

Chapter 2

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

2.1 Introduction

The proliferation of highly capable mobile devices, such as smartphones and tablets, coupled with the introduction of resource demanding mobile services has exponentially increased the demand for wireless access Sesia et al. (2009). A tremendous amount of mobile data, especially mobile video traffic, is rapidly straining the capacity of current wireless cellular networks (Cisco 2011). Consequently, novel wireless networking paradigm is needed to meet the challenges of this unprecedented growth in the demand for the wireless spectrum (Camps-Mur et al. 2013).

To deal with this wireless capacity crunch, device-to-device (D2D) communication underlaid over cellular network has recently been proposed as a means to boost the overall wireless network capacity (Xu et al. 2014). D2D communication benefits from the fact that two user equipments (UEs) in proximity of one another can establish a direct communication link over the licensed band while bypassing the cellular infrastructure such as the base stations (BSs). One common form of D2D communication is the network-controlled one in which the BS manages the switching between direct and cellular links (Min et al. 2011a). Due to the proximity of the involved users, if well-designed, D2D communication can dramatically improve the wireless network capacity while reducing energy consumption (Quek et al. 2013). It can also assist in off-loading the cellular traffic from the BSs while extending their coverage (Yaacoub 2014).

If UEs' resource blocks (RBs) can be shared, local users will be able to exchange data (Song et al. 2014). For example, the BS can send a frequently requested content to a number of devices who, in turn, can utilize D2D communication to spread the content to other interested users (Qualcomm 2012). By doing so, within a certain geographical area, instead of servicing a request multiple times, the BS would only transmit contents which are not locally available. In this case, the BS's traffic is significantly reduced, and thus, the cellular network capacity is increased. To successfully achieve this goal, one main design challenge is to incentivize content owners to participate and cooperate with other devices via D2D. If most users are unwilling to

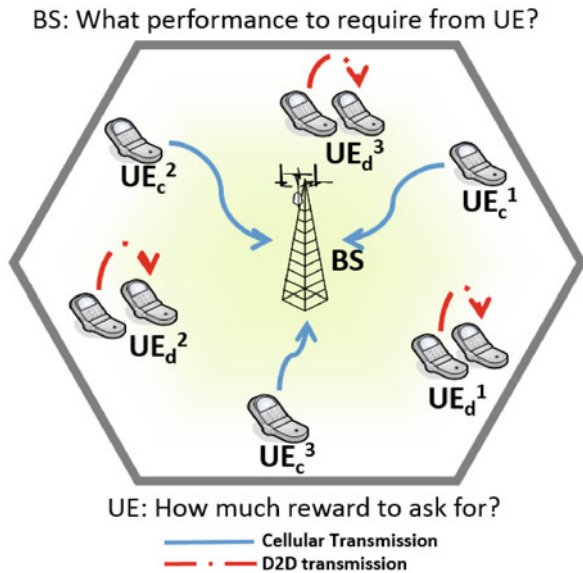
provide their contents via D2D communication, then the BS will still need to serve the users via the conventional cellular network. Consequently, it is unable to increase the network capacity. Clearly, the willingness of users to participate and share data is of great importance to reap the benefits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

Indeed, it is necessary to introduce effective incentive mechanisms that can encourage users to participate in content sharing. In order to provide incentives, the BS can offer rewards to users' UEs for the usage of their resources (storage, power, time, etc.) as well as for potential privacy risks arising from D2D, since UEs' RBs are open to the BS. For example, if the user is willing to share its content and assists the BS to transmit the data, the BS will offer a reward to compensate for this user's participation. The reward can be in the form of monetary remuneration or free data among others (Golrezaei et al. 2013).

Intuitively, a well-designed incentive mechanism should reward UEs based on their contributions: devices that contribute more must get higher rewards than devices with less contributions. Users with high preference toward participation will be more likely to contribute. However, each user will attempt to harness as much reward as possible by claiming that it is a high preference user, which brings difficulty to the BS in reward design. This problem is exacerbated by *information asymmetry*—the BSs may not be aware of the actual preference, which is naturally known by the users. To this end, our main goal is to propose an incentive mechanism by overcoming this information asymmetry in a D2D network as shown in Fig. 2.1.

