

Vehicle-Assisted Device-to-Device Data Delivery for Smart Grid

Nan Cheng, *Student Member, IEEE*, Ning Lu, *Student Member, IEEE*, Ning Zhang, *Student Member, IEEE*, Tingting Yang, Xuemin (Sherman) Shen, *Fellow, IEEE*, Jon W. Mark, *Life Fellow, IEEE*

Abstract—In this paper, we propose a heterogeneous framework to deliver the smart grid (SG) data cost effectively. The data generated by distributed SG loads and generation units should be delivered to the utility control center within the tolerated delay, which is crucial for SG applications. To this end, a heterogeneous communication framework is proposed, where the cellular network provides ubiquitous yet expensive data transmission and vehicle-assisted device-to-device (D2D) communications are leveraged to offload the cellular network by delivering the delay-tolerant SG data in a store-carry-and-forward fashion with low cost. To improve the offloading and cost performance of the proposed framework, we put effort in the following aspects: i) optimal forwarding schemes to optimally select vehicles to carry and forward the data; ii) mode selection and dynamic resource allocation to maximize the amount of data delivered by D2D communications, reduce the cost of SG data delivery, and guarantee the fairness among SG users. Simulation results are given to validate proposed approaches and demonstrate that the proposed framework is efficient in saving cost for the utility and offloading the cellular network.

Index Terms – device-to-device communications, vehicular communication, smart grid, offloading, resource allocation.

I. INTRODUCTION

Smart grid (SG) has recently attracted much research attention from both power and communication fields. SG refers to a modernized and advanced power system which aims to monitor, manage, and deliver electric power in a more efficient and reliable manner by incorporating state-of-the-art communication, computing, and control technologies into the traditional power grid [1]. With SG, many benefits could be achieved, such as generation diversification, demand response, reduction of overall carbon footprint, etc. [2].

In SG, smart meters and other intelligent devices are densely deployed throughout the grid for monitoring, management, and control. SG data is generated by these devices and should be reliably transmitted to the utility to carry out SG functionalities. A salient feature of SG data is that the amount of the SG data is tremendous. For example, compared with the current monthly metering, the smart meters measure and store meter readings much more frequently (e.g., every 2 minutes), which

yields a 8,000-fold increase in daily data [3]. It is predicted that the total amount of SG data will increase to over 75,200 Tbytes in 2015 [4]. In addition to the data volume, delay requirements of SG applications vary from seconds to hours. In other words, some applications can tolerate certain delays, e.g., the economic dispatch is performed every five minutes for California Independent System Operator (CAISO) [5]. A recent study [6] presents different categories of SG applications and specifies the delay and bandwidth requirements of different SG applications. In this paper, the proposed vehicle-assisted data delivery framework is targeted on delay-tolerant SG applications, examples of which are given in Table I.

Transmitting the massive SG data is about to swamp existing communication infrastructures, and thereby poses cumbersome challenges. Power Line Communication (PLC) has been considered as a candidate for transferring the data of SG applications [7], which can offer local area network (LAN) connectivity, Internet access, and certain command and control capabilities. However, low penetration of PLC devices, the interoperability problem, and short communication range become impediments for the success of PLC in the market [7], [8]. Smart energy profile (SEP) solutions are proposed to use ZigBee, WiFi and PLC for metering and home area networks (HANs) [9]. However, the limitation in capacity and communication range of such technologies makes them proper for microgrid network infrastructure rather than the long-distance data transmission. In addition, the cost might be very high to deploy the fiber-optic network in all the distributed SG loads and generation units [10]. Recently, cellular technology, e.g., GSM, 3G, and LTE, has emerged as a viable alternative for SG data transmission. IEEE Standards Board has approved P2030 smart grid interoperability standards development to make guidelines for smart grid interoperability of energy technology and information technology operation with the electric power system. In P2030, 3G cellular systems have been recommended as the communication backhaul network for SG. However, the mobile data tsunami, i.e., the explosive growth of mobile data traffic, has already introduced an overloading problem in the cellular network (CN) [11]. Thus, the transmission of the massive SG data may very likely further congest the CN, and degrade the performance of both SG and other mobile applications. Moreover, the cost (e.g., subscription fees) of using CNs to transmit a large amount of SG data may be prohibitive. Therefore, to mitigate the congestion of CNs and reduce the cost incurred by SG data transfer, an efficient heterogeneous data delivery framework is necessary, which can deliver the SG data by means of both cellular network and complementary network technologies.

N. Cheng, N. Lu, N. Zhang, X. Shen and Jon W. Mark are with the Department of Electrical and Computer Engineering, University of Waterloo, 200 University Avenue West, Waterloo, ON N2L 3G1, Canada (e-mail: {nScheng, n7lu, n35zhang, sshen, jwmark}@uwaterloo.ca).

T. Yang is with Navigation College, Dalian Maritime University, 1 Linghai Road, Dalian, Liaoning 116026, China (e-mail: {yangtingting820523@163.com}).

