity among CSPs further impede the efficient solutions. As such, matrix manipulations [93] are utilized to assist the analysis.

Before the game equilibrium analysis, some mathematical preliminaries on matrix notation are briefly presented as follows.

1) Given two matrices: $\mathbf{W}' = [w'_{ij}]_{m \times n}$ and $\mathbf{W}'' = [w''_{ij}]_{m \times n}$. The Hadamard product of the two matrices, $\mathbf{W}' \circ \mathbf{W}'' = [w'_{ij}w''_{ij}]_{m \times n}$, has the same dimension as the operands.

2) Given two matrices: $\mathbf{W}' = [w'_{ij}]$ with dimension of $m \times n$ and $\mathbf{W}''$ with dimension of $p \times q$. The Kronecker product of $\mathbf{W}'$ and $\mathbf{W}''$ is a $mp \times nq$ matrix, defined by

$$\mathbf{W}' \otimes \mathbf{W}'' = \begin{pmatrix} w'_{11}\mathbf{W}'' & \cdots & w'_{1n}\mathbf{W}'' \\ \vdots & \ddots & \vdots \\ w'_{m1}\mathbf{W}'' & \cdots & w'_{mn}\mathbf{W}'' \end{pmatrix}.$$

3) Given a matrix $\mathbf{W} = [w_{ij}]$, if $w_{ij} > 0, \forall i, j$, $\mathbf{W}$ is called a positive matrix.

5.2 Multi-Leader Multi-Follower Game Equilibrium Analysis

This section applies backward induction methods to study the Stackelberg equilibrium. The MU-level non-cooperative game in Stage II with the given strategies of CSPs is analyzed by finding the Nash equilibrium solutions to the MU-level game. Then, the Nash equilibrium solutions of the MU-level game is substituted into the CSP-level non-cooperative game in Stage I, which proves the existence and uniqueness of the Stackelberg equilibrium.

5.2.1 Solutions to the MU-level Non-Cooperative Game

The MU-level non-cooperative game is denoted as $\mathcal{G} = (\mathbf{Q}, \mathbf{u})$, where $\mathbf{Q} := (Q_i)_{i=1}^N$, $\mathbf{u} := (u_i)_{i=1}^N$. In the following, the existence and uniqueness of the solutions to MU-level game are studied by capitalizing on the Variational Inequalities (VI) theory. As per in [94], the corresponding VI problem $\mathcal{VI}(\mathcal{Q}, \mathcal{U})$ of the MU-level game $\mathcal{G}(\mathbf{Q}, \mathbf{u})$ can be formulated, where $\mathcal{Q} = Q_1 \times Q_2 \times \cdots \times Q_N$, $\mathcal{U} := (-\nabla_{\mathbf{x}_i} u_i)_{i=1}^N$.

The VI problem is equivalent to the MU-level game, i.e., $\mathcal{VI}(\mathcal{Q}, \mathcal{U}) \equiv \mathcal{G}(\mathbf{Q}, \mathbf{u})$, provided that the following two conditions hold. The first is that the strategy space of MUs Q_i is closed and convex, and the second is that u_i is continuously differentiable and concave in $\mathbf{x}_i$ for the given $\mathbf{x}_{-i}$. As $\frac{\partial^2 u_i}{\partial x_{ik}^2} = -2b_{ik} < 0$, the second condition is satisfied. In the following, the first condition is also proved to be satisfied.

Assumption 5.1 $2b_{ik} > \sum_{j \in \mathcal{N}} g_{ij}^k + 2 \sum_{s \in \mathcal{K}} |\zeta_i^{ks}|$.

Following [20, 63, 89], the above assumption is set to ensure that the MUs will not unboundedly increase the participation level. x_{ik}^* is denoted as the optimal participation level of MU i in CSP k , and it is observed from the first order optimality condition that

$$\frac{\partial u_i}{\partial x_{ik}} = a_{ik} - 2b_{ik}x_{ik} + \sum_{j \in \mathcal{N}} g_{ij}^k x_{jk} + 2 \sum_{s \in \mathcal{K}} \zeta_i^{ks} x_{is} + r_{ik} - c_{ik}. \quad (5.6)$$

When $x_{ik} = x_{ik}^*$, $\left. \frac{\partial u_i}{\partial x_{ik}} \right|_{x_{ik} = x_{ik}^*} = 0$. Define $x_{ik}^\dagger = \max_{i \in \mathcal{N}, k \in \mathcal{K}} \{x_{ik}^*\}$, and

$$\left. \frac{\partial u_i}{\partial x_{ik}} \right|_{x_{ik} = x_{ik}^\dagger} = a_{ik} - 2b_{ik}x_{ik}^\dagger + \sum_{j \in \mathcal{N}} g_{ij}^k x_{jk}^* + 2 \sum_{s \in \mathcal{K}} \zeta_i^{ks} x_{is}^* + r_{ik} - c_{ik} = 0. \quad (5.7)$$

Then,

$$\begin{aligned} 2b_{ik}x_{ik}^\dagger &= a_{ik} + r_{ik} - c_{ik} + \sum_{j \in \mathcal{N}} g_{ij}^k x_{jk}^* + 2 \sum_{s \in \mathcal{K}} \zeta_i^{ks} x_{is}^* \\ &\leq a_{ik} + r_{ik} - c_{ik} + \sum_{j \in \mathcal{N}} g_{ij}^k x_{ik}^\dagger + 2 \sum_{s \in \mathcal{K}} \zeta_i^{ks} x_{ik}^\dagger. \end{aligned} \quad (5.8)$$

Under Assumption 5.1, it can be concluded that

$$\begin{aligned} x_{ik}^\dagger (2b_{ik} - \sum_{j \in \mathcal{N}} g_{ij}^k - 2 \sum_{s \in \mathcal{K}} \zeta_i^{ks}) &\leq a_{ik} + r_{ik} - c_{ik} \\ x_{ik}^\dagger &\leq \frac{a_{ik} + r_{ik} - c_{ik}}{2b_{ik} - \sum_{j \in \mathcal{N}} g_{ij}^k - 2 \sum_{s \in \mathcal{K}} \zeta_i^{ks}}. \end{aligned} \quad (5.9)$$

Therefore, the first condition that Q_i is closed and convex is satisfied. Until now, the VI problem is equivalent to the MU-level game, i.e., $\mathcal{VI}(\mathcal{Q}, \mathcal{U}) \equiv \mathcal{G}(\mathbf{Q}, \mathbf{u})$. The existence and uniqueness of game follow from the unique solution to the VI problem [94]. In the following, the existence and uniqueness of the solution to VI problem $\mathcal{VI}(\mathcal{Q}, \mathcal{U})$ will be proved.

5.2.1.1 Existence

First, $\mathcal{Q}$ is convex and compact. $\mathcal{Q}$ is convex due to the linear combination of Q_i . Since Q_i is closed and bounded as demonstrated above, the compactness of $\mathcal{Q}$ immediately follows. Second, $\mathcal{U}$ is continuous. Therefore, $\mathcal{VI}(\mathcal{Q}, \mathcal{U})$ has a nonempty solution set, the existence is finally achieved [94].

5.2.1.2 Uniqueness

Before studying the uniqueness, for ease of reference, the following notations are defined. $\mathbf{A} = [\mathbf{a}_1, \mathbf{a}_2, \dots, \mathbf{a}_N]^\top$, where $\mathbf{a}_i = [a_{i1}, a_{i2}, \dots, a_{iK}]$, $i \in \mathcal{N}$. $\mathbf{C} = [\mathbf{c}_1, \mathbf{c}_2, \dots, \mathbf{c}_N]^\top$ where $\mathbf{c}_i = [c_{i1}, c_{i2}, \dots, c_{iK}]$, $i \in \mathcal{N}$. $\mathbf{B} = \text{diag}[\mathbf{b}_1, \mathbf{b}_2, \dots, \mathbf{b}_N]$ where $\mathbf{b}_i = \text{diag}[b_{i1}, b_{i2}, \dots, b_{iK}]$, $i \in \mathcal{N}$. $\mathbf{Z} = \text{diag}[\mathbf{Z}_1, \mathbf{Z}_2, \dots, \mathbf{Z}_N]$, where $\mathbf{Z}_i = [\zeta_i^{ks}]_{k,s \in \mathcal{K}, i \in \mathcal{N}}$. $\mathbf{G} = [\mathbf{G}_{ij}]_{i,j \in \mathcal{N}}$, where $\mathbf{G}_{ij} = \text{diag}[g_{ij}^1, g_{ij}^2, \dots, g_{ij}^K]$. With these notations, Eq. (5.6) can be reformulated as $\mathcal{U} = -(\mathbf{A} - 2\mathbf{B}\mathbf{X} + \mathbf{G}\mathbf{X} + 2\mathbf{Z}\mathbf{X} + \mathbf{R} - \mathbf{C})$. The uniqueness of the solutions to VI problem $\mathcal{VI}(\mathcal{Q}, \mathcal{U})$ can be proved provided that $\mathcal{U}$ is strictly monotone.

