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*Research Article*

# A New Multicasting Device-to-Device Communication Control Scheme for Virtualized Cellular Networks

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With the explosion in the number of wireless services, the unprecedented growth of mobile date traffic has brought a heavy burden on the traditional cellular networks. To meet the explosive traffic services, the potential of network virtualization and multicasting device-to-device (MD2D) technology have been proposed as a promising solution for next-generation networks. In this paper, we propose a novel MD2D control scheme for virtualized cellular networks, which enables device clustering for local MD2D services to obtain the finest system performance. By taking into consideration dynamic situations and competitive environments, we formulate our control algorithms as a game model with imperfect system information. Inspired by the incentive mechanism and evolutionary decision process, the proposed game approach can guide selfish mobile devices toward honest behaviors, and the MD2D services are provided based on the step-by-step interactive feedback process. Through numerical evaluation and simulation analysis, we not only quantify the outcome of our proposed scheme's system throughput, bandwidth utilization, and MD2D service efficiency, but also provide the performance comparison with existing schemes. Finally, we provide further challenges and various opportunities in the research area of MD2D-enabled cellular network operations.

## 1. Introduction

Over the past decades, the increasing popularity of smart mobile devices and multimedia applications has given rise to the substantial growth in wireless traffic services. Compared with 4G networks, one of the major differences in future 5G networks is to provide seamless connectivity for any type of devices and applications that may benefit from being connected in the user's environment. Network virtualization has been proposed as a promising solution for future 5G networks. This technique is the process of combining hardware and software network resources and network functionality into a single, software-based administrative entity, a virtual network. In summary, the concept of network virtualization is to create logical partitions of some existent physical network resources in an efficient manner. To implement the network virtualization, resource slicing is necessary. The fundamental principle of network slicing is to create multiple virtual networks for specific needs over a common physical infrastructure [1–6].

Another promising technology is device-to-device (D2D) communications. D2D communication enables direct communication between mobile devices without traversing the fixed core network infrastructure. It will facilitate the interoperability to improve the spectral efficiency in crowded communication networks. Recently, D2D communication in a cellular network has gained much attention. The main advantages of D2D communication in cellular networks are (i) offloading the overloaded cellular traffic, (ii) extending the cellular coverage, (iii) improving energy efficiency, and (iv) allowing high rate transmission; it is significantly more reliable than that from the base station (BS) to the mobile devices due to the much stronger channels between the devices [7, 8].

A further improvement of D2D is to allow individual devices to form clusters where one device can broadcast information to multiple receivers. Multicasting through D2D (MD2D) communication is appealing when the same data is requested by multiple devices in restricted geographical areas. By leveraging the multicast nature of wireless communications, MD2D technology delivers the shared content to multiple users simultaneously. In particular, as the traffic of local content sharing grows rapidly, MD2D scenarios are reasonably possible. However, the MD2D implementation

leads to a more challenging and complex control problem in real-world cellular network operations. To better cope with the shift from sender-driven cellular networking paradigm to receiver-driven MD2D paradigm, some technical issues should be considered to effectively mitigate the traffic load in BSs [9–11].

By sharing the virtualized network resource, the integration of MD2D and cellular network infrastructure can further facilitate the improvement of application services. Compared with traditional cellular networks, this approach can maximize the system efficiency while ensuring differentiated service requirements [3, 12]. In MD2D-enabled cellular networks, wireless bandwidth resource is virtualized and sliced into multiple resource units. To support MD2D services, mobile devices within physical proximity are clustered, and one device is selected as a header. Therefore, multiple clusters can be formed simultaneously, and the bandwidth slices are assigned to each MD2D header. Finally, virtual MD2D communication networks are locally activated by the headers.

In MD2D-enabled cellular networks, there are multiple type services and scenarios: local file streaming, device discovery, and group communications [13]. In the local file streaming, local users may send the same streaming messages to the neighbor users. Device discovery is referring to the process of detecting surrounding devices. Group communications are required to provide public safety services such as police, fire, and ambulance. In the aforementioned service scenarios, MD2D communication network has certain conveniences; it may be assisted by the cellular network infrastructure which is not available to ad hoc networks [13].

To maximize the MD2D assisted cellular network performance, the adaptive selection of MD2D headers is essential. However, a mobile device acting as a cluster header has to sacrifice its energy for MD2D services. Therefore, we should induce selfish devices to participate in header activities by paying an appropriate incentive. In this study, the major goal is to develop a novel MD2D-enabled cellular network control scheme. In the proposed scheme, header selection and incentive payment algorithms are designed and each algorithm is integrated to work together. This joint approach can further facilitate the improvement of cellular network efficiency. However, it is extremely challenging. Therefore, we need a new control paradigm.

The remainder of this paper is structured as follows. The related studies are introduced in Section 2. The system model in Section 3 includes symbol notations, along with the network infrastructure, followed by the considered problem formulation. In addition, we explain the proposed algorithms based on the game model and then present our approach with some mathematical concepts. In Section 4, the simulation results are presented and analyzed. Finally, we discuss and conclude this study with future work in Section 5.

## 2. Related Work

MD2D assisted cellular network technology has been envisioned to provide a necessary infrastructure when 5G networks finally roll out. Recently, various papers have been published. A. Bhardwaj et al. formulate the network resource allocation problem in the cellular network with D2D multicast groups [14]. They develop the *Device-to-Device Multicast Resource Allocation* (*D2DMRA*) scheme to satisfy users in cellular networks and D2D groups. To minimize the interference among users while maximizing the total system throughput, the *D2DMRA* scheme analyzes a joint power and channel allocation process. In particular, users in D2D multicast group can reuse resources of cellular networks under the wireless interference constraints. With resource reusability, authors have explored the possibility of optimizing system capacity along with augmented energy efficiency. Finally, they show that the *D2DMRA* scheme performs better compared with existing methods in terms of system throughput and efficiency [14].