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Table I
EXAMPLES OF DELAY-TOLERANT SG APPLICATIONS

Delay-tolerant SG application	Bandwidth
Demand response	low
Advanced metering	moderate
Site security with video surveillance	high
Distributed generation and distributed storage	low
Client/server and host/terminal	moderate

As a promising solution to offload CNs, device-to-device (D2D) communication technology has gained much attention recently. The basic tenet of D2D communications is that mobile users can communicate directly with each other instead of using CNs and the backhaul networks. By utilizing the proximity of mobile users and direct data transmission, D2D communications can typically offload CNs, reduce the cost, and provide better quality of service (QoS) for mobile users [12]. WiFi access points (APs) deployed at hotspots such as home, malls, and work places by individuals or cellular carriers can also be used to offload CNs [13]. Mobile users can download and upload data through APs instead of cellular base stations (BSs) when WiFi access is available. Basically, D2D communications can be classified into two categories: fully controlled D2D mode and loosely controlled D2D mode [14]. In the fully controlled mode, D2D users are completely controlled by the CN, including device discovery, connection setup, and others. The device discovery and D2D connection setup can be done quickly since the BS controls the whole network and has deep contextual information. There are two resource reuse modes in fully controlled D2D communications, i.e., underlaying D2D communication and overlaying D2D communication. In underlaying D2D communication, cellular resources are reused for D2D communications. In order to control the interference, the spectrum resource should be carefully allocated. The overlaying D2D communication is employed in the paper, where dedicated cellular resources are allocated for D2D communications. The amount of allocated resources depends on targeted performance of cellular and D2D communications as well as the status of the cellular network, such as the number of users, traffic load, etc. As D2D communications share the cellular licensed band, D2D users are charged by the cellular operator. In loosely controlled mode, D2D communications are carried out with less or no involvement of the CN, and usually use the unlicensed band, such as WiFi or Bluetooth. Therefore, the charge for this mode is typically lower than that of fully controlled D2D mode. Considering features of different modes, it would be wise to choose the appropriate mode under different circumstances.

In this paper, we propose a heterogeneous data delivery framework where a vehicle-assisted two-hop D2D communication network serves as a complementary network to the CN to transmit SG data, in order to offload the CN and reduce the cost for SG data transmission. In the proposed framework, entities that produce, store, and transmit SG data are named data sources (DSs), which can be distributed SG loads such as houses and buildings, and SG generation units such as wind

turbines and photovoltaic panels. D2D communications are utilized to forward SG data from DSs to passing vehicles. When a vehicle contacts roadside access points (RAPs), it can upload the carried data to the utility control center (UCC). RAPs can be drive-thru WiFi network deployed throughout the city by cellular carriers, or the roadside infrastructure deployed by the electric utility. If the data fails to be delivered before the deadline (i.e., delay requirement), it is transmitted through the CN immediately. Such a vehicle-assisted data dissemination network is usually referred to as vehicular delay-tolerant network (VDTN) [15]. More specifically, to maximize the chance of data delivery, two optimal forwarding schemes are proposed for DSs to select the best vehicle to carry the data. Since different D2D transmission modes can achieve different data delivery performance and incur different costs, a mode selection scheme is proposed to minimize the overall expected cost for the utility. As D2D communications share the cellular resources in fully controlled mode, the cellular resources may not be sufficient to support all D2D communications simultaneously, especially when the density of DSs is high in a certain geographic area. Hence, we present a dynamic resource allocation scheme to maximize the average data delivery ratio, reduce the cost, and guarantee fairness among DSs.

The reasons for using vehicle-assisted SG data delivery are as follows. Firstly, Internet access is predicted to become a standard feature of motor vehicles [16]. Therefore, vehicles can have the communication capability with cellular BSs or WiFi APs. Secondly, the mobility of vehicles introduces intermittent connectivity to RAPs and facilitates opportunistic delivery for the delay-tolerant SG data. Some measurements have been done to evaluate the performance of such vehicle drive-thru networks as well as proposed enhanced mechanisms, such as fast connection establishment and reliable data transfer, to improve the performance that may be degraded by the high vehicle mobility [17]–[19]. It is shown that a vehicle can meet an AP to initial data transfer every tens of seconds in average, and transmit maximum 100 MB of data in one such transmission opportunity. It is shown that the store-carry-and-forward paradigm is suitable for disseminating delay-tolerant data, especially when the vehicle density is high, e.g., 4000 vehicle/mi² in the downtown area of San Francisco [20]. Last but not least, the deployment of the carrier-WiFi networks facilitates the vehicle-assisted SG data delivery. One of the notable issues in providing WiFi access to vehicles is the authentication and association process, which could cost a considerable amount of the short connection time resulted by high mobility of vehicles. The problem can be addressed by recent advances in Passpoint/Hotspot 2.0, which makes WiFi more competitive to provide secure connectivity and seamless roaming [21]. In Hotspot 2.0, a new pre-association protocol is introduced, where mobile devices are allowed to obtain the information about the services and service providers that can be reached via a hotspot before it associates. Based on the information, the mobile devices can identify which access points are suitable, and authenticate to a remote service provider (e.g., a mobile network operator), which is much faster than requiring authentication before learning such information. Assisted by Hotspot 2.0, pioneering mobile