The Jacobian matrix of $\mathcal{U}$ is $\mathbf{J}_{\mathcal{U}} = \frac{\partial \mathcal{U}}{\partial \mathbf{X}^\top} = 2\mathbf{B} - 2\mathbf{Z} - \mathbf{G}$. It is observed that for any $(K(i-1) + k)$ th row of $\mathbf{J}_{\mathcal{U}}$, the magnitude of the diagonal entry is $|2b_{ik}|$, and therefore the

sum of the magnitudes of all non-diagonal entries in that row is $\sum_{j \in \mathcal{N}} |-g_{ij}^k| + 2 \sum_{s \in \mathcal{K}} |-\beta_i^{ks}|$. Under Assumption 5.1, it can be inferred that $|2b_{ik}| = 2b_{ik} > \sum_{j \in \mathcal{N}} g_{ij}^k + 2 \sum_{s \in \mathcal{K}} |\beta_i^{ks}| > \sum_{j \in \mathcal{N}} |-g_{ij}^k| + 2 \sum_{s \in \mathcal{K}} |-\beta_i^{ks}|$, which indicates that $\mathbf{J}_{\mathcal{U}}$ is strictly diagonally dominant. Moreover, given that $b_{ik} > 0, \forall i \in \mathcal{N}, \forall k \in \mathcal{K}$, $\mathbf{J}_{\mathcal{U}}$ is positive definite and therefore $\mathcal{U}$ is strictly monotone. Therefore, the uniqueness of the solutions to VI problem $\mathcal{VI}(\mathcal{Q}, \mathcal{U})$ follows [94].

Since $\mathbf{J}_{\mathcal{U}} = 2\mathbf{B} - 2\mathbf{Z} - \mathbf{G}$ is invertible,

$$\mathbf{X}^* = (2\mathbf{B} - 2\mathbf{Z} - \mathbf{G})^{-1}(\mathbf{A} + \mathbf{R} - \mathbf{C}), \quad (5.10)$$

which is the unique Nash equilibrium solutions to the MU-level game. $\mathbf{D}$ is denoted as $(2\mathbf{B} - 2\mathbf{Z} - \mathbf{G})^{-1}$, where $\mathbf{D} = [d_{ij}]_{NK \times NK}$, and $\mathbf{X}^* = \mathbf{D}(\mathbf{A} + \mathbf{R} - \mathbf{C})$.

5.2.1.3 Substitutability and Complementarity

This part analytically studies the impacts of the substitutability and complementarity on the Nash equilibrium solutions to the MU-level game. In economics, cross elasticity of demand (XED) metric measures the ratio of the percentage change in quantity demand for one goods to the percentage change in price of another goods [95].

In crowdsensing, the CXEP metric is similarly defined to represent the crowdsensing cross elasticity of participation, which means the ratio of the percentage change in a participation level in a CSP to the percentage change in reward of another CSP. For ease of elaborations, a simple scenario with two CSPs and one MU, named Alice, is considered. The reward offered by CSP 1 and CSP 2 is r_1 and r_2 , respectively. The participation level of Alice in CSP 1 and CSP 2 is x_1 and x_2 , respectively. Then,

$$CXEP_{12} = \frac{\Delta x_2 / x_2}{\Delta r_1 / r_1} = \frac{\partial x_2}{\partial r_1} \frac{r_1}{x_2}. \quad (5.11)$$

Substitute services will have a negative CXEP, as the reward of CSP 1 decreases, Alice will participate in CSP 2 more and vice versa. On the contrary, complementary

services will have a positive CXEP, as the reward of CSP 1 increases followed by the increase of participation in CSP 2.

Here some implications about the relationship between the sign of ζ_i^{ks} and CXEP are discussed. Two cases are specially discussed, one is that each pair of CSPs are substitutable, and the other is that each pair of CSPs are complementary. Since the impacts of substitutability and complementarity are the focus, social network effects between MUs here will be ignored here. In this case, the MUs' participation vector will be $\tilde{\mathbf{X}}^* = (2\mathbf{B} - 2\mathbf{Z})^{-1}(\mathbf{A} + \mathbf{R} - \mathbf{C})$. Let $\tilde{\mathbf{J}}_{\mathcal{U}} = 2\mathbf{B} - 2\mathbf{Z}$ and $\tilde{\mathbf{D}} = \left(\tilde{\mathbf{J}}_{\mathcal{U}}\right)^{-1}$. Let $\tilde{\mathbf{J}}_{\mathcal{U}} = \text{diag}[\tilde{\mathbf{J}}_{\mathcal{U}}^1, \dots, \tilde{\mathbf{J}}_{\mathcal{U}}^i, \dots, \tilde{\mathbf{J}}_{\mathcal{U}}^N]$, where $\tilde{\mathbf{J}}_{\mathcal{U}}^i$ is a square matrix with dimension of $K \times K$. The CXEP matrix is defined as $\partial\tilde{\mathbf{X}}^* / \partial\mathbf{R}^\top = \tilde{\mathbf{D}}$. $\tilde{\mathbf{D}}$ is a block diagonal matrix in which all the off-diagonal blocks are zero, and all the diagonal blocks (denoted as $\tilde{\mathbf{D}}^i = [\tilde{D}_i^{sk}]$, $i \in \mathcal{N}$, $s, k \in \mathcal{K}$) are square matrices with dimension of $K \times K$. According to Equation (5.11), for an MU $i \in \mathcal{N}$, the CXEP of any pair of CSP s and CSP k for the MU can be denoted by $\tilde{D}_i^{sk}$, $s, k \in \mathcal{K}$. If ζ_i^{ks} is positive, $\forall i \in \mathcal{N}$, $\forall s, k \in \mathcal{K}$, from Proposition 5.1, it can be inferred that $\tilde{\mathbf{D}}^i$ is a positive matrix for any $i \in \mathcal{N}$. In summary, positive ζ_i^{ks} indicates positive CXEP. This is in line with the previous definition that the positive value of ζ_i^{ks} represents the complementarity of different CSPs.

Proposition 5.1 *If $\zeta_i^{ks} > 0$, $\forall i \in \mathcal{N}, \forall s, k \in \mathcal{K}$, then $\tilde{\mathbf{D}}^i$ is a positive matrix.*

Proof. When $\zeta_i^{ks} > 0$, $\forall i \in \mathcal{N}$, $\forall s, k \in \mathcal{K}$, all diagonal elements of $\tilde{\mathbf{J}}_{\mathcal{U}}^i$ are positive and all off-diagonal elements are negative. Scale $\tilde{\mathbf{J}}_{\mathcal{U}}^i$ by a positive factor so that all the diagonal elements are smaller than 1. Let $\mathbf{W} := \mathbf{I}_K - \tilde{\mathbf{J}}_{\mathcal{U}}^i$, where $\mathbf{I}_K$ is an identity matrix of size K . Due to Assumption 5.1, $\sum_{j=1}^K |w_{ij}| < 1$, $\forall i \in \{1, 2, \dots, K\}$. Hence $\|\mathbf{W}\|_\infty < 1$, and the spectral radius of $\mathbf{W}$ is smaller than 1. As

$$\tilde{\mathbf{D}}^i = (\mathbf{I}_K - \mathbf{W})^{-1} = \mathbf{I}_K + \mathbf{W} + \mathbf{W}^2 + \mathbf{W}^3 + \dots, \quad (5.12)$$

and $\mathbf{W}$ is a positive matrix, it can be concluded that $\tilde{\mathbf{D}}^i$ is also a positive matrix. The proof is then completed. $\square$

If $\zeta_i^{ks} < 0, \forall i \in \mathcal{N}, \forall s, k \in \mathcal{K}$, Gauss-Jordan elimination [93] can be employed to transform the augmented matrix of $\tilde{\mathbf{J}}_{\mathcal{U}}^i$ and prove that all off-diagonal elements in $\tilde{\mathbf{D}}^i$ are negative. It can be concluded that negative ζ_i^{ks} indicates negative CXEP, which can further show the substitutability relationship between two different CSPs.