In this respect, there is a need to design a mechanism in which UEs will be rewarded in accordance with their preference. Contract theory, a powerful framework

Fig. 2.1 The reward assignment problem faced by the BS



from microeconomics, provides a useful set of tools for modeling incentive mechanisms under information asymmetry (Werin and Wijkander 1992). Using contract theory, one can analyze the interactions between an employer who is trying to offer proper contracts and employees whose skills are not known a priori (Bolton and Dewatripont 2004). A contract is essentially a certain reward that will be given to the employee in return for its services. In a D2D context, this contractual situation can be used to study the interactions between BSs, acting as employers and, UEs, acting as devices whose preferences are unknown to the BSs. Here, the contract will represent the rewards provided by the BS to a certain D2D-capable UE who will provide the required resources and quality-of-service via D2D participation. The main advantages of adopting contract theory in a D2D scenario include the following: (1) ability to incorporate semi-distributed network control in which the BS can control the D2D communication links; (2) notions such as self-revealing contracts suitable to handle information asymmetry, and (3) ability to devise optimal reward and incentive mechanisms that can induce cooperation between UEs.

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

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

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

2.2 Related Work

D2D communication has been subject to many recent research works such as in (Min et al. 2011c; Yu et al. 2011). Due to the shared resources between direct D2D communication and traditional infrastructure-based communication, new resource allocation techniques are needed for D2D deployment (Zulhasnine et al. 2010). One major challenge in D2D is interference management (Song et al. 2014). The common mechanism is to limit maximum transmit power of D2D transmitter so as not to generate harmful interference from D2D systems to cellular networks (Min et al. 2011b).

Some interference management strategies are also proposed to enhance the overall capacity of cellular networks and D2D system. For example, the work in (Tanbourgi et al. 2014) introduces the idea of cooperative interference cancellation (CIC) between close-by UEs using D2D communications for improving the throughput of cellular networks in the downlink (DL) period. Another work in (Zhang et al. 2013) formulates the interference between different D2D and cellular communication links as an interference-aware graph and proposes an interference-aware graph-based resource-sharing algorithm. Several works study the use of D2D communication as a means to optimize resource usage and maintain an efficient coexistence between the D2D services and main cellular network (Xing et al. 2009).

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

Here, we note that the contract theory has been used in areas such as mobile cloud computing and cognitive radio. For instance, in (Knapper et al. 2011), the authors study the use of contract theory as a means to optimize the economic revenues of a cloud server in a mobile cloud computing environment. Existing works such as (Gao et al. 2011, 2013), and (Duan et al. 2014a) focus on the efficiency of resource allocation in cognitive radio networks. The work in (Jin et al. 2012) introduces the concept of insurance into the model, in which if the primary owner (PO) cannot provide the channel purchased by a secondary user (SU), PO needs to pay a certain amount of indemnity to the SU. In (Gao et al. 2014), the authors develop a contract-theoretical mechanism to model the possibility of secondary users relaying data for primary users to improve data rates. The work in Duan et al. (2014b) develops the incentive compatible contracts to encourage users to participate in data acquisition and distributed computing programs.

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

2.3 System Model

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

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

2.3.1 Transmission Data Rate

The performance R is measured by the UE's transmission data rate. We consider the uplink (UL) scenario since UL resource sharing in D2D communications only affects the BS, and the incurred interference can be mitigated by BS coordination (Feng et al. 2013).

The transmission data rate is related to the signal to interference plus noise ratio (SINR). In a cellular network with D2D underlaid, the receiver suffers interference from cellular and D2D communications due to resource sharing. When D2D communication is in the UL band, the source UE transmits data to the destination UEs using the uplink band of the cellular band. The interference comes from the other UEs (both cellular UE and D2D UE) (Xu et al. 2012). Thus, the transmission data rate of a D2D UE i in the UL band with co-channel interference is given by

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

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

2.3.2 User Equipment Type

We define the UE type to be a representation of each UE's preference toward joining D2D communication. Given a fixed reward, a high-type UE will be more eager to contribute in the transmission and provide a high data rate. Naturally, high-type UEs are more preferred by the BS and will receive more reward. Here, we consider that the number of UE types belong to discrete, finite space. In Sect. 2.4.2.2, we will extend the results to the continuum case.