network operators (MNOs), e.g., AT&T, China Mobile, have rolled out carrier-WiFi networks and integrated them with the cellular network. Carrier-WiFi is a powerful, cost-effective and manageable tool for MNOs to increase the network capacity, and can provide the support of easy access, guaranteed quality of service (QoS), security and roaming with advanced WiFi functionality, as well as new business models and services. Furthermore, the carrier-WiFi networks can be used to deliver the SG data in order to avoid the security problems that are led by public WiFi access and also save the capital and operational expenditure of utility to deploy and maintain RAPs.

The contributions of the paper are as follows. First, an heterogeneous data delivery framework is designed to incorporate D2D communications and vehicle-assisted data delivery to offload SG data from CNs and reduce the data transfer cost. To the best of our knowledge, this work represents the first study that considers the effect of the opportunistic data delivery on designing aspects of D2D communications. Second, optimal forwarding schemes are proposed, through which optimal vehicles are selected to carry and forward the data, in order to improve the probability of successful delivery. Third, mode selection and resource allocation schemes are provided in order to maximize the total average delivery ratio, guarantee fairness among DSs, and reduce the cost for the utility.

Implementing the proposed heterogeneous data delivery framework, the cellular network can be considerably offloaded, since a large amount of SG data is delivered through RAPs using WiFi. In addition, the delivery performance of data in areas with poor cellular coverage can be improved. Through the reward mechanism and resource allocation scheme, the money paid by the utility to transfer SG data can be saved. Moreover, the proposed data delivery framework can be also applied to other data upload/download scenarios with little changes.

The remainder of this paper is organized as follows: Section II reviews the related works. Section III describes the system model. In Section IV, two data forwarding schemes based on optimal stopping rules are proposed and analyzed. In Section V, the mode selection and resource allocation schemes are introduced. Section VI evaluates the performance of the proposed framework. Section VII concludes the paper.

II. RELATED RESEARCH WORK

D2D communication technology is a recent research focus and is in active development, mostly in the context of LTE cellular networks. With D2D communications, different transmission modes may coexist. For instance, in our vehicle-assisted D2D offloading framework, the existence of both WiFi and cellular radios provides three available modes for data transmission, which is described in Section III-C. Typically, the communication mode is selected based on different criteria. In [22], the optimal mode is selected for all the devices based on the system equation, which captures the information of link gains, noise levels, etc. Another considered criterion is to maximize the power-efficiency, which is achieved by a joint mode selection and power allocation scheme proposed in

[23]. The mode selection based on transmission cost and rate requirement is studied in [24] for LTE-advanced networks. In this paper, different from existing works, the mode selection scheme is designed to minimize the cost for the utility by considering the delivery performance, i.e., the amount of data delivered by D2D communications, and the transmission cost of each mode.

In D2D communication underlying CNs, the resources such as power and time-frequency resources should be scheduled carefully to reduce interference and improve network performance. In addition, in SG, when DS density is high, it is required to efficiently allocate the limited resources. The resource allocation problem in D2D communications is discussed in [25]–[27]. In [25], three D2D modes, namely non-orthogonal sharing, orthogonal sharing, and cellular mode are studied and the optimal transmission power is given. In [26], optimal power allocation is analyzed for the secondary users which opportunistically use D2D mode and licensed resources. In [27], a network-assisted method is proposed to intelligently manage resources of devices. Resource blocks (RBs) and power are jointly allocated to guarantee the signal quality of all users. In our proposed resource allocation scheme, the main target is to maximize the overall data delivery performance and guarantee fairness among DSs.

The feasibility of vehicle-assisted data delivery for delay-tolerant applications is validated in [15], [28]. In [15], a vehicle-assisted data forwarding scheme is proposed, taking the predictable vehicle mobility into consideration. The optimal packet transmission in vehicular delay-tolerant networks is studied in [28]. An optimal decision is obtained based on the constrained Markov decision process and then the optimal packet transmission rate is chosen.

III. SYSTEM MODEL

In this paper, we propose an D2D data delivery framework which utilizes vehicles, road side networks, and D2D communications to assist to deliver the delay-tolerant SG data¹. SG data can be forwarded to and carried by vehicles and uploaded to UCC through RAPs, instead of being transmitted through the CN. A summary of the mathematical notations used in this paper is given in Table II. The framework is applicable to different vehicle densities and mobility patterns, and roadside access point (RAP) deployments, though they might have impacts on the performance of the framework.

A. Network Model

As shown in Fig. 1, we consider an urban area with DSs generating and transferring SG data. LTE CNs, which support both common cellular communications and the D2D underlay communications, are assumed to fully cover the area. DSs and vehicles are considered to be equipped with both a WiFi radio and a cellular radio to transmit SG data, as assumed in [10]. RAPs are connected to the UCC and deployed throughout the city. DSs are geographically divided into clusters. Denote by \mathcal{C} the set of DSs within a cluster with the area of Ω . Let ρ be

¹From now on, we use SG data and delay-tolerant SG data interchangeably.