5.2.2 Solutions to the CSP-level Non-Cooperative Game

This section studies the Nash equilibrium solutions to the CSP-level non-cooperative game, which is the reward strategies that no CSP can increase its profit by choosing different strategies given the other CSPs' strategies unchanged [12].

Recall that $\mathbf{D} = [d_{ij}]$ is a matrix with dimension of $NK \times NK$, a set $\mathcal{S}_{NK} \triangleq \{1, 2, \dots, NK\}$ is defined. The e th elements in vectors $\mathbf{A}$, $\mathbf{R}$ and $\mathbf{C}$ are denoted as a_e , r_e and c_e , respectively, $e \in \mathcal{S}_{NK}$. The participation level that MU i has in CSP k can be formulated as follows:

$$x_{ik} = \sum_{e \in \mathcal{S}_{NK}} d_{K(i-1)+k,e} (a_e + r_e - c_e). \quad (5.13)$$

By substituting Eq. (5.13) into the profit function given in Eq. (5.3), the profit of each CSP $k \in \mathcal{K}$ can be given by

$$\begin{aligned} \Pi_k &= \mu \sum_{i \in \mathcal{N}} (s_{ik} x_{ik} - t_{ik} x_{ik}^2) - \sum_{i \in \mathcal{N}} r_{ik} x_{ik} \\ &= \mu \sum_{i \in \mathcal{N}} s_{ik} \sum_{e \in \mathcal{S}_{NK}} d_{K(i-1)+k,e} (a_e + r_e - c_e) \end{aligned} \quad (5.14)$$

$$\begin{aligned} &- \mu \sum_{i \in \mathcal{N}} t_{ik} \left[\sum_{e \in \mathcal{S}_{NK}} d_{K(i-1)+k,e} (a_e + r_e - c_e) \right]^2 \\ &- \sum_{i \in \mathcal{N}} r_{ik} \sum_{e \in \mathcal{S}_{NK}} d_{K(i-1)+k,e} (a_e + r_e - c_e). \end{aligned} \quad (5.15)$$

The next subsection proves that at least one Nash equilibrium solution exists in the CSP-level non-cooperative game and then proves the uniqueness of the solution.

5.2.2.1 Existence

To prove the existence of Nash equilibrium solutions in the CSP-level game, the first-order optimality condition of the profit function is checked as follows:

$$\begin{aligned}
\frac{\partial \Pi_k}{\partial r_{ik}} &= \mu \sum_{f \in \mathcal{N}} s_{fk} d_{K(f-1)+k, K(i-1)+k} \\
&\quad - \mu \sum_{f \in \mathcal{N}} t_{fk} \frac{\partial \left[\sum_{e \in \mathcal{S}_{NK}} d_{K(f-1)+k, e} (a_e + r_e - c_e) \right]^2}{\partial \sum_{e \in \mathcal{S}_{NK}} d_{K(f-1)+k, e} (a_e + r_e - c_e)} \frac{\partial \sum_{e \in \mathcal{S}_{NK}} d_{K(f-1)+k, e} (a_e + r_e - c_e)}{\partial r_{ik}} \\
&\quad - \frac{\partial \sum_{i \in \mathcal{N}} r_{ik}}{\partial r_{ik}} \sum_{e \in \mathcal{S}_{NK}} d_{K(i-1)+k, e} (a_e + r_e - c_e) \\
&\quad - \sum_{i \in \mathcal{N}} r_{ik} \frac{\partial \sum_{e \in \mathcal{S}_{NK}} d_{K(i-1)+k, e} (a_e + r_e - c_e)}{\partial r_{ik}} \\
&= \mu \sum_{f \in \mathcal{N}} s_{fk} d_{K(f-1)+k, K(i-1)+k} \\
&\quad - 2\mu \sum_{f \in \mathcal{N}} t_{fk} \left[\sum_{m \in \mathcal{S}_{NK}} d_{K(f-1)+k, m} (a_m + r_m - c_m) \right] d_{K(f-1)+k, K(i-1)+k} \\
&\quad - \sum_{e \in \mathcal{S}_{NK}} d_{K(i-1)+k, e} (a_e + r_e - c_e) - \sum_{f \in \mathcal{N}} r_{fk} d_{K(f-1)+k, K(i-1)+k}. \tag{5.16}
\end{aligned}$$

Then, the second-order derivative of the profit is expressed as follows:

$$\frac{\partial^2 \Pi_k}{\partial r_{ik}^2} = -2\mu \sum_{f \in \mathcal{N}} t_{fk} \left(d_{K(f-1)+k, K(i-1)+k} \right)^2 - 2d_{K(i-1)+k, K(i-1)+k}, \tag{5.17}$$

where μ and t_{fk} are assumed to be positive. From Proposition 5.2, it can be inferred that all the diagonal elements of $\mathbf{D}$ are positive, and hence $\frac{\partial^2 \Pi_k}{\partial r_{ik}^2} < 0$. In addition, the CSPs' strategy spaces are convex and compact, and hence the existence of the solutions to the CSP-level non-cooperative game is guaranteed.

Proposition 5.2 $d_{ii} > 0, \forall i \in \mathcal{S}_{NK}$.

Proof. Let $\mathbf{J}_{\mathcal{U}} = [J_{ij}]_{NK \times NK}$, and $(\mathbf{J}_{\mathcal{U}})^*$ be the adjugate of $\mathbf{J}_{\mathcal{U}}$.

Firstly, the cofactor of any diagonal elements of $\mathbf{J}_{\mathcal{U}}$, i.e., J_{ii} , is considered. Under Assumption 5.1,

$$J_{j,j} > \sum_{f \in \mathcal{S}_{NK}} J_{j,f} > \sum_{f \in \mathcal{S}_{NK}, f \neq i} J_{j,f}, \forall j \in \mathcal{S}_{NK}, j \neq i. \quad (5.18)$$

From Eq. (5.18), it can be inferred that all cofactors of the diagonal elements of $\mathbf{J}_{\mathcal{U}}$ are positive, which indicates that the algebraic cofactors of all diagonal elements of $\mathbf{J}_{\mathcal{U}}$ are also positive. In addition, in Section 5.2.1.2, $\mathbf{J}_{\mathcal{U}}$ is proved to be positive definite, i.e., $|\mathbf{J}_{\mathcal{U}}| > 0$. Since $\mathbf{D} = \frac{(\mathbf{J}_{\mathcal{U}})^*}{|\mathbf{J}_{\mathcal{U}}|}$, it can be concluded that the diagonal elements of $\mathbf{D}$ are all positive. The proof is then completed. $\square$

5.2.2.2 Uniqueness

Before analyzing the uniqueness, for ease of reference, the following notations are defined. $\mathbf{S} = [\mathbf{s}_1, \mathbf{s}_2, \dots, \mathbf{s}_N]^\top$, where $\mathbf{s}_i = [s_{i1}, s_{i2}, \dots, s_{iK}]$, $i \in \mathcal{N}$. $\mathbf{T} = \text{diag}[\mathbf{t}_1, \mathbf{t}_2, \dots, \mathbf{t}_N]$, where $\mathbf{t}_i = \text{diag}[t_{i1}, t_{i2}, \dots, t_{iK}]$, $i \in \mathcal{N}$. $\mathbf{1}_{NN} = [\mathbf{1}]_{N \times N}$, $\mathbf{I}_K$ is an identity matrix of size K and $\mathbf{I}_{NK}$ is an identity matrix of size NK . In addition, recall that “ $\circ$ ” represents Hadamard product and “ $\otimes$ ” represents Kronecker product. From Eq. (5.16), by leveraging the first-order optimality condition and matrix formulation,

$$\begin{aligned} \frac{\partial \Pi_k}{\partial r_{ik}} &= \mu [\mathbf{D} \circ (\mathbf{1}_{NN} \otimes \mathbf{I}_K)] \mathbf{S} - 2\mu [\mathbf{D} \circ (\mathbf{1}_{NN} \otimes \mathbf{I}_K)] [\mathbf{T}\mathbf{D}(\mathbf{A} - \mathbf{C} + \mathbf{R})] \\ &\quad - \mathbf{D}(\mathbf{A} - \mathbf{C} + \mathbf{R}) - [\mathbf{D} \circ (\mathbf{1}_{NN} \otimes \mathbf{I}_K)] \mathbf{R}. \end{aligned} \quad (5.19)$$

Therefore, the Jacobian matrix of the profit of each CSP $k \in \mathcal{K}$ can be written by

$$\nabla \frac{\partial \Pi_k}{\partial r_{ik}} = - \left\{ 2\mu [\mathbf{D} \circ (\mathbf{1}_{NN} \otimes \mathbf{I}_K)] \mathbf{T}\mathbf{D} + \mathbf{D} + \mathbf{D} \circ (\mathbf{1}_{NN} \otimes \mathbf{I}_K) \right\}. \quad (5.20)$$

The Schur product theorem [96] indicates that the Hadamard product of two matrices which are both positive definite is also positive definite. Moreover, Theorem 4.2.12

in [97] indicates that the Kronecker product of two matrices which are both positive definite is also positive definite. Since $\mathbf{J}_{\mathcal{U}}$ is positive definite, $\mathbf{D} = (\mathbf{J}_{\mathcal{U}})^{-1}$ is also positive definite, and $\nabla \frac{\partial \Pi_k}{\partial r_{ik}}$ is then negative definite. Until now, the uniqueness of the Nash equilibrium solutions to CSP-level non-cooperative game has been proved [12]. Therefore, the Stackelberg equilibrium is unique [12].