The *Matching Theory based Device-to-Device Delivery* (*MTD2DD*) scheme is a three-dimensional iterative matching algorithm to ensure the quality of service requirements of both cellular and D2D users [15]. By using Bayesian nonparametric approach, the social relationship among users is estimated. And then, the proposed iterative matching algorithm matches between transmitters and receivers and between D2D links and wireless bandwidth, respectively. To simplify the matching problem complexity, a three-dimensional matching problem is transformed into a two-sided matching problem. Therefore, the *MTD2DD* scheme provides a suboptimal solution, which can approach the performance of the exhaustive optimal algorithm with a much lower complexity. Finally, the performance is evaluated through simulations. Simulation results validate the excellent performance with a much lower computational complexity [15].

Li Wang et al. propose the *Social Characteristics based Device-to-Device Clustering* (*SCD2DC*) scheme to share the wireless bandwidth [16]. They investigate novel approaches to form D2D clusters while exploiting the proximity property of D2D communications. To effectively form clusters, they consider D2D users' social interactions to take advantage of user behavioral information. Therefore, the main idea is to incorporate both social interactions and physical relationships among D2D users. In the *SCD2DC* scheme, two clustering methods are developed; one is based on the Chinese restaurant process, and the other is designed to enhance the traditional Chinese restaurant process. Both methods characterize the formation of clusters by taking into account the physical distance and the social relationship among users. Finally, performance analysis presents the advantages of the *SCD2DC* scheme in terms of system throughput and energy efficiency [16].

Currently, game theory has been shown to be an effective tool to study and analyze the interaction among individual network agents. However, the outcome of classical game theory such as the Nash equilibrium solution is generally not unique or optimal. This situation motivates new game models, whose main objective is to lead the institutions governing the interactions of a game to implement a socially desirable solution [17, 18]. The incentive mechanism design and evolutionary game are effective game models to obtain finest solutions under the circumstance of asymmetric information.

In particular, the incentive mechanism design induces that truthful action is a dominant strategy for each game player, and evolutionary game focuses on the information incompleteness under the uncertain environment.

In this study, we design a new incentive mechanism to pay a reward for MD2D headers and a novel evolutionary game model to select headers for MD2D clusters. Based on the jointly design process, we can obtain the synergy effect while improving total system performance. The major contributions of our proposed scheme are as follows: (i) to employ a game-based approach to provide satisfactory 5G network services; (ii) to ensure the reciprocal combination of optimality and practicality; (iii) to capture dynamic interactions of network agents depending on their different viewpoints; and (iv) to improve the cellular network performance through the MD2D technique. In this paper, we compare the proposed scheme with the existing *D2DMRA* [14], *MTD2DD* [15], and *SCD2DC* [16] schemes and demonstrate that our approach can significantly outperform these existing schemes.

## 3. The Proposed MD2D-Enabled Network Control Scheme

In this section, we first introduce the MD2D assisted cellular network infrastructure. Then, based on the game model, the incentive mechanism and MD2D header selection algorithm are explained in detail. Finally, the proposed scheme is presented in the eight-step procedures.

*3.1. Incentive Mechanism Design for MD2D Headers.* In MD2D-enabled cellular networks, there are two transmission manners: one is the direct communication with the BS; the other is the MD2D transmission assisted by MD2D headers. Therefore, there are multiple cellular users and MD2D users. We denote the set of cellular users as $\mathscr{C} = \{c_1 \dots c_n\}$ and the set of MD2D users as $\mathscr{D} = \{d_1 \dots d_m\}$. For the MD2D service, our cluster formation process categorizes groups of some proximal MD2D users into multiple clusters. For each cluster, cluster header should be selected. Cellular users communicate via the evolved node base station (eNB), while MD2D users directly communicate from the cluster header. The general cellular network architecture with MD2D technique is shown in Figure 1.

In the cluster based MD2D communications, the cluster head selection is very crucial and important. To improve the efficiency of MD2D services, MD2D headers cover as many as neighboring devices. In the proposed scheme, the eNB has a predetermined threshold ($\Upsilon$) to be MD2D header candidates; $\Upsilon$ is the number of reachable neighbor devices. The mobile devices, which can cover $\Upsilon$ neighbor devices, report their cost ($\phi$) to serve MD2D services. From the eNB viewpoint, this information must be credible. However, the $\phi$ value is a privately known information for each device. Therefore, we should develop a procedure to induce header candidates to reveal truthfully their private information. In this study, we adopt the main concept of incentive mechanism design, which can give MD2D devices incentives to truthfully reveal their private information.

Before explaining our incentive mechanism, we first introduce the useful preliminaries. Assume that one mobile device in $\mathscr{C}$ has $\Upsilon$ neighboring devices. If this device has been selected as a header, i.e., $d_i \in \mathscr{D}$, $d_i$'s consuming energy cost is $\phi_{d_i}$ to provide MD2D services. As a rational game player, $d_i$ act self-interestedly. Therefore, the eNB should pay a reward for the $d_i$ to compensate its cost. In our incentive mechanism, the function $\mathscr{F}_\chi(\phi_{d_i}) : \mathbb{R} \longrightarrow [0, 1]$ is adopted to determine how much contribution to be procured from $d_i$ as a MD2D header. Based on the $\phi_{d_i}$ value, $\mathscr{F}_\chi(\phi_{d_i})$ is defined as follows [19, 20]:

$$\mathscr{F}_\chi\left(\phi_{d_i}\right) = \ln\left(e - \frac{\phi_{d_i}}{\chi}\right), \quad \text{s.t.}, 0 \le \frac{\phi_{d_i}}{\chi} \le (e-1) \tag{1}$$

where $\chi$ is a control parameter to adjust the range of $\mathscr{F}_\chi(\phi_{d_i})$ function where $0 \le \mathscr{F}_\chi(\phi_{d_i}) \le 1$. According to (1), the incentive payment ($I_{d_i}$) for $d_i$ can be calculated. From the viewpoint of mobile device, it is not necessary to report his true cost. Therefore, $d_i$ can inform the eNB of his cost $\tilde{\phi}_{d_i}$; the superscript "~" indicates that $d_i$ can misreport his true value $\phi_{d_i}$. Based on $d_i$'s declaration of his cost $\tilde{\phi}_{d_i}$, $d_i$'s pro forma contribution is defined as $\tilde{\phi}_{d_i} \times \mathscr{F}_\chi(\tilde{\phi}_{d_i})$. And then, $I_{d_i}(\tilde{\phi}_{d_i})$ can be derived as follows [19, 20]:

$$I_{d_i}\left(\tilde{\phi}_{d_i}\right) = \left(\tilde{\phi}_{d_i} \times \mathscr{F}_\chi\left(\tilde{\phi}_{d_i}\right)\right) + \int_{\omega=\tilde{\phi}_{d_i}}^{\infty} \mathscr{F}_\chi(\omega)\, d\omega \tag{2}$$