Definition 2.1 There are N D2D UE pairs in a D2D underlaid cellular network. The UEs' preferences are sorted in an ascending order and classified into N types: type-1, ..., type- i , ..., and type- N . The type of UE includes properties such as the privacy concern, battery remain, and the willingness to share data. θ_i denotes the type of UE and follows

$$\theta_1 < \dots < \theta_i < \dots < \theta_N, \quad i \in \{1, \dots, N\}. \quad (2.2)$$

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

Instead of offering the same contract to all UEs, the BS will offer different contract bundles according UE-type θ . The UEs are free to accept or decline any type of contracts. If the UE declines to receive any contract, we assume that the UE signs a contract of $(T(0), 0)$, where $T(0) = 0$. In the following subsections, we will give the utility function of the BS and UEs based on the signed contract.

2.3.3 Base Station Model

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

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

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

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

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

2.3.4 User Equipment Model

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

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

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

2.3.5 Social Welfare

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

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

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

2.4 Proposed Solution

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

2.4.1 Conditions for Contract Feasibility

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

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

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

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

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

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

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

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

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

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

Lemma 2.1 For any feasible contract (T, R) , $T_i > T_j$ if and only if $\theta_i > \theta_j$, and $T_i = T_j$ if and only if $\theta_i = \theta_j$.

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

According to the IC constraint, we have

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

$$\theta_j v(T_j) - R_j \geq \theta_j v(T_i) - R_i, \quad (2.11)$$

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

$$\begin{aligned}
\theta_i v(T_i) + \theta_j v(T_j) &\geq \theta_i v(T_j) + \theta_j v(T_i), \\
\theta_i v(T_i) - \theta_j v(T_i) &\geq \theta_i v(T_j) - \theta_j v(T_j), \\
v(T_i)(\theta_i - \theta_j) &\geq v(T_j)(\theta_i - \theta_j).
\end{aligned} \tag{2.12}$$

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

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

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

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

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

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

Definition 2.4 Monotonicity: For any feasible contract (T, R) , the reward T follows

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

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

Proposition 2.1 As a strictly increasing function of T , the contribution R satisfies the following condition intuitively

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

Proposition 2.1 shows that an incentive compatible contract requires a high performance of UE if it receives a high reward and vice versa.

Lemma 2.2 For any feasible contract (T, R) , the utility of each type of users must satisfy

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

Proof From Definition 2.4 and Proposition 2.1, we know that UEs who ask for more rewards must be able to provide larger transmitting rates, i.e., the two constraints $T_i > T_j$ and $R_i > R_j$ are imposed together. If $\theta_i > \theta_j$, we have

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

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

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

2.4.2 Optimal Contract

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

2.4.2.1 Case of Discrete Type

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

$$\begin{aligned}
&\max_{(T, R)} \sum_{i=1}^N \lambda_i (R_i - cT_i), \\
&s.t., \\
&\quad (a) \quad \theta_i v(T_i) - R_i \geq 0, \\
&\quad (b) \quad \theta_i v(T_i) - R_i \geq \theta_i v(T_j) - R_j, \\
&\quad (c) \quad 0 \leq T_1 < \dots < T_i < \dots < T_N, \\
&\quad \quad i, j \in \{1, \dots, N\}, \quad i \neq j.
\end{aligned} \tag{2.18}$$

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

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

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

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

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

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

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

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

In Lemma 2.1, we have shown that $T_i \geq T_j$ whenever $\theta_i \geq \theta_j > 0$, the second inequality becomes

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

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

Thus, we have

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

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

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

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

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

Second, we prove all the UICs can be reduced.