Furthermore, the closed-form Nash equilibrium solution can be obtained by setting Eq. (5.19) to $\mathbf{0}$, which is given by

$$\begin{aligned} \mathbf{R}^* = & \{[\mathbf{D} \circ (\mathbf{1}_{NN} \otimes \mathbf{I}_K)] (2\mu \mathbf{T} \mathbf{D} + \mathbf{I}_{NK}) + \mathbf{D}\}^{-1} \\ & \times \{\mu [\mathbf{D} \circ (\mathbf{1}_{NN} \otimes \mathbf{I}_K)] [\mathbf{S} - 2\mathbf{T} \mathbf{D} (\mathbf{A} - \mathbf{C})] - \mathbf{D}(\mathbf{A} - \mathbf{C})\}. \end{aligned} \quad (5.21)$$

5.2.3 Discussions on Cooperative/Collusive Reward Strategies in CSP-level

Note that the previous analysis is based on a socially-aware MCS scenario with multiple competitive CSPs, where all CSPs competitively and selfishly determine their individual reward strategies for profit maximization. This subsection briefly studies the scenario where multiple CSPs cooperate together to maximize the aggregate profit by jointly determining the optimal reward strategies. In this regard, the optimal reward scheme is obtained by solving the following cooperative/collusive reward problem:

$$\begin{aligned} \underset{\mathbf{R}}{\text{maximize}} \quad \Pi = & \sum_{k \in \mathcal{K}} \Pi_k = \sum_{k \in \mathcal{K}} \mu \sum_{i \in \mathcal{N}} (s_{ik} x_{ik} - t_{ik} x_{ik}^2) - \sum_{k \in \mathcal{K}} \sum_{i \in \mathcal{N}} r_{ik} x_{ik} \\ = & \mu (\mathbf{S}^\top \mathbf{X} - \mathbf{X}^\top \mathbf{T} \mathbf{X}) - \mathbf{R}^\top \mathbf{X}, \end{aligned} \quad (5.22)$$

$$\text{subject to} \quad \mathbf{X} = \mathbf{D} (\mathbf{A} + \mathbf{R} - \mathbf{C}).$$

By substituting the closed-form expression of $\mathbf{X}$ into the objective function in the above collusive reward problem,

$$\begin{aligned} \Pi = \mu \left[\mathbf{S}^\top \mathbf{D} (\mathbf{A} + \mathbf{R} - \mathbf{C}) - (\mathbf{A} + \mathbf{R} - \mathbf{C})^\top \mathbf{D} \mathbf{T} \mathbf{D} (\mathbf{A} + \mathbf{R} - \mathbf{C}) \right] \\ - \mathbf{R}^\top \mathbf{D} (\mathbf{A} + \mathbf{R} - \mathbf{C}). \end{aligned} \quad (5.23)$$

By utilizing the first-order optimality condition,

$$\mu[\mathbf{D}\mathbf{S} - 2\mathbf{D}\mathbf{T}\mathbf{D}(\mathbf{A} + \mathbf{R} - \mathbf{C})] - \mathbf{D}(\mathbf{A} + \mathbf{R} - \mathbf{C}) - \mathbf{D}\mathbf{R} = \mathbf{0}. \quad (5.24)$$

With minor steps, the optimal collusive reward strategy of CSPs is uniquely expressed by

$$\mathbf{R}^* = \frac{1}{2}(\mathbf{D} + \mu\mathbf{D}\mathbf{T}\mathbf{D})^{-1}[\mu(\mathbf{D}\mathbf{S} - 2\mathbf{D}\mathbf{T}\mathbf{D}(\mathbf{A} - \mathbf{C})) - \mathbf{D}(\mathbf{A} - \mathbf{C})]. \quad (5.25)$$

5.2.4 Discussions on Stackelberg Equilibrium

Until now, the Stackelberg equilibrium in either competition or cooperation scenarios is existent and unique. In socially-aware crowdsensing applications, the solution of the Stackelberg game, i.e., the Stackelberg equilibrium has a practical market meaning of importance. Specifically, if the existence of Stackelberg equilibrium is confirmed, the CSPs and the MUs can potentially reach a market agreement to trade sensing contributions with rewards. If the uniqueness of the Stackelberg equilibrium is proved, the agreement is uniquely determined given with any initial market constraints, and hence the market can always reach a stable trading patterns between the CSPs and the MUs.

Note that the closed-form solutions of reward strategies in above sections are calculated and derived in a centralized way. In practice, the strategies are updated in a distributed way. In the following, the iteration process of the multi-CSP multi-MU game is elaborated in competition scenario by leveraging the best response dynamics algorithm to jointly optimize the profits of CSPs and the utilities of MUs in a distributed manner.

The detailed steps of the distributed algorithm for finding the Stackelberg equilibrium is presented in Algorithm 5.1. Moreover, as the uniqueness of the Stackelberg equilibrium is satisfied, the best response dynamics algorithm shown in Algorithm 5.1 is guaranteed to converge [12].

Algorithm 5.1 Best Response Dynamics-based Algorithm to Find Stackelberg Equilibrium in Multi-CSP Multi-MU Game

1: **Input:**

Initial input $\mathbf{x}_i > \mathbf{0}$, where $i = 1, 2, \dots, N$, $n = 1$, a pre-determined threshold value of ϵ ;

2: **repeat**

3: Best response updating for utility optimization of MUs (Internal Loop): Each MU $i \in \mathcal{N}$ observes the announced reward strategies $\mathbf{r}^k$, $\forall k \in \mathcal{K}$, and decides on their individual participation levels $\mathbf{x}_i^{(n)}$ by maximizing the derived utilities u_i in (5.2);

4: Best response updating for profit optimization of CSPs (External Loop): Based on the MU behaviors $\mathbf{x}_i$ in previous iteration, CSPs obtain the optimal reward strategies $\mathbf{r}^{k(n)}$ by maximizing their individual profits Π_k in (5.3);

5: $n = n + 1$;

6: **until** $\left\| \sum_{k=1}^K \Pi_k(\mathbf{r}^{k(n)}) - \sum_{k=1}^K \Pi_k(\mathbf{r}^{k(n-1)}) \right\| \leq \epsilon$

Output: The optimal strategies of participation levels $\mathbf{x}_i^* = \mathbf{x}_i^{(n)}$ and the optimal reward strategies $\mathbf{r}^{k*} = \mathbf{r}^{k(n)}$, where $i = 1, 2, \dots, N$, $k = 1, 2, \dots, K$.

5.2.5 Discussions on Asymmetric Social Influence

It can be proved that the proposed approach is not restricted to the symmetry assumption.

1) Solutions to the MU-level Non-Cooperative Game:

First, the existence of the Nash equilibrium of the MU-level non-cooperative game can still be achieved with asymmetric social influence. However, the uniqueness is not satisfied. Recall that in Section IV-A, $\mathbf{J}_{\mathcal{U}}$ is proved to be positive definite and hence strictly monotone, thereby demonstrating the uniqueness. When $\mathbf{G}$ is asymmetric, $\mathbf{J}_{\mathcal{U}}$ is asymmetric too, hence it cannot prove that $\mathcal{U}$ is strictly monotone by leveraging the positive definiteness of $\mathbf{J}_{\mathcal{U}}$. In this case, the Assumption 5.1 needs to update in the manuscript as Assumption R5.1 as follows: $2b_{ik} > \sum_{j \in \mathcal{N}} g_{ij}^k + 2 \sum_{s \in \mathcal{K}} |\zeta_i^{ks}|$ and $2b_{ik} > \sum_{j \in \mathcal{N}} g_{ji}^k + 2 \sum_{s \in \mathcal{K}} |\zeta_i^{sk}|$.