Table II
THE USEFUL NOTATIONS.

Symbol	Description
\mathcal{C}	The set of DSs in a cluster with $ \mathcal{C} = N$
ρ	The average density of DSs
λ_i	The vehicle arrival rate of S_i
S_i	An arbitrary DS i
μ_i	$\frac{1}{\mu_i}$ is the average meeting time of vehicles passing S_i
P_i	The allowed transmission power of S_i when reuses the LTE UL resources
\mathcal{C}_C	The cost for transmitting a DB using M_C
\mathcal{C}_{DC}	The cost for transmitting a DB using M_D
γ	Reward parameter M_C and M_D
T	Request interval
t_g	Generation interval
\mathcal{D}_F	First contact delay
Ψ_i	The long-term average data delivery ratio
P_t, P_r	D2D transmission and receive power using M_C
α, c	Path-loss exponent and path-loss constant
d	D2D transmission range
$Q_i(k)$	The virtual queue backlog of S_i in the k -th request interval
I	Interference-plus-noise power

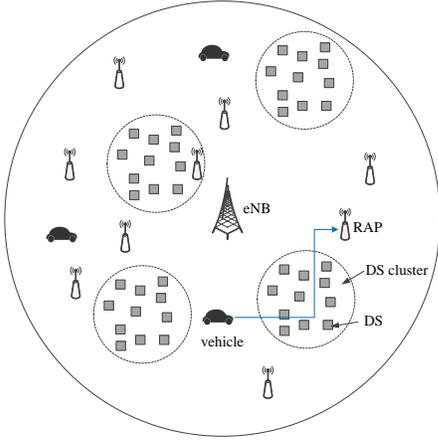


Figure 1. Network model.

the average density of DSs in a cluster. The number of DSs in the cluster is $N = |\mathcal{C}|$, with the expectation $\mathbb{E}[N] = \rho\Omega$.

B. Application Model

We aim to utilize D2D communications to transfer the delay-tolerant SG data to UCC. Each DS generates a data block (DB, denoted by \mathbf{B}) every generation interval (GI) t_g by aggregating the data from smart meters, sensors, and generation units in a small geographic area (e.g., a building) using HAN technologies, and temporarily stores it. The utility requests the data from all DSs every request interval (RI) which is denoted by T ($T > t_g$). $N_B = \lfloor \frac{T}{t_g} \rfloor$ represents the number of DBs generated in a DS within an RI. Thus, DBs generated within an RI should be successfully delivered before the end of the RI.

C. Communication Model

As shown in Fig. 2, a two-hop vehicle-assisted forward-carry-and-upload D2D communication framework is proposed

for SG data delivery as a complementary network to the CN. In our framework, we define D2D communications using WiFi radios as WiFi mode (M_W), and D2D communications using cellular radios as cellular mode (M_C). Correspondingly, the original cellular communications through the CN and the Evolved Node B (eNB) is defined as direct cellular mode (M_D). In M_W , a standard WiFi technology is used, e.g., IEEE 802.11g, while in M_C , the underlying cellular resources are utilized for D2D communications. Vehicles are identified as delivery agents of SG data. In the first communication hop, the DS chooses a passing vehicle as the D2D receiver and forwards the stored DBs, by either M_W or M_C . In the second communication hop, the vehicle carrying DBs tries the best effort to upload the data when it encounters an RAP.

Each DB can be forwarded to at most one vehicle. By doing so, there is only one duplication of each DB, which yields an optimal throughput of the network [29]. At the end of an RI, DBs which are not received are considered not deliverable through D2D communications, and thus are transferred through M_D . The pros and cons of different D2D modes are listed as follows.

- M_W : A loosely controlled D2D mode which uses the free WiFi band. The communication radius is assumed to be 100 meters, which is the communication range for reliable and high-rate data transmission based on [30], [31]. Because of the high vehicle mobility, there may be some problem of communication between vehicle and RAPs. It is shown in [30] and many other measurement papers that the communication between a vehicle and an RAP can experience three phases. When the vehicle just moves in or will leave the coverage area of the RAP, the data transmission is very unreliable and inefficient because of the connection establishment delay, low SNR, and slow rate adaption, etc. Thus, we consider the communication range of M_W to be 100 meters, within which the performance of data transmission is good.
- M_C : A fully controlled D2D mode which reuses the LTE

uplink (UL) resources. We assume that D2D communications non-orthogonally share the UL resources with the cellular users, in which a resource can be shared by both a D2D pair and a common cellular user, rather than exclusively allocated to either of them. Similar assumption can be seen in [25], [32]. The transmission power \mathbf{P} is controlled to manage the interference to eNB or to guarantee a minimum rate of normal cellular users. A way to achieve this can be found in [25]. The transmission range is determined by the allowed transmission power, but is typically larger than that of M_W .