Proof From the IC constraint, we have the following two LUICs:

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

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

In Lemma 2.1 we have shown that $T_i \geq T_j$ whenever $\theta_i \geq \theta_j > 0$, the second inequality can be derived as

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

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

Thus, we have

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

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

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

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

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

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

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

can easily imply that the LUIC,

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

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

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

$$\begin{aligned} & \max_{(T, R)} \sum_{i=1}^N \lambda_i (R_i - cT_i), \\ & s.t. \\ & (a) \quad \theta_1 v(T_1) - R_1 = 0, \\ & (b) \quad \theta_i v(T_i) - R_i = \theta_i v(T_{i-1}) - R_{i-1}, \\ & (c) \quad 0 \leq T_1 < \dots < T_i < \dots < T_N, \\ & \quad \quad i \in \{1, \dots, N\}. \end{aligned} \quad (2.36)$$

To solve this problem, we can first formulate and solve the relaxed problem without the monotonicity condition and then consider the standard procedure of the Lagrangian multiplier. Then, we check whether the solution to this relaxed problem satisfies the monotonicity condition or not (Bolton and Dewatripont 2004).

The optimal contract solved by this optimization problem will give zeros utility for the lowest type of UEs. If $N = 2$, there are only two types of UEs, the high-type and the low type. By solving this optimization problem, the low-type UEs will obtain a zero utility contract and the high-type UEs can receive a positive utility. In general cases when $N > 2$, a similar conclusion is also provided in (Bolton and Dewatripont 2004; Gao et al. 2011, 2014), all types of UEs will get a positive utility except the lowest type UE who will get a zero utility.

2.4.2.2 Case of Continuum Type

In the previous case, there are N types of UEs from θ_1 to θ_N . In practice, the number of UEs types can be infinite. In this subsection, we will give an analysis about the continuum-type case with type θ which has the probability density function (PDF) $f(\theta)$ (with cumulative distribution function (CDF) $F(\theta)$ on the interval $[\underline{\theta}, \bar{\theta}]$). The contract that a BS offers to the UE is written as $[T(\theta), R(\theta)]$. T is monotonously increasing in R as in the discrete case. If no trading happens between the BS and the

UE, the contract is set as $T(\theta) = 0$ and $R(\theta) = 0$. Similar to the discrete-type case, we can write the BS's optimization problem as follows.

$$\begin{aligned} & \max_{\{T(\theta), R(\theta)\}} \int_{\underline{\theta}}^{\bar{\theta}} [R(\theta) - cT(\theta)] f(\theta) d\theta, \\ & s.t. \\ & (a) \quad \theta v[T(\theta)] - R(\theta) \geq 0, \\ & (b) \quad \theta v[T(\theta)] - R(\theta) \geq \theta v[T(\hat{\theta})] - R(\hat{\theta}), \\ & \quad \theta, \hat{\theta} \in [\underline{\theta}, \bar{\theta}]. \end{aligned} \quad (2.37)$$

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

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

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

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

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

Step 2: Reduce IC constraints. To reduce the IC constraints, we give Lemma 2.3 that using two other constraints to replace all IC constraints (Bolton and Dewatripont 2004).

Lemma 2.3 *The IC constraint is equivalent to the following two conditions:*

1. *Monotonicity*

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

2. *Local incentive compatibility*

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

Proof The monotonicity can be easily derived following the steps in Lemma 2.1 and Definition 2.4. The local incentive compatibility can be proved by contradiction. Suppose we have the monotonicity and local incentive compatibility, and the IC constraint cannot be held. Then, with at least one $\hat{\theta}$ violates the IC constraint

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

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

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

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

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

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

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

$$\begin{aligned} & \max_{(T(\theta), R(\theta))} \int_{\underline{\theta}}^{\bar{\theta}} [R(\theta) - cT(\theta)] f(\theta) d\theta, \\ & s.t. \\ & (a) \quad \underline{\theta} v[T(\underline{\theta})] - R(\underline{\theta}) \geq 0, \\ & (b) \quad \theta v'[T(\theta)] \frac{dT(\theta)}{d\theta} = R'(\theta), \\ & (c) \quad \frac{dT(\theta)}{d\theta} \geq 0, \\ & \quad \theta \in [\underline{\theta}, \bar{\theta}]. \end{aligned} \quad (2.45)$$

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

2.4.3 Practical Implementation

By solving the proposed problem, we could provide UEs with the optimal contract that can incentivize them to participate in D2D communication. To implement the proposed approach in a practical D2D network, we can follow the next steps. From the system model, we have the initial information such as the cellular network radius S ,

the cellular users' transmit power P_c , the number of UE types N , and the probability λ_i that UE belongs to θ_i . With those initial values, the BS can obtain the optimal contract (T, R) . Once there are UEs requesting contents, the BS acts in the following stages.