It is observed that for any $(K(i-1) + k)$ th row of $\mathbf{J}_{\mathcal{U}} + \mathbf{J}_{\mathcal{U}}^\top$, the magnitude of the diagonal entry is $|4b_{ik}|$, and the sum of the magnitudes of all non-diagonal entries

in that row is $\sum_{j \in \mathcal{N}} |-g_{ij}^k| + \sum_{j \in \mathcal{N}} |-g_{ji}^k| + 2 \sum_{s \in \mathcal{K}} |-\beta_i^{ks}| + 2 \sum_{s \in \mathcal{K}} |-\beta_i^{sk}|$. By adding up the two in-equations in Assumption R1, it can be inferred that $|4b_{ik}| = 4b_{ik} > \sum_{j \in \mathcal{N}} g_{ij}^k + 2 \sum_{s \in \mathcal{K}} |\beta_i^{ks}| + \sum_{j \in \mathcal{N}} g_{ji}^k + 2 \sum_{s \in \mathcal{K}} |\beta_i^{sk}| = \sum_{j \in \mathcal{N}} |-g_{ij}^k| + \sum_{j \in \mathcal{N}} |-g_{ji}^k| + 2 \sum_{s \in \mathcal{K}} |-\beta_i^{ks}| + 2 \sum_{s \in \mathcal{K}} |-\beta_i^{sk}|$. This indicates that $\mathbf{J}_{\mathcal{U}} + \mathbf{J}_{\mathcal{U}}^\top$ is strictly diagonally dominant and hence is positive definite. Consequently, the utilities of MUs, $(u_i)_{i=1}^N$, are diagonally strictly concave, which means for any $\mathbf{X}', \mathbf{X}'' \in \mathcal{Q}$, $\mathcal{Q} = \prod_{i=1}^N \mathcal{Q}_i$:

$$(\mathbf{X}' - \mathbf{X}'')^\top (\nabla \mathbf{u}(\mathbf{X}'')) + (\mathbf{X}'' - \mathbf{X}')^\top (\nabla \mathbf{u}(\mathbf{X}')) > 0, \quad (5.26)$$

$$(\mathbf{X}' - \mathbf{X}'')^\top (-\nabla \mathbf{u}(\mathbf{X}') + \nabla \mathbf{u}(\mathbf{X}'')) > 0, \quad (5.27)$$

$$(\mathbf{X}' - \mathbf{X}'')^\top (\mathcal{U}(\mathbf{X}') - \mathcal{U}(\mathbf{X}'')) > 0. \quad (5.28)$$

Eq. (5.28) indicates that $\mathcal{U}$ is strictly monotone. Therefore, the uniqueness of the solutions to VI problem $\mathcal{VI}(\mathcal{Q}, \mathcal{U})$ follows.

2) Solutions to the CSP-level Non-Cooperative Game:

Recall that when $g_{ij}^k = g_{ji}^k$, $\mathbf{D} = (2\mathbf{B} - 2\mathbf{Z} - \mathbf{G})^{-1}$ is symmetric and hence $\mathbf{D}^\top$ can be simplified as $\mathbf{D}$. However, when $g_{ij}^k \neq g_{ji}^k$, the asymmetric $\mathbf{D}$ can complicate the technical analysis. Nevertheless, the analytical solution for the profit maximization of the CSP is still structurally the same as that in Section IV-B. Specifically,

$$\begin{aligned} \frac{\partial \Pi_k}{\partial r_{ik}} = & \mu [\mathbf{D}^\top \circ (\mathbf{1}_{NN} \otimes \mathbf{I}_K)] \mathbf{S} - 2\mu [\mathbf{D}^\top \circ (\mathbf{1}_{NN} \otimes \mathbf{I}_K)] [\mathbf{T}\mathbf{D}(\mathbf{A} - \mathbf{C} + \mathbf{R})] \\ & - \mathbf{D}(\mathbf{A} - \mathbf{C} + \mathbf{R}) - [\mathbf{D}^\top \circ (\mathbf{1}_{NN} \otimes \mathbf{I}_K)] \mathbf{R}. \end{aligned} \quad (5.29)$$

$$\nabla \frac{\partial \Pi_k}{\partial r_{ik}} = - \left\{ 2\mu [\mathbf{D}^\top \circ (\mathbf{1}_{NN} \otimes \mathbf{I}_K)] \mathbf{T}\mathbf{D} + \mathbf{D} + \mathbf{D}^\top \circ (\mathbf{1}_{NN} \otimes \mathbf{I}_K) \right\}. \quad (5.30)$$

Certain assumption is needed to ensure that the matrix $\nabla \frac{\partial \Pi_k}{\partial r_{ik}} + (\nabla \frac{\partial \Pi_k}{\partial r_{ik}})^\top$ is positive definite [12]. Furthermore, the closed-form Nash equilibrium solution can be obtained as

follows:

$$\begin{aligned} \mathbf{R}^* = & \left\{ \left[\mathbf{D}^\top \circ (\mathbf{1}_{NN} \otimes \mathbf{I}_K) \right] (2\mu \mathbf{T} \mathbf{D} + \mathbf{I}_{NK}) + \mathbf{D} \right\}^{-1} \\ & \times \left\{ \mu \left[\mathbf{D}^\top \circ (\mathbf{1}_{NN} \otimes \mathbf{I}_K) \right] [\mathbf{S} - 2\mathbf{T} \mathbf{D} (\mathbf{A} - \mathbf{C})] - \mathbf{D} (\mathbf{A} - \mathbf{C}) \right\}. \end{aligned} \quad (5.31)$$

3) Discussions on Cooperative/Collusive Reward Strategies in CSP-level:

The consideration of asymmetric social influence also affects the cooperative/collusive reward strategies in CSP-level. However, the objective function of CSPs will keep the same form:

$$\begin{aligned} \underset{\mathbf{R}}{\text{maximize}} \quad \Pi = & \sum_{k \in \mathcal{K}} \Pi_k = \sum_{k \in \mathcal{K}} \mu \sum_{i \in \mathcal{N}} (s_{ik} x_{ik} - t_{ik} x_{ik}^2) - \sum_{k \in \mathcal{K}} \sum_{i \in \mathcal{N}} r_{ik} x_{ik} \\ = & \mu (\mathbf{S}^\top \mathbf{X} - \mathbf{X}^\top \mathbf{T} \mathbf{X}) - \mathbf{R}^\top \mathbf{X}, \end{aligned} \quad (5.32)$$

$$\text{subject to} \quad \mathbf{X} = \mathbf{D} (\mathbf{A} + \mathbf{R} - \mathbf{C}).$$

When $\mathbf{D} \neq \mathbf{D}^\top$, by substituting the closed-form expression of $\mathbf{X}$ into the objective function in the above collusive reward problem,

$$\begin{aligned} \Pi = \mu \left[\mathbf{S}^\top \mathbf{D} (\mathbf{A} + \mathbf{R} - \mathbf{C}) - (\mathbf{A} + \mathbf{R} - \mathbf{C})^\top \mathbf{D}^\top \mathbf{T} \mathbf{D} (\mathbf{A} + \mathbf{R} - \mathbf{C}) \right] \\ - \mathbf{R}^\top \mathbf{D} (\mathbf{A} + \mathbf{R} - \mathbf{C}). \end{aligned} \quad (5.33)$$

By utilizing the first-order optimality condition,

$$\mu [\mathbf{D}^\top \mathbf{S} - 2\mathbf{D}^\top \mathbf{T} \mathbf{D} (\mathbf{A} + \mathbf{R} - \mathbf{C})] - \mathbf{D} (\mathbf{A} + \mathbf{R} - \mathbf{C}) - \mathbf{D}^\top \mathbf{R} = \mathbf{0}. \quad (5.34)$$

With minor steps, the optimal collusive reward strategy of CSPs is uniquely expressed by

$$\mathbf{R}^* = (\mathbf{D} + \mathbf{D}^\top + \mu \mathbf{D}^\top \mathbf{T} \mathbf{D})^{-1} [\mu (\mathbf{D}^\top \mathbf{S} - 2\mathbf{D}^\top \mathbf{T} \mathbf{D} (\mathbf{A} - \mathbf{C})) - \mathbf{D} (\mathbf{A} - \mathbf{C})]. \quad (5.35)$$