Generally, utility function in game theory corresponds to the player's received benefit minus the incurred cost. Therefore, $d_i$'s utility function with his reporting $\tilde{\phi}_{d_i}(U_{d_i}(\tilde{\phi}_{d_i}))$ is given by

$$U_{d_i}\left(\tilde{\phi}_{d_i}\right) = I_{d_i}\left(\tilde{\phi}_{d_i}\right) - \left(\tilde{\phi}_{d_i} \times \mathscr{F}_\chi\left(\tilde{\phi}_{d_i}\right)\right) \tag{3}$$

To elicit the $d_i$'s truthfulness, the payoff of $U_{d_i}(\tilde{\phi}_{d_i})$ should be maximized when $d_i$ truthfully report his $\phi_{d_i}$ value.

**Theorem 1.** *According to our incentive payment given by (1)-(3), truthful cost reporting is a dominant strategy for each MD2D device.*

*Proof of Theorem 1.* See the text in Appendix for details. □

*3.2. Evolutionary Game Model in the MD2D Header Selection Algorithm.* Traditionally, the basic idea of game theory is to investigate individual players' decisions, and the payoff to each player depends on the decisions made by all. Therefore, a key question in game theory is to reason about the behaviors when players take part in a given game. However, the classical game theory requires the players to make rational choices; each player must perfectly analyze his strategic choice. However, this assumption is obviously not satisfied under real world environments. In reality, game players make decisions irrationally due to the limited information about available strategies. To overcome this fundamental problem, J. Smith had the insight that game theory could be used to predict the evolutionary outcome under frequency-dependent selection

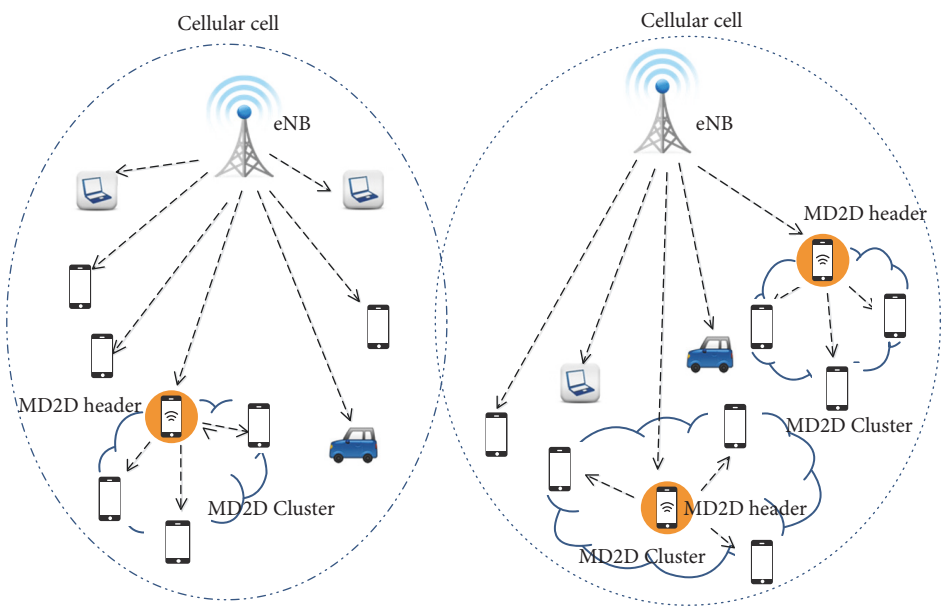


Figure 1: MD2D assisted cellular network infrastructure.

and had develop a new game theory model, called the evolutionary game theory [21].

The evolutionary game theory has captured the players' dynamics as an evolving game. During the evolutionary game, players learn how to select their strategies like as an evolution test where losing strategies are eliminated and winning strategies remain. The solution concept of evolutionary game is the evolutionarily stable strategy (ESS). In a given environment, players are repeatedly and randomly playing a game and reach a specific strategy through the operation of natural selection. That strategy, which cannot be invaded by any alternative strategy, is defined as the ESS. Replicator dynamics (RD) describe the evolution in the proportion of each strategy to reach an ESS. Through the evolution process, each player changes his strategy to get a higher payoff. Note that the higher the payoff of a player's strategy, the more possibility the strategy to be selected by a player. Therefore, the payoff of a strategy can be interpreted as its fitness, and the strategy with higher fitness has more chance to be the ESS [21, 22].

In this study, we design a new evolutionary game model for the eNB. Unlike the classical evolutionary game model, our proposed game is an asymmetric game. Therefore, there are two kinds of game players, i.e., the eNB and MD2D headers, and they have different strategy sets. For the MD2D headers, the strategy is the cost of MD2D services. According to our incentive mechanism, the best strategy of each header is to report truthfully its own cost. For the eNB, the strategy is how to select MD2D headers; after selecting MD2D headers, virtualized bandwidth slice is assigned to each header for local MD2D services. To maximize the MD2D efficiency, the eNB dynamically selects the MD2D headers and iteratively changes his current strategy while repeatedly monitoring the system outcome. Based on the reported information and real-time feedback verification, our incentive mechanism and evolutionary game model are coupled with each other in an interactive relationship.