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

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

2.5 Simulation Results and Analysis

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

First of all, we donate the optimal contract solved in the previous section by *information asymmetry*. For comparison purposes, we introduce another two incentive mechanisms. The first one is the optimal contract under *no information asymmetry* (i.e., the BS is aware of the types of UEs), which is the optimal outcome that we can achieve and serve as the upper bound. The second contract is the *linear pricing* which is also under the information asymmetry that the BS has no acknowledgment of the UE type. In this *linear pricing* mechanism, the BS will only specify a unit price P for data rate, and the UEs will request the amount of reward T which corresponding to a certain amount of data rate, to maximize their own utilities.

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

Table 2.1 Physical layer parameters

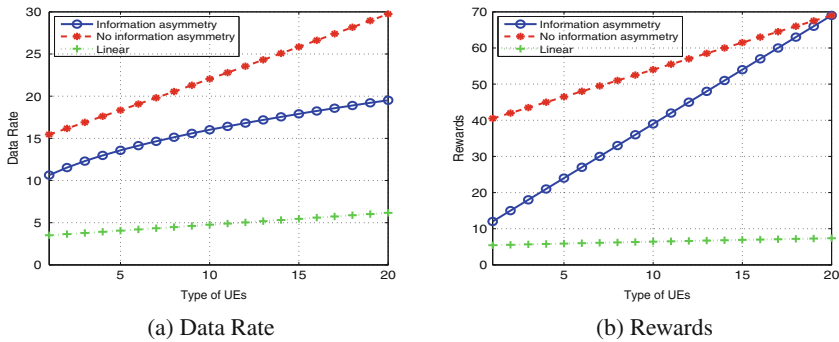
Parameter	Value
Cellular area radius	500 m
Maximum D2D distance	30 m
number of UE types	20
Noise spectral density	-174 dBm/Hz
Noise figure	9 dB at device
Antenna gains	BS: 14 dBi; device: 0 dBi
Transmit power	BS: 46 dBm; device: 23 dBm

2.5.1 Contract Feasibility

2.5.1.1 Monotonicity

In Fig. 2.2a, b, we compare the required transmission data rate and reward of different type UEs to show the monotonicity of the contract.

In Fig. 2.2a, we see that required transmission data rate increases with the UE type, which is consistent with our system model. The difference among the three mechanisms is that the required data rate under *no information asymmetry* and *linear pricing* is linear function of type and is a concave function of type under *information asymmetry*. Among the three mechanisms, the *no information asymmetry* contract requires the highest data rate from the UE, followed by the optimal contract under *information asymmetry*. The lowest data rate is required under the *linear pricing* contract. Similarly, the reward shown in Fig. 2.2b also proves our assumption that reward T is a strictly increasing function of UE type.

**Fig. 2.2** Contract monotonicity

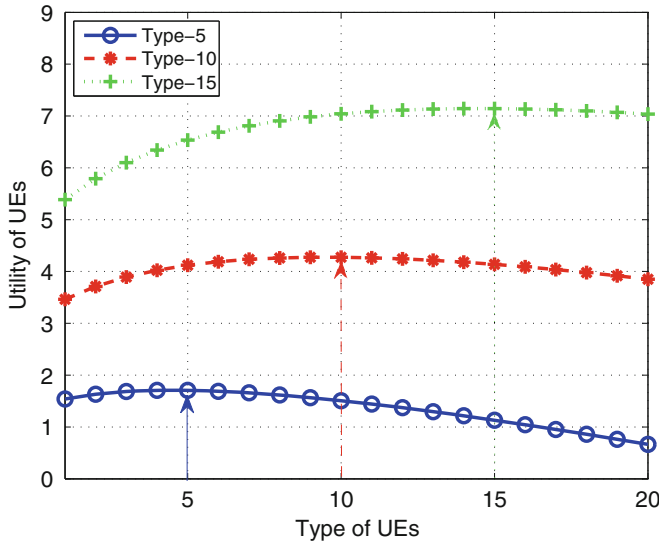


Fig. 2.3 Contract incentive compatibility

2.5.1.2 Incentive Compatibility

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

Moreover, Fig. 2.3 shows that when the three types of users select the same contracts, their utilities follow the inequality $u_5 < u_{10} < u_{15}$. This corroborates the result shown by the (2.16) in Lemma 2.2: the higher the type of the UE, the larger the utility it can receive when selecting the same contract.