5.3 Performance Evaluation

This section examines and assesses the system performance of the proposed multi-leader multi-follower game-based incentive mechanisms in socially-aware crowdsensing, and studies the impacts of some parameters of crowdsensing on the behaviors and performance. Assume there are a set of K CSPs together with N MUs in certain socially-aware crowdsensing applications. The internal utility coefficients of MUs, i.e., a_{ik} and b_{ik} follow the normal distribution $\mathcal{N}(\mu_a^k, 1)$ and $\mathcal{N}(\mu_b^k, 1)$. The social tie g_{ij}^k follows $\mathcal{N}(\mu_g^k, 0.001)$. The internal revenue coefficients of CSPs, i.e., s_{ik} and t_{ik} follow $\mathcal{N}(\mu_s^k, 1)$ and $\mathcal{N}(\mu_t^k, 0.01)$. The substitutability or complementarity of crowdsensing services from any two CSPs k and s in terms of MUs follows a normal distribution $\mathcal{N}(\mu_z, 0.01)$. Unless otherwise stated, $N = 50$, $K = 5$, $a_i^k = 10$, $b_i^k = 10$, $\mu_g^k = 0.06$ (for strong network effects), $\mu_g^k = 0.02$ (for weak network effects), $c_{ik} = 5$, $\mu = 8$, $\mu_s = 20$, $\mu_t = 1$, $\mu_z = 1$ or 0.5 (for strong and weak complementarity) and $\mu_z = -1$ or -0.5 (for strong and weak substitutability), $i \in \mathcal{N}$, $k \in \mathcal{K}$. The simulations are performed for over 100 rounds to obtain the average results.

At first, the system performance when the CSPs are substitutable with the varied number of MUs, is illustrated in Fig. 5.2. From Fig. 5.2, the total participation levels of MUs, the total profits of CSPs, and the total reward are all improved as the number of MUs increases. The reason is that existing MUs will be encouraged to contribute more efforts by the coming MUs due to the underlying network effects, and meanwhile the coming MUs contribute their participation levels. The total participation levels hence increase. The CSPs tend to offer greater reward to compensate for the cost of the coming MUs, leading to the greater profit. Moreover, the strong network effects can promote the greater participation levels of MUs. This consequently contributes to the greater profit of CSPs. As the strength of network effects is strong, the CSPs are able to reduce the reward to save the cost. The system performances under the competition and cooperation scenarios are compared also in Fig. 5.2. As CSPs are substitutable, they will compete

Figure 5.2: System performance when the CSPs are substitutable v.s. the number of MUs.

Figure 5.3: System performance when the CSPs are complementary v.s. the number of MUs.

with each other by offering greater reward. However, under the cooperation scenario, the CSPs are allowed to collude together to offer smaller reward and save more cost. Though the total participation levels of MUs are reduced, the aggregate profits of CSPs increase. Next the system performance with complementary CSPs is studied in Fig. 5.3. Under the competition scenario, one interesting observation is that the CSPs incline to offer smaller reward. The reason is that the greater reward will encourage the greater participation levels of MUs, which hence benefit other CSPs. Therefore, each CSP does not provide too much reward but try to gain more benefits from the greater rewards

offered by other CSPs. By contrast, the CSPs offer greater rewards by taking advantage of the complementarity of their crowdsensing services under the cooperation scenario. This therefore improves the participation levels of MUs, leading to the greater aggregate profits of MUs consequently.

Figure 5.4: System performance when the CSPs are substitutable v.s. the number of CSPs.

Figure 5.5: System performance when the CSPs are complementary v.s. the number of CSPs.

The system performance when the CSPs are substitutable with the varied number of CSPs in is investigated in Fig. 5.4. It can be observed that the total participation levels

of MUs, the total profits of CSPs and the total reward are all improved when the number of CSPs increases. The reason is that the coming CSPs will offer reward to recruit MUs for sensing data contribution. Meanwhile, the MUs will have more options to choose, thereby providing more flexibilities for MUs. Consequently, the participation levels of MUs increase, which hence improves the total profits of CSPs. With strong network effects, the CSPs are able to reduce the reward, leading to the greater profits. Meanwhile, the cooperation help the CSPs to achieve the greater aggregate profits of them, which is consistent with the previous conclusions. Next the system performance with complementary CSPs is examined in Fig. 5.5. As the services from CSPs are complementary, the existing CSPs benefit from the coming of new CSPs in terms of promoting the participation levels of MUs. In this case, the CSPs are able to reduce the reward slightly and hence save the cost, thereby achieving the greater profits. Similar to the major insights from Fig. 5.3, the CSPs incline to offer smaller reward under the competition scenario than that under the cooperation scenario. Moreover, the participation levels of MUs under the cooperation scenario are greater than that under the competition scenario. Consequently, the profits achieved under the cooperation scenario is greater.

Furthermore, the system performance with substitutable CSPs when the revenue coefficient μ of CSPs is varied, is shown in Fig. 5.6. The total participation levels of MUs, the total profits of CSPs and the total reward all increase as the revenue coefficient μ increases. The reason is that the larger value of μ allows the CSPs to obtain more revenue transformed from the sensing contribution. Therefore, the CSPs are encouraged to offer greater reward to attract MUs, which therefore improves the total participation levels of MUs and total profits of CSPs. Moreover, the total participation levels of MUs decreases as the level of substitutability increases. The reason is that stronger substitutability indicates that the services provided by different CSPs tend to be more similar. In this case, the MUs can satisfy their needs by only selecting one or some of the CSPs. Meanwhile,

Figure 5.6: System performance when the CSPs are substitutable v.s. the average revenue coefficient of CSPs.

Figure 5.7: System performance when the CSPs are complementary v.s. the average revenue coefficient of CSPs.

the stronger substitutability will intensify the competitions between different CSPs. Consequently, the CSPs incline to offer greater reward to retain or even incentivize the MUs. Given the decreasing participation levels of MUs and the increasing reward offered to MUs, the total profits of CSPs decrease due to the high level of substitutability. Next the system performance with complementary CSPs is studied in Fig. 5.7. By contrast, the total reward decreases when the complementarity becomes strong. The reason is that the utilities of MUs will benefit more from participating in multiple complementary CSPs

Figure 5.8: Case study on two substitutable CSPs under different substitutability scenarios v.s. the strength of network effects.

Figure 5.9: Case study on two complementary CSPs under different complementarity scenarios v.s. the strength of network effects.

when the strength of complementarity increases. Therefore, the participation levels of MUs increase, which allows the CSPs to reduce the reward to save more cost and achieve the greater profits. From Figs. 5.2-5.7, it can be concluded that the CSPs will achieve the greater profits under the cooperation scenario regardless of whether they are substitutable or complementary. If the CSPs are strongly complementary, the cooperation becomes more necessary to achieve greater profits.

Then the simulations on a case study of the crowdsensing market with 50 MUs and

3 CSPs is conducted. Specifically, the services of CSP A and CSP B are complementary ($\zeta_i^{AB} = 1$), the services of CSP A and CSP C are complementary ($\zeta_i^{AC} = 0.5$), and the services of CSP B and CSP C are substitutable ($\zeta_i^{BC} = -0.5$). The parameter settings (e.g., s_{ik}, t_{ik}) for different CSPs are set as the same to better focus on the impacts of complementarity and substitutability. The adjacency matrix $\mathbf{g}^k, \forall k$, is generated as follows:

$$\begin{cases} g_{i,i+1}^k = 0.2 \times \left(0.5 - \left(0.5 - \frac{i-1}{N}\right)^2\right), & i \in [1, N-1]; \\ g_{i+1,i}^k = 0.2 \times \left(0.5 - \left(0.5 - \frac{i-1}{N}\right)^2\right), & i \in [1, N-1]; \\ g_{i,j}^k = 0, & \text{otherwise.} \end{cases} \quad (5.36)$$

From the above equation, only MUs who are adjacent in indexes will impact each other. Fig. 5.10 shows that it leads to diverse participation levels for different MUs. Considering the centrality degree, the MUs in the middle position are the most influenced ones (with external incentive) and hence they will have the highest participation levels. From the perspective of the CSPs, these MUs in the middle position are also offered the lowest reward to save the cost. On the contrary, the MUs at the both ends are least influenced by others, and hence they will be offered with the highest reward. As the services offered by CSP A are complementary to those of CSPs B and C , CSP A achieves the highest profit because of the greatest participation levels of MUs. Also, as the service complementarity of CSP A and B is higher than that of CSP A and C . Therefore, CSP B encourages the greater participation from MUs and derives the higher profit than that of CSP C . The performance comparison between the proposed scheme with the single-leader multi-follower scheme is illustrated in Fig. 5.10. In single-leader multi-follower scheme [74], each CSP is not aware of the interactions with other CSPs, which means that the CSPs do not consider the sustainability/complementarity while optimizing the incentive reward as a single leader. Therefore, all the CSPs set the same reward because of the same parameter settings. This however results in the lower participation levels of MUs and eventually reduces the profit of all CSPs.