To represent the *RD* for the MD2D header selection problem, let $H$ be a number of MD2D header candidates and $\mathscr{P}_i$ is the propensity for the $i$th header candidate selection. $\mathbb{H}$ is the $(H+1)$-dimensional vector $[\mathscr{P}_1 \ldots \mathscr{P}_i \ldots \mathscr{P}_H, \mathscr{P}_{H+1}]$ where $\mathscr{P}_{H+1}$ represent a no-header selection strategy. $\widetilde{\mathscr{P}}_j$ stands for the RD of $\mathscr{P}_{1\le j\le H+1}$. The RD of $\mathscr{P}_j$ $(\widetilde{\mathscr{P}}_j)$ is defined as

$$\widetilde{\mathscr{P}}_j = \left(\left(\mathscr{P}_j \times U_j^{eNB}\right) - \left(\frac{1}{(H+1)} \times \sum_{k=1}^{H+1}\left(\mathscr{P}_k \times U_k^{eNB}\right)\right)\right) \quad (4)$$

$$\text{s.t., } U_j^{eNB} = \delta \times \left(\frac{1}{\left(1+\exp\left(\left(\mathscr{T}_j^{eNB} - \mathscr{T}_{-j}^{eNB}\right)/\mathscr{T}_{-j}^{eNB}\right)\right)} - \gamma\right) \quad (5)$$

where $\mathscr{T}_j^{eNB}$, $\mathscr{T}_{-j}^{eNB}$ are the eNB's traffic load with the $j$th MD2D header candidate selection and without that candidate selection, respectively. $\delta$ and $\gamma$ are adjusting parameters to measure the system payoff. In order to implement the RD process for MD2D services, we partition the time-axis into equal intervals, and the RD process is repeated at each time period. At the end of each iteration, the eNB evaluates periodically the current RD. The RD of each eNB's strategy is used to update the $\mathbb{H}$ vector, which represents the strategy propensity to make a decision for the next iteration. If the $j$th MD2D header candidate is selected at time $t-1$ period, the $\mathbb{H}$ vector for the next $t$ time period $(\mathbb{H}^t)$ is estimated as follows:

$$\mathbb{H}^t = \mathbb{H}^{t-1} + \left[\frac{\widetilde{\mathscr{P}}_1^{t-1}}{\beta}, \ldots, \frac{\widetilde{\mathscr{P}}_j^{t-1}}{\beta}, \ldots, \frac{\widetilde{\mathscr{P}}_{H+1}^{t-1}}{\beta}\right] \quad (6)$$

Table 1: System parameters used in the simulation experiments.

| Application Type | Bandwidth Request | Joining probability for the MD2D service |
|---|---|---|
| I | 50 Mbits per unit_time | binomial distribution B(1, 1/2) |
| II | 100 Mbits per unit_time | binomial distribution B(1, 1/3) |
| III | 200 Mbits per unit_time | binomial distribution B(1, 1/4) |
| IV | 250 Mbits per unit_time | binomial distribution B(1, 1/2) |
| Parameter | Value | Description |
| $n$ | 1000 | Number of mobile devices in the cellular network |
| C | 10GHz | the Bandwidth capacity (C) of each microcell |
| $\Upsilon$ | 10 | the predefined number of reachable neighbor devices |
| $\chi$ | 60 | a control parameter to adjust the range of $\mathscr{F}$ function |
| $\phi_d$ | $0 < \phi_d \leq 100$ | the $d$'s energy cost for MD2D communications |
| $\delta$ | 5 | an adjusting parameter to measure the system payoff |
| $\gamma$ | 0.5 | an adjusting parameter to measure the system payoff |
| $\beta$ | 1 | a control factor to adjust the convergence rate |
| $\varepsilon$ | 0.05 | a pre-defined minimum bound for RD |

where $\beta$ is a control factor to adjust the convergence rate and $\widetilde{\mathscr{P}}_j^{t-1}$ is the RD of $\mathscr{P}_j$ at time $t-1$. According to (6), $\mathbb{H}$ values are adjusted periodically at each time step for the next strategy selection. This interactive feedback process continues until the ESS is obtained while capturing how the eNB adapts his strategies to achieve a better payoff. If the eNB cannot benefit by changing his current selected strategies, a satisfactory solution is obtained over a game processing time. To evolve into the ESS, it is a practical and suitable approach in real world network operations.

*3.3. Main Steps of Proposed MD2D Assisted Network Control Scheme.* By modeling and studying interactions among network agents, game theory provides the main control methods envisioned to operate future communications systems. However, in many cases, the assumptions made in traditional game theory are unrealistic with respect to the requirement of perfect information about network environments. In addition, the inevitable burden of computation complexity is needed to get the idealistic solution of game theory. Therefore, the relaxation of the classical game theory assumptions is necessary for practical implementations. In this study, we design a new MD2D-enabled cellular network control scheme based on the incentive mechanism and evolutionary game model. As we assert throughout this paper, our joint approach is effectively advantageous and can prove to be of value to rational network agents that have to operate and interact each other under uncertain environments. The principle novelties of this study are a judicious mixture of competition and cooperation game methods and its feasible self-adaptability for network dynamics in providing a desirable solution in the real-world MD2D assisted cellular network operations. The main steps of the proposed scheme are described as follows.

*Step 1.* At the initial time, system factors and control parameters are determined by the simulation scenario (see simulation assumptions and Table 1). At first, all cellular mobile devices communicate via the eNB and all the bandwidth resource is operated proprietarily by the eNB.

*Step 2.* During the operation of cellular networks, each mobile device monitors its neighboring devices. If the number of reachable neighboring devices is larger than the threshold ($\Upsilon$), that mobile device becomes a MD2D header candidate.

*Step 3.* Periodically, the eNB collects the $\widetilde{\phi}$ values from the MD2D header candidates.

*Step 4.* For the next time period, the eNB stochastically selects a MD2D header according to the current propensity vector $\mathbb{H}$. And then, a virtualized bandwidth slice is assigned to the selected header for the MD2D services.

*Step 5.* At each time period, the eNB re-estimates each strategy's selection propensity based on the RD. According to (4) and (6), the eNB estimates the outcome of current decision and adaptively adjusts the $\mathbb{H}$ vector values in parallel with system evolution.