2.5.2 System Performance

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

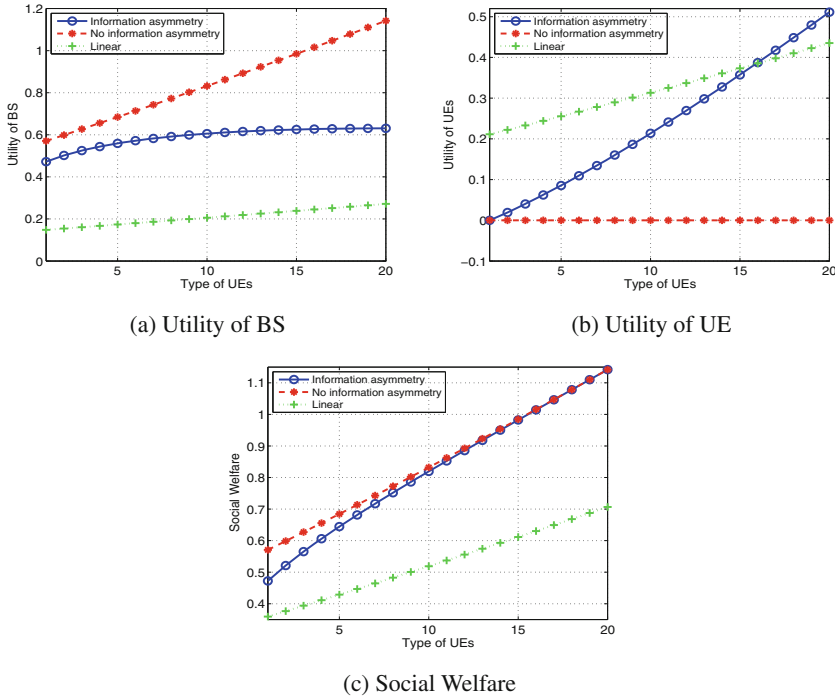


Fig. 2.4 System performance of different types of UEs

2.5.2.1 The UE Type

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

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

In Fig. 2.4b, we compare 20 types of UEs' utilities. These results proved the monotonicity of the contract that the higher the type of UE, the larger the utility it can receive under *information asymmetry*. All the types of UEs enjoy a positive utility except the lowest type (i.e., *type-1*) UE, which is consistent with our conclusion in

Sect. 2.4.2.2. However, the UE's utility remains 0 disregarding the type of UE under *no information asymmetry*. This is due to the fact that when the BS is available at the UE's type, it will adjust the contract to maximize its own utility while leave the UE a 0 utility. Overall, we see that *linear pricing* gives the UEs the highest utility, followed by the optimal contract under *information asymmetry*, then the ideal case with *no information asymmetry*. However, for some of the high-type UEs can obtain higher utility from the optimal contract under *information asymmetry* than the *linear pricing*.

In Fig. 2.4c, we see that the social welfare shows similar performance with that of the BS. One interesting point is that, the social welfare of the highest type UE has the same value under *no information asymmetry* and *information asymmetry*. This is in accordance with the conclusion we made in Sect. 2.4.2.2 that the highest type UE will result in an efficient trading as if there is no information asymmetry. For other high-type UEs under *no information asymmetry*, they also have close optimal efficient trading with the BS. The *linear pricing* mechanism gives the lowest social welfare (i.e., trading efficiency) since no information retrieving strategy has been applied.