(a) Participation levels of MU i in all CSPs, and rewards for MU i offered by all CSPs

Figure 5.10: A case study of system performance for crowdsensing market with 3 CSPs and 50 MUs.

In addition, a case study is conducted on two substitutable and complementary CSPs ($s_{i1} = 15$, $s_{i2} = 20$, $\forall i \in \mathcal{N}$) competing each other under different scenarios with the varied strength of network effects, which are given in Figs. 5.8 and 5.9, respectively. It can be observed from Figs. 5.8 and 5.9 that CSP 2 offers greater reward than CSP 1 regardless of whether they are substitutable or complementary. The larger value of s_{ik} denotes the greater internal valuation rate induced by contribution of MUs as per Eq. 5.3. In this

case, CSP 2 tends to offer greater reward as it will have greater revenue given with the same contribution of MUs compared with CSP 1. Therefore, the participation levels of MUs in CSP 2 is greater, and CSP 2 achieves greater profit. Under both the substitutable and complementary scenarios, the profit of each CSP as well as the participation levels of MUs in each CSP increase but the reward decreases. Again, the reason is that the utilities of MUs are positively improved in presence of underlying network effects, and the participation levels in both CSPs are promoted. Consequently, the reward can be reduced to save the cost, and profit of each CSP increases. Furthermore, when the substitutability of CSPs 1 and 2 becomes strong, the participation levels of MUs in both CSPs 1 and 2 decrease and the two CSPs need to offer greater reward to compete with each other. In this case, the profits of CSPs 1 and 2 both decrease simultaneously. By contrast, when the complementarity of CSPs 1 and 2 becomes strong, CSP 1 is able to reduce the reward as it predicts CSP 2 with the larger value of s_{ik} will offer greater reward. In other words, CSP 1 expects that the reward offered by CSP 2 will improve the utilities of MUs, which consequently benefits CSP 1 itself as the services provided by CSPs 1 and 2 are complementary.

Lastly, a case study is presented on two substitutable and complementary CSPs ($s_{i1} = 15$, $s_{i2} = 20$, $\forall i$) under competition and cooperation scenarios when the strength of network effects varies, as illustrated in Fig. 5.11 and 5.12, respectively. Figs. 5.11 and 5.12 show that the cooperation between two CSPs decreases the reward for both CSPs under substitutable scenario but increases the reward for both CSPs under complementary scenario. The reason is that both of the CSPs incline to offer greater reward in competition with the other under substitutable scenario. This incurs the unnecessary reward cost, which reduces the profit consequently. The cooperation allows the CSPs to reduce the reward and hence save the cost. However, under complementary scenario, both of the CSPs tend to offer smaller reward as they expect the other one will benefit from its own reward cost. Therefore, the cooperation allows both of CSPs to offer

Figure 5.11: Case study on two substitutable CSPs under competition and cooperation scenarios v.s. the strength of network effects.

Figure 5.12: Case study on two complementary CSPs under competition and cooperation scenarios v.s. the strength of network effects.

necessarily greater reward to well motivate MUs, and finally achieve greater profit for both of them. In addition, it can be concluded from the results in Figs. 5.8-5.12 that the cooperation will achieve the greater profits for both of the two CSPs when they are strongly complementary and underlying network effects are strong.

5.4 Summary

This work proposes a hierarchical game approach to study incentive mechanisms in socially-aware crowdsensing. In particular, the multi-leader multi-follower game model has been employed to model the two-stage interactions among multiple crowdsensing service providers and multiple mobile users.

The future work includes the study about competitive incentive mechanisms of socially-aware crowdsensing under information asymmetry, where the private information of users, e.g., social ties, is not perfectly known by the service providers. Another direction is to explore the bounded rationality of social behaviors of crowdsensing users in presence of social network effects.

Chapter 6

Conclusions and Future Work

This thesis has mainly studied the incentive mechanisms in order to support socially-aware crowdsensing by leveraging a hierarchical Stackelberg game-based approach. This thesis has introduced the background basics of mobile crowdsensing and socially aware crowdsensing with some real-world applications/services, discussed the importance of incentive mechanisms, and pointed out some potential issues therein. Chapter 2 provides a literature review on related work and highlighted the major differences and significance of this work compared with other studies in the literature. In Chapter 3, the incentive mechanisms have been addressed and examined in socially-aware mobile crowdsensing, where the impacts of social network effects are analytically and numerically studied. Chapter 4 studies and evaluated the vital importance of complete information on social network effects on the revenue of crowdsensing service provider, and explored how the service providers are guided to regulate the incentive mechanisms with incomplete information on social network effects. Chapter 5 revisits the design of incentive mechanism for socially-aware crowdsensing in presence of multiple service providers, and investigated how the strategic interactions among service providers and social network effects jointly influence the users behaviors and in return impact the incentive strategies.

This chapter first summarizes the main contributions of this thesis, and then lists a number of promising future directions for the further in-depth work to explore.

6.1 Conclusions

In socially-aware crowdsensing, a crowdsensing service provider needs to offer the reward to encourage the users to participate in a crowdsensing campaign. How to strategically design the reward leads to an incentive mechanism problem. Meanwhile, there are a series of issues that inherently exist in socially-aware crowdsensing making the incentive problem more challenging to solve. In response to this, this thesis aims to address these issues by leveraging a hierarchical Stackelberg game-based approach.

Chapter 3 develops a two-stage game theoretic model, and analyzed each stage using backward induction. The Crowdsensing Service Provider (CSP) sets the incentive mechanism in the first stage, and the Mobile Users (MUs) decide their participation level in response to the observed reward in the second stage. Taking the social (local) network effects among the MUs into account, the optimal incentive mechanism is proposed, i.e., discriminatory reward and uniform reward under complete information scenario, where the closed-form expression for optimal reward is obtained. Performance evaluations have verified that the network effects significantly improve the participation level and the revenue of CSP. Further, it has been validated that the discriminatory reward mechanism helps the CSP to achieve greater revenue gain.

In Chapter 4, a novel socially-aware incentive mechanism has been proposed by leveraging the underlying social network effects to attract participants to crowdsensing platform. This chapter focuses on designing incentive mechanism with the consideration of incomplete information on social network effects, which is commonly applicable to some of the real-world crowdsensing applications. Specifically, this chapter formulates the Bayesian Stackelberg game to analyze and evaluate the impacts of uncertainty of social network effects, which utilizes the structural properties from the underlying social domain. The unique Bayesian Stackelberg equilibrium has been considered as the opti-

mal solution. Performance evaluation of this game model has shown the impressive role of social network effects in crowdsensing incentivizing.

Chapter 5 proposes a hierarchical game approach to study incentive mechanisms in socially-aware crowdsensing. In particular, the multi-leader multi-follower game model has been employed to model the two-stage interactions among multiple crowdsensing service providers and multiple mobile users. The social influence of users and the interconnections of service providers have been jointly and formally integrated into the game modeling. The game model has also been leveraged to jointly investigate the profit maximization of service providers and utility maximization of users.

In a summary, this thesis, have tackled a number of inherent issues while designing incentive mechanisms for socially-aware crowdsensing by using a hierarchical Stackelberg game. Hope the insight from this thesis can be useful and provide guiding information to the operation and implementation of real-world socially-aware crowdsensing applications/services, thereby leading to a economically sustainable paradigm of socially-aware crowdsensing.

6.2 Future Work

There are a number of promising research directions that can be explored in the future work.

6.2.1 General Multi-leader Multi-follower Game

One natural direction is to study the multi-leader multi-follower game with incomplete information, where the private information of CSPs and MUs are not publicly shared. A Bayesian multi-leader multi-follower game can be formulated where the CSPs play a non-cooperative Bayesian game and the MUs play a non-cooperative Bayesian game. This game model is more general but more challenging to solve. Moreover, when there exist

a large number of CSPs and MUs in the game, the constrained optimization methods in typical game theory cannot be easily applied due to the huge complexity of implementation as the players have high-dimensional strategies space. In this case, the Alternating Direction Method of Multipliers (ADMM) can be a suitable approach [98, 99] to search for the game equilibrium solutions in a distributed manner. Essentially, the convergence of ADMM has been proved to be independent of the network size [98]. As such, ADMM-based algorithms can be a promising direction to study and assess a more general multi-leader multi-follower game model.