*Step 6.* Based on the evolutionary approach, this iterative feedback procedure continues. When the change of RD for all strategies is within a predefined minimum bound ($\varepsilon$), this change can be negligible; the ESS has been converged.

*Step 7.* Game processing is temporarily over. However, under the dynamic MD2D-enabled cellular network environment, the eNB is constantly self-monitoring the network system; proceed to Step 2 when the next game iteration is needed.

## 4. Simulation Results and Discussion

In this section, we perform simulations to examine the performance of our proposed protocol and compare it with

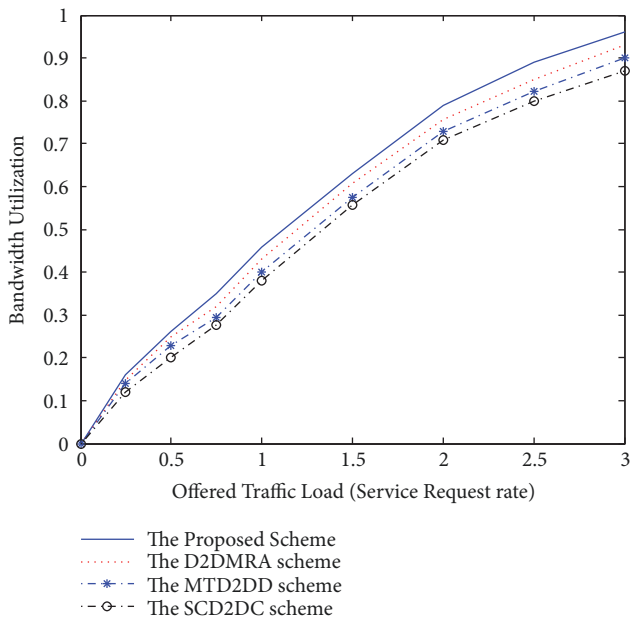


Figure 2: Bandwidth utilization.

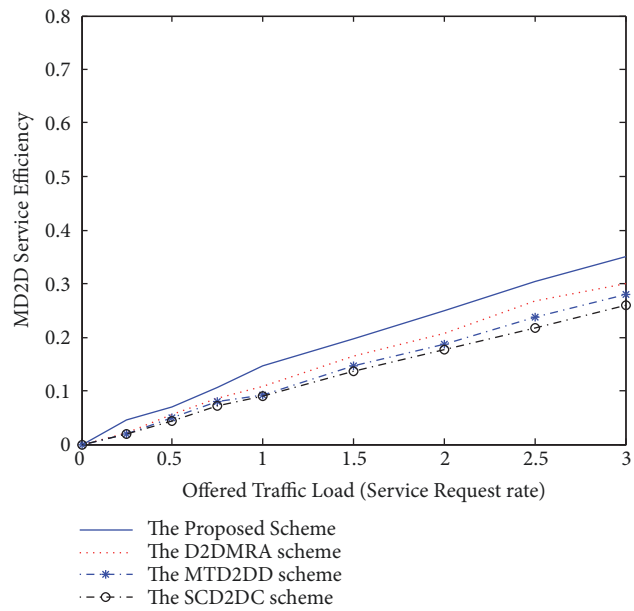


Figure 3: MD2D service efficiency.

that of the *D2DMRA* [14], *MTD2DD* [15], and *SCD2DC* [16] schemes. To ensure a fair comparison, we have considered the following assumptions and scenario.

(i) Simulated cellular network system consists of seven microcells for MD2D services.

(ii) There are 1000 mobile devices; they are randomly distributed in the cellular area.

(iii) Service request rate per each mobile device is Poisson process ($\rho$). The offered rate range is varied from 0 to 3.0.

(iv) Bandwidth capacity (C) of each microcell is 10GHz.

(v) Virtualized bandwidth slice is 50MHz unit. Multiple units can be assigned to each MD2D header.

(vi) Network performance measures obtained on the basis of 100 simulation runs are plotted as functions of the offered traffic rate distribution ($\rho$).

(vii) In order to represent various communication services, four different traffic types are assumed based on bandwidth requirement. They are generated with equal probability.

(viii) A mobile device, running the same application type with the MD2D header, can be a member of MD2D communications. Joining probability for the MD2D service is decided according to the binomial distribution.

(ix) For simplicity, we assume the absence of physical obstacles in the experiments.

According to the simulation metrics, bandwidth utilization, normalized MD2D service efficiency, and system throughput, the performance is evaluated mainly to demonstrate the validity of our proposed method. In Table 1, simulation parameters are presented. Each parameter has its own characteristics.

Figure 2 reflects the relationship between the bandwidth utilization of the schemes and the offered service requests rates. Obviously, the bandwidth utilization increases along with the growing rate of service requests. With taking into account the mobile device's status, we strategically select the MD2D headers. And then, the sliced bandwidth is allocated to the selected MD2D headers for MD2D services. Therefore, small virtual networks for MD2D services are effectively formed. Through our effective bandwidth virtualization, the proposed scheme can improve the bandwidth utilization compared to other existing schemes. From low to high service request intensities, our evolutionary game based approach can adaptively respond to the current network situation and outperforms the existing methods.

Figure 3 compares the normalized MD2D service efficiency in MD2D assisted cellular networks. In this simulation, the MD2D service efficiency is measured as the service outcome per cost. In this study, we adopt the incentive mechanism design to pay a reward for MD2D headers and select the most adaptable headers based on the evolutionary process. Based on the dynamic feedback interaction process, we can significantly enhance the MD2D efficiency. The simulation results in Figure 3 validate the payment appropriateness of our incentive mechanisms compared with the other existing schemes. Under the scenario where the eNB has incomplete information about the MD2D headers, we can provide an effective and practical implementation way.