- M_D : Common cellular communications through eNBs. Data can be transmitted with a negligible delay. As we discussed, this mode would pose a burden on the CN for handling SG data traffic.

D. Cost and Reward Model

We define the cost as the money paid for delivering SG data, including using D2D and cellular communications. Different transmission modes incur different cost. M_W uses free WiFi band, and thus the cost is neglected in this paper. DSs using M_C reuse cellular resources and may require the involvement of the eNB such as device discovery, session set up, and interference management. Thus, M_C incurs cost \mathcal{C}_C to transmit each DB. The cost of M_D , denoted by \mathcal{C}_{DC} , is the highest among the three modes². Normally accessing WiFi can incur some cost. However, since the cost is much lower than \mathcal{C}_C and \mathcal{C}_{DC} , in this paper, we simply set it to zero.

In our framework, DSs pay the cost for using M_C and M_D . Since SG has yet to become reality, there remains great uncertainty as to how to use cellular communications. For example, the deployment strategy for cellular devices is not clear. For some small-scale customer-owned sites, the communication modules are expected to be deployed by the owners [33]. Therefore, we consider that DSs deploy cellular devices, and thus pay \mathcal{C}_C and \mathcal{C}_{DC} for each DB transmission using M_C and M_D , respectively. Benefited from the transmitted SG data, the utility rewards DSs for transmitting the SG data. For simplicity, we consider

$$\mathbb{R}_i = \gamma \mathcal{C}. \quad (1)$$

where \mathbb{R}_i is the reward given to DS i (denoted by \mathbf{S}_i) for transferring a DB, \mathcal{C} is the cost to transmit a DB, and $\gamma \geq 1$ is called reward parameter. To motivate DSs to transmit SG data using D2D communications, $\gamma > 1$ for M_C and $\gamma = 1$ for M_D . Note that for M_W , \mathbb{R}_i is set to a constant θ .

E. Mobility Model

Vehicles on the road typically have different velocities and directions. We consider independent movements of vehicles, i.e., the trajectory of one vehicle is independent with that of others. At a specific time instant, the remaining time for a

vehicle to meet the next RAP is referred to as the meeting time of the vehicle, which is denoted by T_m . Due to the intermittent connectivity between vehicles and RAPs, it is considered that T_m follows an exponential distribution with parameter μ , i.e., $T_m \sim Exp(\mu)$, where $X \sim Exp(\alpha)$ denotes that random variable X follows an exponential distribution with parameter α . A similar model can be seen in [34]. Furthermore, vehicle arrivals at \mathbf{S}_i follow a Poisson process $N = (N_t)_{t \geq 0}$ with parameter λ_i . Note that λ_i depends on the communication range of \mathbf{S}_i , denoted by R_i , and a larger R_i implies a larger λ_i . Also the road traffic can impact μ and λ_i , e.g., λ_i in rush hour is often larger than that at night at the same location. It is assumed that vehicles are equipped with GPS devices and digital maps which contain the location information of the deployed RAPs. Thus, a vehicle can estimate T_m at any time, using its current location, navigation, and RAP information.

IV. OPTIMAL STOPPING BASED OPPORTUNISTIC FORWARDING

In this section, optimal forwarding schemes are proposed for DSs to optimally choose vehicles as D2D receivers to forward DBs in order to maximize the successful delivery probability, based on the deadline of the DB, and the statistics of vehicle arrival and meeting time. The performance of the proposed forwarding schemes, including expected delivery delay and delivery probability, is theoretically analyzed. The result will be used for designing mode selection and resource allocation schemes in Section V.

A. Problem Formulation

Since a DB can be forwarded only once to a vehicle, and all DBs which are not delivered by the deadline will be transmitted using the most expensive M_D , it is expected that DSs should optimally choose vehicles to forward DBs so that the probability that data is successfully delivered is as high as possible. In this way, more data can be delivered by D2D communications, which can efficiently offload the CN and reduce the cost for the utility.

Consider a typical DB, say B_j . The delivery probability of B_j , denoted by $P_{d,j}$, is defined as the probability that B_j is successfully delivered to UCC before its deadline, by using D2D communications. Denote by v_j the vehicle which is chosen to carry B_j , t_0 the generation instant of B_j , t_{req} the request instant of B_j , and $T_l = t_{req} - t_0$ the life time of B_j , as shown in Fig. 3. Also denote by t_f the instant when B_j is forwarded to v_j , t_r the instant when v_j meets the first RAP after carrying B_j , and t_u the instant when B_j is received by UCC. The first contact delay (FCD) of B_j , denoted by $\mathcal{D}_{F,j}$, is defined as the time duration from the generation of B_j to the time v_j meets the first RAP after carrying B_j , i.e., $\mathcal{D}_{F,j} = t_r - t_0$.