6.2.2 Time-dependent Incentive Mechanisms

Recall that this thesis addresses the incentive mechanism by using a hierarchical Stackelberg game which is a one-shot game, where the MUs and CSPs are assumed to interact with each other and determine their strategies only once. However, such a one-shot incentive mechanism may not be applicable in some real-world services. In this case, the possible direction is to investigate the time-dependent incentive scheme [38] where MUs arrive dynamically and meanwhile the CSP offers the reward in a dynamic game with multiple rounds. The participants can be forward-looking while experiencing the social network effects [100]. Along with this direction, there will be some changes in the game modeling while designing incentive mechanisms with dynamical reward. First, the objective of CSPs may change. Instead of simply maximizing the immediate (one-shot) utility, the long-term utility will be more essential since the utility will fluctuate with the arriving MUs. Due to the social network effects, the utilities of MUs also depend on the participation levels of previous existing participants. As such, the CSPs need to predict the upcoming participation levels in the long term while taking advantage of social network effects, such that they can regulate their incentive policies accordingly and strategically.

6.2.3 Bounded Rationality of Socially-aware Behaviors

In the context of game theory, it is assumed that the players are fully rational and all aim for their payoff maximization. Such a game modeling of MU and CSP behaviors in crowdsensing may be affected by the internal bounded rationality. Consequently, the prediction of MUs' participation or the reward incentive can be intractable. Therefore, the actual decision-making process is not consistent with the one that uses a traditional game-theoretic model with fully rational players. A more general theoretical model termed Bounded Rationality (BR) from *behavioral economics* can be a suitable approach for analyzing human behaviors more psychologically and more accurately [101]. The model of BR tackles the limitations of rational decision-makings which lead the players to taking non-optimal strategies in some occasions. BR can result from many factors including limited resources, partial knowledge, human's emotion or internal habits, and other external influence [102]. There are different kinds of BR models such as prospect theory, anchoring theory, and framing effect. For example, prospect theory refers to the phenomena that people react differently to potential losses and gains. Players are often risk-averse while facing a risky choice with potential gains but risk-seeking while coping with a risky choice leading to losses. Therefore, the model of BR can play an important role in incentive mechanisms for socially-aware crowdsensing applications, especially when the decision-makers, e.g., CSPs and MUs, tend to suffer from bounded rationality.

6.2.4 Contract Theory in Socially-aware MCS

Contract theory [12] models the relation between a seller and buyers with asymmetric information condition. The buyers are characterized by types that are private information. The seller, called the contract designer, proposes a list of contract items. The buyers can only accept or reject the contract. Contract theory is also an efficient tool while designing incentive mechanisms in crowdsensing services, where CSPs offer a menu

of contract items and MUs can select one item. More specifically, the contract item can be a tuple in the form of $\langle participation, reward \rangle$ or $\langle cost, reward \rangle$. A number of existing studies have leveraged contract theory in crowdsensing services [13, 103]. However, few of these studies considered contracting with network effects. In typical incentive mechanism, MUs only care about their own utility while deciding on one contract item. Nevertheless, in socially-aware crowdsensing, MUs' decisions are often influenced by their socially-connected friends and acquaintances. Therefore, it is critical to take the social network effects into consideration while applying contract theory, which can be a promising research direction.

6.2.5 Emerging Networking Technology Utilization

The last decade has witnessed many emerging networking technologies such as blockchain and Artificial Intelligence (AI). With the help of these technologies, traditional incentive mechanisms in crowdsensing can achieve better performance in various aspects. On one hand, the blockchain makes it possible for the realization of decentralized crowdsensing system, thereby guaranteeing the system reliability and privacy-preserving incentive mechanism in crowdsensing services. The majority of existing crowdsensing platforms depend on central servers, which are subject to the weakness of traditional trust-based model, e.g., privacy leakage. Additionally, high service fees from the crowdsensing platform may hinder the development of crowdsensing. If the crowdsensing platform can be designed in a decentralized framework, i.e., the sensing tasks can be solved by a set of workers without dependence from any other trusted authorities, the MUs' privacy can be guaranteed and high transaction fees are relieved. Blockchain can also ensure the quality of sensing data uploaded from MUs, where the miners are responsible to verify the data quality and record the data into blocks [47]. The incentive reward can be offered based on the data quality of MUs according to the blockchain records. On the other hand, the

AI schemes, e.g., deep reinforcement learning (DRL), can be a efficient tool to seek for the optimal incentive schemes without knowing any prior information in the system [104], where the method of DRL is especially suitable to tackle the real-time decision-making problems [105]. Several pioneer studies have proposed basic system architecture by leveraging blockchain or AI while designing incentive mechanisms in traditional crowdsensing application/services. Nevertheless, the incentive studies with blockchain and AI for socially-aware crowdsensing remain largely unexplored.

6.2.6 Miscellaneous

Besides the incentive mechanism, there are also some miscellaneous open issues in socially-aware crowdsensing, which are listed as follows.

- **Privacy Preservation in Socially-aware Crowdsensing:** In traditional crowdsensing, sensing information from the users is modified in order to protect their privacy, such as adding noise to the original data. Most of the existing research attempts assume independence among the information from different individuals in addressing privacy-preserving information collection problem. Under this assumption, the individual's information contribution will not cause privacy leakage to others. However, in socially-aware crowdsensing, individuals who have social ties/influence may share some common or overlapped interests. Thus, the information correlation can cause privacy leakage to other individuals even though they do not contribute the information. In this regard, a malicious attacker may infer individual private information by exploiting such information correlations. In [48], the authors studied a privacy-preserving information collection problem with the consideration of information correlation and social relationship. Therein, the social relationship is assumed to be public knowledge, and the individual user's privacy loss under data correlation is characterized. However, the social relationship may be

kept private by the users, and they may report it untruthfully. This can adversely affect information accuracy as well as quality and usefulness of the services.

- **Massive Data Storage in Socially-aware Crowdsensing:** Existing crowdsensing services rely on the centralized cloud-based architecture, where the users sense and report information to a central server for processing and performing analysis. The cloud-based crowdsensing service provider often suffers from limitations of the centralized architecture such as high operational cost, performance bottleneck, and a single point of failure/attack. For socially-aware crowdsensing, the data sharing scheme leveraging the smart devices is introduced in [106]. By utilizing their social ties or links, users are encouraged to share information directly rather than to report and save it in the server. This can shift part of the storage function to the distributed users and thus alleviate data transfer loads of the server.
- **Security in Socially-aware Crowdsensing:** Malicious users can launch different attacks to socially-aware crowdsensing. One of the common attacks is the Sybil attack. For example, multiple fake users can generate falsified nutrition information about food from certain places. To address such an attack, users can cooperate with each other to detect and avoid misbehaving attackers in traditional crowdsensing services. Especially in socially-aware crowdsensing, social relationship can be used to identify fake users. For example, fake users usually have strong social ties only among themselves, but not with other parts of the population.

List of Publications

JOURNAL ARTICLES

- 1) **Jiangtian Nie**, Jun Luo, Zehui Xiong, Dusit Niyato and Ping Wang, “A stackelberg game approach toward socially-aware incentive mechanisms for mobile crowdsensing”, *IEEE Transactions on Wireless Communications*, vol. 18, no. 1, pp. 724–738, 2018.
- 2) **Jiangtian Nie**, Jun Luo, Zehui Xiong, Dusit Niyato, Ping Wang and Mohsen Guizani, “An Incentive Mechanism Design for Socially Aware Crowdsensing Services with Incomplete Information”, *IEEE Communications Magazines*, vol. 57, no. 4, pp. 74–80, 2019.
- 3) **Jiangtian Nie**, Jun Luo, Zehui Xiong, Dusit Niyato, Ping Wang and H. Vincent Poor, “A Multi-Leader Multi-Follower Game-Based Analysis for Incentive Mechanisms in Socially-Aware Mobile Crowdsensing”, *IEEE Transactions on Wireless Communications*, Early Access.

CONFERENCE PROCEEDINGS

- 4) **Jiangtian Nie**, Zehui Xiong, Dusit Niyato, Ping Wang and Jun Luo, “A Socially-Aware Incentive Mechanism for Mobile Crowdsensing Service Market”, in *Proceedings of IEEE GLOBECOM*, 2018, pp. 1–7.
- 5) **Jiangtian Nie**, Jun Luo, Zehui Xiong, Dusit Niyato, Ping Wang and Yang Zhang, “Incentive Mechanism for Socially-Aware Mobile Crowdsensing: A Bayesian Stackelberg Game”, in *Proceedings of International Conference on Wireless Algorithms, Systems, and Applications (WASA)*, 2020, pp. 394–406.

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