The system throughput, which is shown in Figure 4, measures the normalized data transmission amount of network access. As a service request increases, the system throughput also increases; the performance trends of all schemes are very similar to each other. However, control decision process in our scheme is designed according to

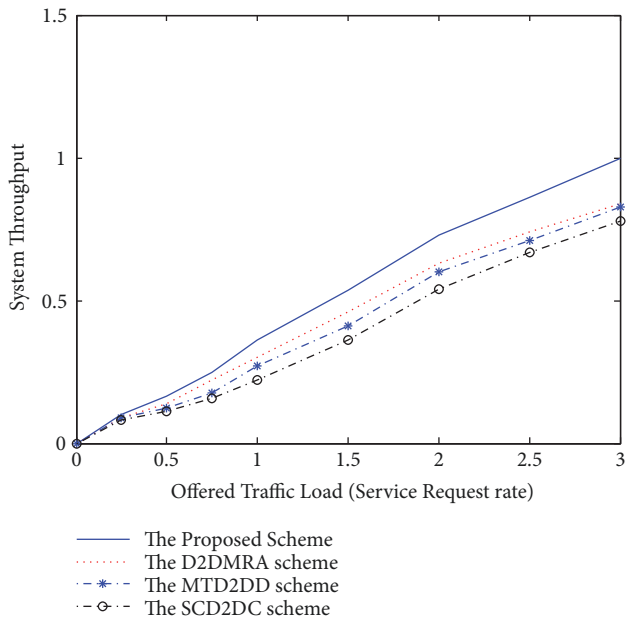


Figure 4: System throughput.

the reciprocal combination of incentive mechanism and evolutionary game model. The proposed joint approach is efficiently advantageous in competitive and cooperative environments. During the step-by-step interactive iteration, our fine-grained adjustment procedure is repeated until the best solution has been found. Therefore, we can obtain a better system throughput than the *D2DMRA* [14], *MTD2DD* [15], and *SCD2DC* [16] schemes.

## 5. Summary and Conclusions

In this paper, we propose a novel MD2D-enabled cellular network control scheme under uncertain environments. In the proposed scheme, we address how to select MD2D headers and how to pay an incentive reward for mobile devices as acting MD2D headers. And then, the MD2D header selection and incentive payment algorithms are described in detail while investigating the reciprocal interactions of them. These two key algorithms are sophisticatedly combined and mutually dependent on each other. To effectively implement our jointly collaborative game approach, we adopt the basic concept of incentive mechanism design and evolutionary game model. Under the dynamic cellular network condition changes, we exploit the step-by-step interactive procedure while dynamically adjusting the time-varying decision parameters. Therefore, we can achieve greater and reciprocal advantages. Extensive simulation results are presented to show that we can benefit from the MD2D-enabled cellular network operations in the bandwidth utilization, normalized MD2D service efficiency, and system throughput.

For the future research, there are various open issues and practical challenges for the MD2D assisted cellular network management. First, we plan to consider the clustering dynamics with the user mobility and look into the use of millimeter wave communications for MD2D services. Second, we will investigate the security problem of MD2D communications. In particular, differential privacy issues can be integrated in the proposed scheme. Third, new bargaining solutions can be developed. In addition, theoretical analysis for optimal bargaining solutions will be a potential direction and another possible extension to this work.

## Appendix

*Proof of the Theorem 1.* To prove $d_i$'s truthfulness, truthful reporting cost information, i.e., $\phi_{d_i}$, by $d_i$, should guarantee a better payoff than any other falsely reported cost information, i.e., $\widetilde{\phi_{d_i}}$. Therefore, we consider two cases, i.e., $\phi_{d_i} < \widetilde{\phi_{d_i}}$ and $\phi_{d_i} > \widetilde{\phi_{d_i}}$, and confirm that $U_{d_i}(\phi_{d_i})$ is always higher than $U_{d_i}(\widetilde{\phi_{d_i}})$.

*Case I.* When $d_i$ report a higher cost information $\widetilde{\phi_{d_i}}$ than its truthful cost information ($\phi_{d_i} < \widetilde{\phi_{d_i}}$), we should verify $U_{d_i}(\phi_{d_i}) \geq U_{d_i}(\widetilde{\phi_{d_i}})$.

$$\begin{aligned}
U_{d_i}(\phi_{d_i}) - U_{d_i}(\widetilde{\phi_{d_i}}) &= \left(I_{d_i}(\phi_{d_i}) - \left(\phi_{d_i} \times \mathcal{F}_\chi(\phi_{d_i})\right)\right) \\
&\quad - \left(I_{d_i}(\widetilde{\phi_{d_i}}) - \left(\phi_{d_i} \times \mathcal{F}_\chi(\widetilde{\phi_{d_i}})\right)\right) \\
&= \left(\left(\phi_{d_i} \times \mathcal{F}_\chi(\phi_{d_i})\right) + \int_{\omega=\phi_{d_i}}^{\infty} \mathcal{F}_\chi(\omega)\, d\omega \right. \\
&\quad \left. - \left(\phi_{d_i} \times \mathcal{F}_\chi(\phi_{d_i})\right)\right) - \left(\left(\widetilde{\phi_{d_i}} \times \mathcal{F}_\chi(\widetilde{\phi_{d_i}})\right)\right. \\
&\quad \left. + \int_{\omega=\widetilde{\phi_{d_i}}}^{\infty} \mathcal{F}_\chi(\omega)\, d\omega - \left(\phi_{d_i} \times \mathcal{F}_\chi(\widetilde{\phi_{d_i}})\right)\right) \\
&= \left(\int_{\omega=\phi_{d_i}}^{\infty} \mathcal{F}_\chi(\omega)\, d\omega\right) - \left(\left(\widetilde{\phi_{d_i}} \times \mathcal{F}_\chi(\widetilde{\phi_{d_i}})\right)\right. \\
&\quad \left. + \int_{\omega=\widetilde{\phi_{d_i}}}^{\infty} \mathcal{F}_\chi(\omega)\, d\omega - \left(\phi_{d_i} \times \mathcal{F}_\chi(\widetilde{\phi_{d_i}})\right)\right) \\
&= \left(\left(\phi_{d_i} \times \mathcal{F}_\chi(\widetilde{\phi_{d_i}})\right) + \int_{\omega=\phi_{d_i}}^{\infty} \mathcal{F}_\chi(\omega)\, d\omega\right) \\
&\quad - \left(\left(\widetilde{\phi_{d_i}} \times \mathcal{F}_\chi(\widetilde{\phi_{d_i}})\right) + \int_{\omega=\widetilde{\phi_{d_i}}}^{\infty} \mathcal{F}_\chi(\omega)\, d\omega\right) \\
&= \left(\left(\phi_{d_i} \times \mathcal{F}_\chi(\widetilde{\phi_{d_i}})\right) - \left(\widetilde{\phi_{d_i}} \times \mathcal{F}_\chi(\widetilde{\phi_{d_i}})\right)\right) \\
&\quad + \int_{\omega=\phi_{d_i}}^{\widetilde{\phi_{d_i}}} \mathcal{F}_\chi(\omega)\, d\omega = \int_{\omega=\phi_{d_i}}^{\widetilde{\phi_{d_i}}} \mathcal{F}_\chi(\omega)\, d\omega \\
&\quad - \left(\left(\widetilde{\phi_{d_i}} - \phi_{d_i}\right) \times \mathcal{F}_\chi(\widetilde{\phi_{d_i}})\right)
\end{aligned} \tag{A.1}$$