To successfully deliver B_j , v_j should contact at least one RAP before t_{req} . We define $T_{EX} = t_u - t_r$ as the time for a DB to be actually received by UCC after the vehicle carrying the DB contacts the first RAP. T_{EX} is a random variable for each DB, depending on the amount of data carried by the vehicle and the communication environment such as

²The actual cost should be based on transmitting unit size of data. In this paper, we assume each DB with the same size for simplicity, and thus the cost is incurred for transmitting each DB.

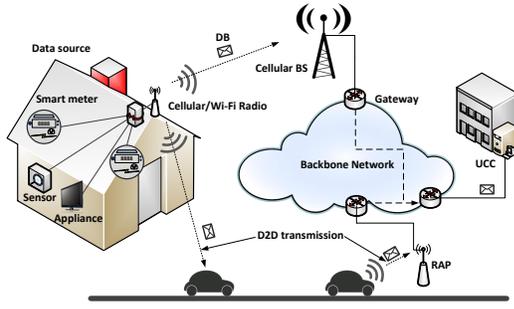


Figure 2. Two-hop communication model.

transmission rate, sojourn contact time with the RAP, vehicle density, etc.. Therefore, the delivery probability of B_j can be represented by the probability that the summation of $D_{F,j}$ and T_{EX} is no larger than T_l , i.e.,

$$P_{d,j} = \Pr(D_{F,j} + T_{EX,j} \leq T_{l,j}) = \mathbf{F}_{T_{EX}}(T_{l,j} - D_{F,j}), \quad (2)$$

where $\mathbf{F}_{T_{EX}}$ is the cumulative distribution function (CDF) of T_{EX} . According to (2), in order to increase the delivery probability, we aim to minimize the FCD of DBs, i.e., to minimize

$$D_{F,j} = T_{va,j} + T_{vd,j}, \quad (3)$$

where $T_{va,j} = t_f - t_0$ is the time duration from the instant when B_j is generated to the instant when B_j is forwarded to v_j , and $T_{vd,j} = t_r - t_f$ is the time duration taking v_j to meet the first RAP after carrying B_j , which follows the same distribution as T_m . For DSs, choosing different vehicles to forward B_j leads to different $D_{F,j}$, because both $T_{va,j}$ and $T_{vd,j}$ are random variables. However, when a vehicle arrives at S_i , $D_{F,j}$ can be observed by S_i based on the following observations. Obviously, S_i has the knowledge of T_{va} when a vehicle arrives. Moreover, vehicles can obtain estimated T_m and provide it to S_i as T_{vd} . To minimize FCD of a DB, DSs should choose a vehicle that offers minimum D_F as the forwarder. It is formulated as an optimal forwarding problem, based on the theory of optimal stopping.

For optimal stopping problem [35], let $G = (G_n)_{n \geq 0}$ be a sequence of random variables, which can be observed at time n . For each stage n , one can make a decision to stop and receive the known reward $R_n = R(G_n)$, where $R(G_n)$ is a function of G_n , or to continue and observe G_{n+1} . However, the past reward cannot be recalled. The optimal stopping problem is to stop at stage n to maximize the expected reward (or minimize the expected cost). In the following, we propose two optimal forwarding schemes in order to minimize FCD.

B. Time Oriented Optimal Forwarding

When B_j is generated in S_i , S_i can decide the best time to set up a D2D link and forward B_j to a vehicle. This forwarding scheme is called Time Oriented Optimal Forwarding (TOOF). Divide T_l into small time slots with identical length Δt_n , and the number of time slots is $N_t = \lfloor \frac{T_l}{\Delta t_n} \rfloor$. Thus, T_{va} can be approximated by $n\Delta t_n$ if B_j is forwarded in the n -th slot. To find the optimal time slot to forward DBs is an optimal

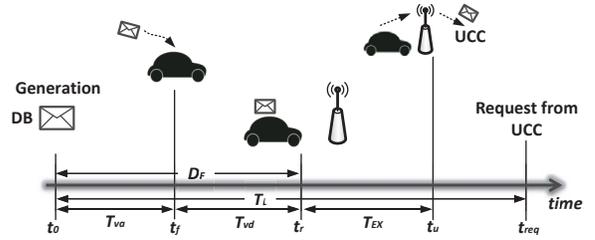


Figure 3. An illustration of time durations in the analysis.

stopping problem with finite horizon N_t . Such a problem can be solved by *backward induction* [36].