2.5.2.2 The Cellular Network Size

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

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

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

From Fig. 2.5c, we can also see the differences in the social welfare under the three different contracts. Social welfare under *no information asymmetry* achieves the highest among the other two. As the BS is informed of the UE type, the transaction achieves the highest efficiency, then followed by the optimal contract achieved under *information asymmetry*. The *linear pricing* presents the worst efficiency. The optimal contract achieved under *information asymmetry* achieves a near-optimal social

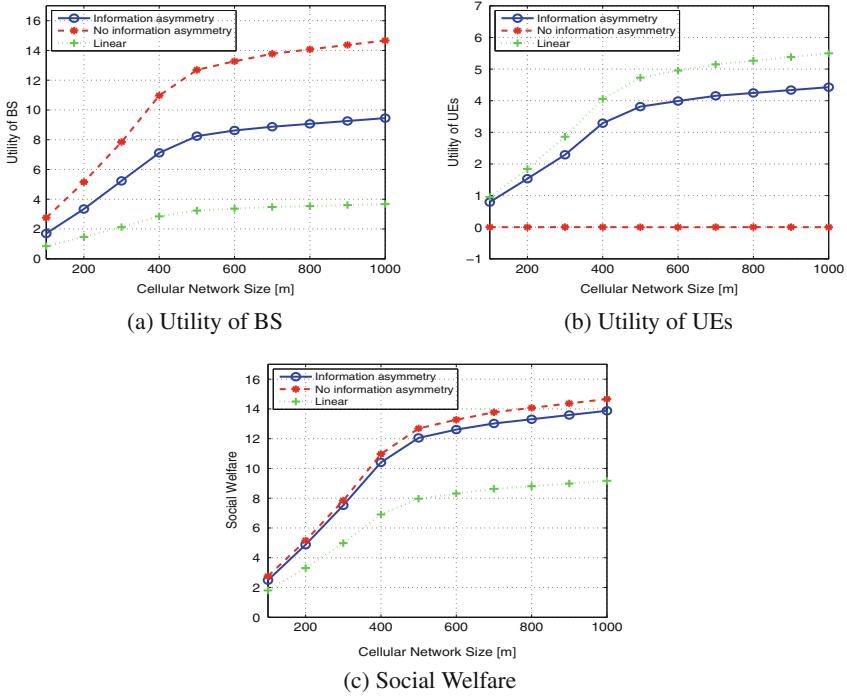


Fig. 2.5 The system performance when the size of cellular network varies

welfare, as it breaks the information asymmetry when the UEs select contracts, their types are revealed to the BS automatically. The *linear pricing* does not account for any type of information and thus has the lowest social welfare.

2.5.2.3 The Maximum D2D Communication Distance

When the size of the cellular network and the BS transmission power are fixed, the interference from cellular communication will be in a certain range. Under this condition, we change the maximum transmission distance of D2D pairs, to see the effects on system performance, in Fig. 2.6.

For the utility of the BS and UEs, Fig. 2.6a, b still exhibit similar properties as shown in Fig. 2.5a, b. The utility that the BS receives is maximized under *no information asymmetry*, followed by *information asymmetry* and *linear pricing*. The UE achieves the maximum utility under *linear pricing*, followed by *information asymmetry* and *no information asymmetry* which equals to 0 all the time. The highest social welfare is achieved under *no information asymmetry*, *information asymmetry* is the second, and *linear pricing* results in the worst social welfare.