The $\mathcal{F}_\chi(\omega)$ function is a monotone decreasing function. Therefore, as seen in Figure 5,

$$\left(\left(\widetilde{\phi_{d_i}} - \phi_{d_i}\right) \times \mathcal{F}_\chi\left(\widetilde{\phi_{d_i}}\right)\right) \le \int_{\omega=\phi_{d_i}}^{\widetilde{\phi_{d_i}}} \mathcal{F}_\chi(\omega)\, d\omega \le \left(\left(\widetilde{\phi_{d_i}} - \phi_{d_i}\right) \times \mathcal{F}_\chi\left(\phi_{d_i}\right)\right) \quad \text{(A.2)}$$

Using (A.1) and (A.2) equations, we can

$$\left(\int_{\omega=\phi_{d_i}}^{\widetilde{\phi_{d_i}}} \mathcal{F}_\chi(\omega)\, d\omega - \left(\left(\widetilde{\phi_{d_i}} - \phi_{d_i}\right) \times \mathcal{F}_\chi\left(\widetilde{\phi_{d_i}}\right)\right)\right) \ge 0 \quad \text{(A.3)}$$

Therefore, we can verify that the case of $\phi_{d_i} < \widetilde{\phi_{d_i}}$, $U_{d_i}(\phi_{d_i})$ is always higher than $U_{d_i}(\widetilde{\phi_{d_i}})$, i.e., $U_{d_i}(\phi_{d_i}) \ge U_{d_i}(\widetilde{\phi_{d_i}})$.

*Case II*. When $d_i$ report a lower cost information $\widetilde{\phi_{d_i}}$ than its truthful cost information ($\phi_{d_i} > \widetilde{\phi_{d_i}}$), we should verify $U_{d_i}(\phi_{d_i}) \ge U_{d_i}(\widetilde{\phi_{d_i}})$.

$$\begin{aligned}
U_{d_i}\left(\phi_{d_i}\right) - U_{d_i}\left(\widetilde{\phi_{d_i}}\right) &= \left(I_{d_i}\left(\phi_{d_i}\right) - \left(\phi_{d_i} \times \mathcal{F}_\chi\left(\phi_{d_i}\right)\right)\right) \\
&\quad - \left(I_{d_i}\left(\widetilde{\phi_{d_i}}\right) - \left(\phi_{d_i} \times \mathcal{F}_\chi\left(\widetilde{\phi_{d_i}}\right)\right)\right) \\
&= \left(\left(\phi_{d_i} \times \mathcal{F}_\chi\left(\phi_{d_i}\right)\right) + \int_{\omega=\phi_{d_i}}^{\infty} \mathcal{F}_\chi(\omega)\, d\omega \right. \\
&\quad \left. - \left(\phi_{d_i} \times \mathcal{F}_\chi\left(\phi_{d_i}\right)\right)\right) - \left(\left(\widetilde{\phi_{d_i}} \times \mathcal{F}_\chi\left(\widetilde{\phi_{d_i}}\right)\right) \right. \\
&\quad \left. + \int_{\omega=\widetilde{\phi_{d_i}}}^{\infty} \mathcal{F}_\chi(\omega)\, d\omega - \left(\phi_{d_i} \times \mathcal{F}_\chi\left(\widetilde{\phi_{d_i}}\right)\right)\right) \\
&= \left(\int_{\omega=\phi_{d_i}}^{\infty} \mathcal{F}_\chi(\omega)\, d\omega\right) - \left(\left(\widetilde{\phi_{d_i}} \times \mathcal{F}_\chi\left(\widetilde{\phi_{d_i}}\right)\right) \right. \\
&\quad \left. + \int_{\omega=\widetilde{\phi_{d_i}}}^{\infty} \mathcal{F}_\chi(\omega)\, d\omega - \left(\phi_{d_i} \times \mathcal{F}_\chi\left(\widetilde{\phi_{d_i}}\right)\right)\right) \\
&= \left(\left(\phi_{d_i} \times \mathcal{F}_\chi\left(\widetilde{\phi_{d_i}}\right)\right) + \int_{\omega=\phi_{d_i}}^{\infty} \mathcal{F}_\chi(\omega)\, d\omega\right) \\
&\quad - \left(\left(\widetilde{\phi_{d_i}} \times \mathcal{F}_\chi\left(\widetilde{\phi_{d_i}}\right)\right) + \int_{\omega=\widetilde{\phi_{d_i}}}^{\infty} \mathcal{F}_\chi(\omega)\, d\omega\right) \\
&= \left(\left(\phi_{d_i} \times \mathcal{F}_\chi\left(\widetilde{\phi_{d_i}}\right)\right) - \left(\widetilde{\phi_{d_i}} \times \mathcal{F}_\chi\left(\widetilde{\phi_{d_i}}\right)\right)\right) \\
&\quad - \int_{\omega=\widetilde{\phi_{d_i}}}^{\phi_{d_i}} \mathcal{F}_\chi(\omega)\, d\omega = \left(\left(\phi_{d_i} - \widetilde{\phi_{d_i}}\right) \times \mathcal{F}_\chi\left(\widetilde{\phi_{d_i}}\right)\right) \\
&\quad - \int_{\omega=\widetilde{\phi_{d_i}}}^{\phi_{d_i}} \mathcal{F}_\chi(\omega)\, d\omega
\end{aligned} \quad \text{(A.4)}$$