In TOOF, there are N_t stages (time slots), i.e., the stage $n = 1, 2, \dots, N_t$. S_i tries to forward B_j no later than stage N_t . Therefore, we can first find the optimal forwarding rule at stage $N_t - 1$. By knowing the optimal forwarding rule at stage $N_t - 1$, we can find the optimal forwarding rule at stage $N_t - 2$, and inductively to stage 1. Let $V_n^{N_t}$ denote the minimum expected FCD to forward B_j starting from stage n , i.e.,

$$V_n^{N_t} = \mathbb{E}[\min\{R_n(T_{vd}), V_{n+1}^{N_t}\}],$$

where $R_n(T_{vd}) = n\Delta t_n + T_{vd}$ and \mathbb{E} is the expectation. With at the last stage N_t , $V_{N_t}^{N_t} = \mathbb{E}[R_{N_t}(T_{vd})] = T_l + \frac{1}{\mu}$, inductively, at stage n ,

$$\begin{aligned} V_n^{N_t} &= \mathbb{E}[\min\{R_n(T_{vd}), V_{n+1}^{N_t}\}] \\ &= \int_0^\infty \min\{n\Delta t_n + T_{vd}, V_{n+1}^{N_t}\} d\mathbf{F}_{T_{vd}}(T_{vd}) \\ &= \int_0^{V_{n+1}^{N_t}} (n\Delta t_n + x)\mu e^{-\mu x} dx + \int_{V_{n+1}^{N_t}}^\infty V_{n+1}^{N_t} \mu e^{-\mu x} dx \\ &= (n\Delta t_n + \frac{1}{\mu})(1 - e^{-\mu V_{n+1}^{N_t}}), \end{aligned} \quad (4)$$

where $\mathbf{F}_{T_{vd}}(x) = 1 - e^{-\mu x}$ is CDF of T_{vd} . Thus, the optimal rule at each stage n , i.e., $V_n^{N_t}$ is obtained, whose value is nondecreasing with n . TOOF is to forward B_j in the first slot n' in which a vehicle can offer $T_{vd} \leq V_{n'+1}^{N_t} - n'\Delta t_n$, using either M_W or M_C .

C. Vehicle Oriented Optimal Forwarding

The time oriented forwarding scheme is to choose the best time to forward the stored DSs, which has a finite horizon. However, if we consider the forwarding problem from the perspective of individual forwarders, i.e., vehicles, the forwarding strategy is different. The forwarding scheme of selecting the exact vehicle to forward the DB is called Vehicle Oriented Optimal Forwarding (VOOF). Let v_1, v_2, v_3, \dots be the vehicles that sequentially pass by S_i after the generation of B_j according to Poisson arrival with parameter λ_i , and X_k be the time duration to wait for v_{k+1} if S_i decides not to forward B_j to v_k . X_0 is the time duration before v_1 comes. Thus, $\{X_k\}$ can be seen as the cost paid to wait for following offers. According to the property of Poisson process, $\{X_k\}$ are i.i.d. random variables following exponential distribution with the mean $\frac{1}{\lambda_i}$. Thus, the problem of choosing a vehicle to forward B_j is then the optimal stopping problem with infinite

horizon, in order to minimize

$$R_k = T_{vd,k} + \sum_{n=0}^{k-1} X_n,$$

where $T_{vd,k}$ is T_{vd} of v_k .

Consider the case that S_i pays X_0 and observes $T_{vd,1} = t_{vd,1}$. Let V^* denote the optimal rule of forwarding B_j to a vehicle. Thus, if $t_{vd,1} > V^*$, S_i should continue to wait for the next vehicle; if $t_{vd,1} \leq V^*$, S_i should forward the DB to this vehicle. If S_i decides to continue, then $t_{vd,1}$ is lost and X_0 has already been paid. Because the past vehicles cannot be used again, when the next vehicle arrives, the problem is like starting over again, and is invariant in time [36]. Thus, the argument of $t_{vd,1}$ can be made at each vehicle arrival. For S_i , if it decides not to choose an arbitrary v_k to forward B_j , then the minimum expected FCD after v_k is $V^* + \mathbb{E}[X_k]$. Thus, V^* satisfies:

$$\begin{aligned} V^* &= \mathbb{E}[\min\{T_{vd,k} + X_k, V^* + X_k\}] \\ &= \mathbb{E}[X_k] + \mathbb{E}[\min\{T_{vd,k}, V^*\}] \\ &= \frac{1}{\lambda_i} + \int_0^{V^*} x d\mathbf{F}_{T_{vd,k}}(x) + \int_{V^*}^{\infty} V^* d\mathbf{F}_{T_{vd,k}}(x) \\ &= \frac{1}{\lambda_i} + \frac{1}{\mu}(1 - e^{-\mu V^*}), \end{aligned} \quad (5)$$

Then, by solving (5), the optimal forwarding rule V^* can be obtained. In VOOF, the first vehicle v_k which can offer $T_{vd,k} \leq V^*$ will be selected to carry B_j .

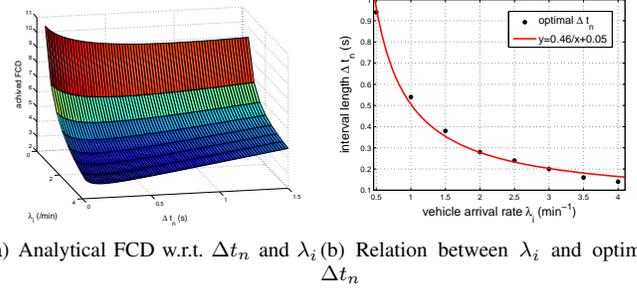
D. Discussion

1) *Difference between TOOF and VOOF*: In TOOF, the DSs know how to optimally forward the DB in a given time interval. However, they do not care which vehicle forwards DBs, or even whether DBs can be forwarded within an arbitrary interval. Furthermore, since the forwarding rule of DBs is related to T_i , a vehicle may not be qualified to carry all DBs given that there are more than one DBs currently stored, which makes this scheme more complex. The calculation of optimal forwarding rule V_n^{Nt} is through backward induction, which is easier than that of VOOF.