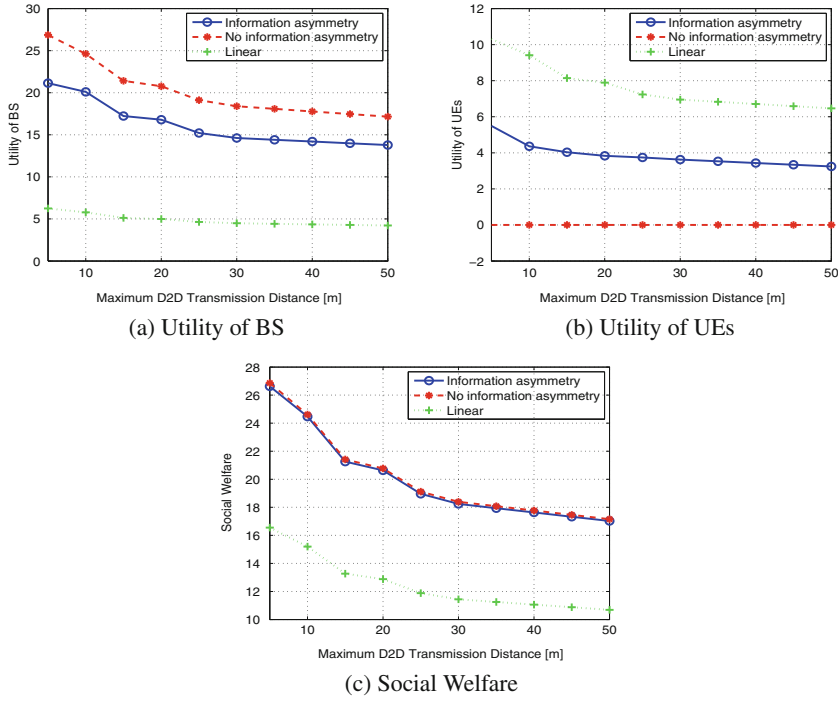


Fig. 2.6 The system performance when the maximum D2D communication distance varies

2.5.2.4 The Number of UE Types

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

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

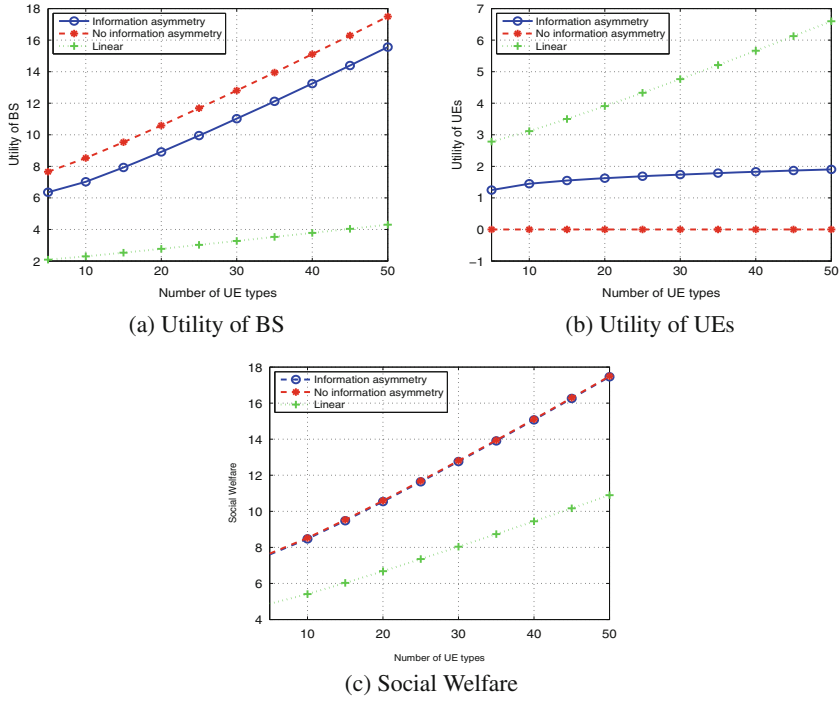


Fig. 2.7 The system performance when the number of UE types varies

2.6 Summary

In this chapter, we have proposed an *adverse selection* model for addressing the problem of incentivizing UEs to participate in D2D communication underlaid over a cellular system. Under the case with information asymmetry in which the UEs' preferences are not available at the BS, we have proposed a self-revealing mechanism based on the framework of contract theory. We have considered the type of UEs under two different scenarios, the discrete-type case and continuum-type case. Simulation results have shown that our proposed approach can potentially incentivize UEs to participate in D2D communication. Furthermore, the optimal contract under *information asymmetry* has been proved to obtain the performance close to the ideal case with *no information asymmetry*, and higher than the *linear pricing* when not trying to retrieve any information at all. As there are many literatures have also covered the *adverse selection* problem in wireless networks, we will start to talk about other contract-theoretical models, such as *moral hazard*, mixed problem, and incomplete contract, which are less covered in the previous literature from the next chapter.

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