As seen in Figure 6,

$$\left(\left(\phi_{d_i} - \widetilde{\phi_{d_i}}\right) \times \mathcal{F}_\chi\left(\phi_{d_i}\right)\right) \le \int_{\omega=\widetilde{\phi_{d_i}}}^{\phi_{d_i}} \mathcal{F}_\chi(\omega)\, d\omega \le \left(\left(\phi_{d_i} - \widetilde{\phi_{d_i}}\right) \times \mathcal{F}_\chi\left(\widetilde{\phi_{d_i}}\right)\right) \quad \text{(A.5)}$$

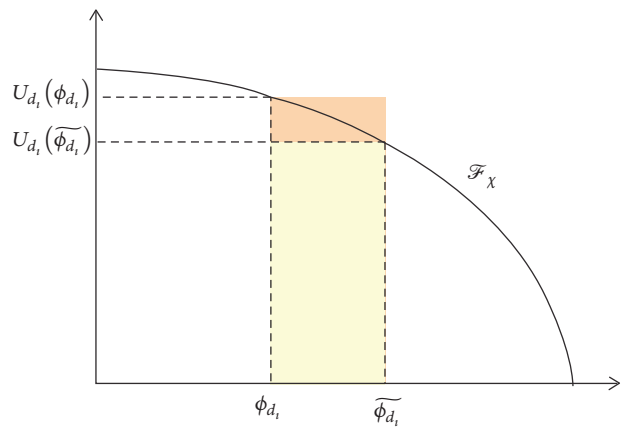


Figure 5: Payoff of $d_i$ with $\phi_{d_i} > \widetilde{\phi_{d_i}}$.

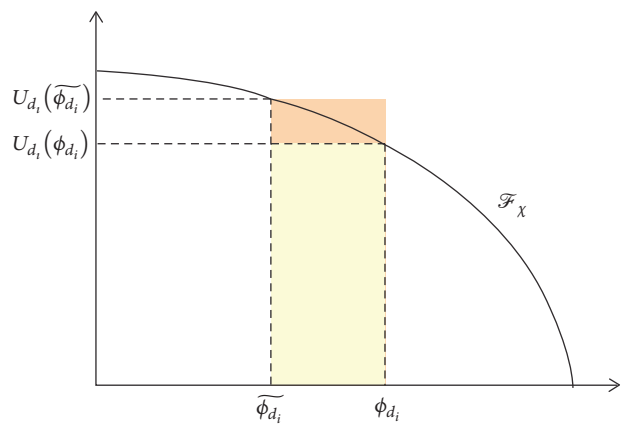


Figure 6: Payoff of $d_i$ with $\phi_{d_i} < \widetilde{\phi_{d_i}}$.

Using (A.4) and (A.5), we can

$$\left(\left(\left(\phi_{d_i} - \widetilde{\phi_{d_i}}\right) \times \mathcal{F}_\chi\left(\widetilde{\phi_{d_i}}\right)\right) - \int_{\omega=\widetilde{\phi_{d_i}}}^{\phi_{d_i}} \mathcal{F}_\chi(\omega)\, d\omega\right) \ge 0 \quad \text{(A.6)}$$

Therefore, we can verify that the case of $\phi_{d_i} > \widetilde{\phi_{d_i}}$, $U_{d_i}(\phi_{d_i})$ is always higher than $U_{d_i}(\widetilde{\phi_{d_i}})$, i.e., $U_{d_i}(\phi_{d_i}) \ge U_{d_i}(\widetilde{\phi_{d_i}})$.

Based on case I and case II, whether $\phi_{d_i} < \widetilde{\phi_{d_i}}$ or $\phi_{d_i} > \widetilde{\phi_{d_i}}$, we can always ensure $U_{d_i}(\phi_{d_i}) \ge U_{d_i}(\widetilde{\phi_{d_i}})$. Therefore, truthful reporting is a dominant strategy for each MD2D device. □

## Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

## Conflicts of Interest

The author, Sungwook Kim, declares that there are no conflicts of interest regarding the publication of this paper.

## Authors' Contributions

The sole author, Sungwook Kim, contributes all this research work.

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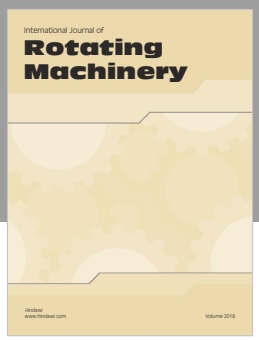

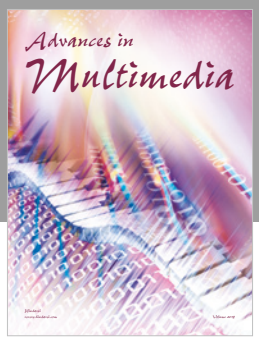

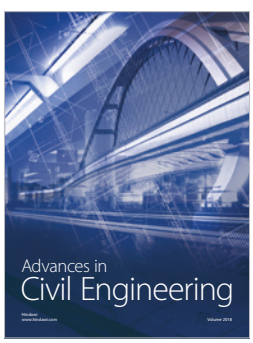

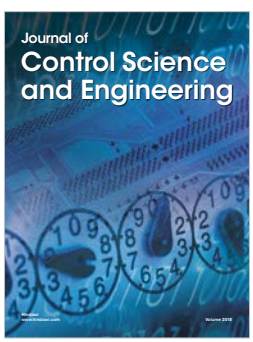

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