In VOOF, the forwarding scheme is from the perspective of individual vehicles. The optimal forwarding rules for different DBs are same and unchanged over time. Therefore, a vehicle that satisfies $T_{vd,k} \leq V^*$ can carry all stored DBs in one time. T_{va} of each vehicle is considered as the summation of a series of i.i.d. random variables. Although accurate, it is more complex to solve the optimal forwarding rule V^* using (5).

2) *Choosing proper Δt_n* : In TOOF, the choice of the interval length, i.e., Δt_n , is crucial for the performance of the scheme. A larger value of Δt_n will reduce the accuracy of estimating T_{va} in the derivation of optimal rules; on the other hand, a smaller value of Δt_n will increase the computational complexity of optimal rule $E(V_n^{Nt})$. The choice of Δt_n is strongly dependent on the vehicle arrival rate λ_i . Intuitively, when the vehicle arrival rate is high, it is better to reduce Δt_n in order to increase the accuracy of the optimal rules. However, when λ_i is small, it is more feasible to increase Δt_n

to reduce unnecessary calculation and the number of intervals in which there is no vehicle arriving. Using the results obtained above, the analytical FCD of TOOF w.r.t. different Δt_n and λ_i is shown in Fig. 4(a). For each value of λ_i , there is an optimal value of Δt_n , in which FCD is minimum. Fig. 4(b) shows the relation between λ_i and optimal Δt_n . It can be seen that optimal Δt_n has an inverse proportional relation with λ_i , which is in accordance with the intuition.



(a) Analytical FCD w.r.t. Δt_n and λ_i (b) Relation between λ_i and optimal Δt_n

Figure 4. Choosing proper Δt_n

3) *Expected First Contact Delay and Delivery Probability*: FCD is crucial for the overall performance of the proposed data delivery method, and our optimal forwarding schemes aim to reduce FCD as much as possible. Therefore, we theoretically analyze FCD and the delivery probability that can be achieved by both forwarding schemes.

Denote $E_{FCD-TOOF}$ by the expected FCD of B_j using TOOF, which can be calculated by

$$E_{FCD-TOOF} = \sum_{i=1}^{N_t} \left(\prod_{k=1}^{i-1} P_{NT,k} \right) (1 - P_{NT,i}) E_{FCD,i}, \quad (6)$$

where $P_{NT,k}$ is the probability that in the k -th slot there is no vehicle chosen to carry B_j and $E_{FCD,i}$ is the expected FCD if B_j is carried by a vehicle in the i -th slot. Since vehicles arrive following a Poisson process, $P_{NT,k}$ can be calculated as follows:

$$P_{NT,k} = \sum_{m=0}^{\infty} P_n(m) P_{NTv,k}^m, \quad (7)$$

where $P_n(m)$ represents the probability that m vehicles arrive within Δt_n and $P_{NTv,k}$ represents the probability that a vehicle arrives within the k -th slot, but is not eligible to carry B_j , i.e., $T_{vd} > V_{k+1}^{Nt} - k\Delta t_n$. $P_n(m) = \frac{e^{-\lambda_i \Delta t_n} (\lambda_i \Delta t_n)^m}{m!}$ for S_i . $P_{NTv,k}$ is calculated as follows:

$$\begin{aligned} P_{NTv,k} &= \Pr((T_{vd} + k\Delta t_n) > V_{k+1}^{Nt}) \\ &= 1 - F_{T_{vd}}(V_{k+1}^{Nt} - k\Delta t_n) \\ &= e^{-\mu(V_{k+1}^{Nt} - k\Delta t_n)}. \end{aligned} \quad (8)$$

$E_{FCD,i}$ can be calculated as the expectation of FCD in (3),

i.e.,

$$\begin{aligned}
 E_{FCD,i} &= \mathbb{E}[T_{vd}|T_{vd} \leq (V_{i+1}^{N_t} - i\Delta t_n)] + i\Delta t_n \\
 &= \frac{\int_0^{V_{i+1}^{N_t} - i\Delta t_n} x dF_{T_{vd}}(x)}{F_{T_{vd}}(V_{i+1}^{N_t} - i\Delta t_n)} + i\Delta t_n \\
 &= \frac{\frac{1}{\mu} - (V_{i+1}^{N_t} - i\Delta t_n + \frac{1}{\mu})e^{-\mu(V_{i+1}^{N_t} - i\Delta t_n)}}{1 - e^{-\mu(V_{i+1}^{N_t} - i\Delta t_n)}} + i\Delta t_n.
 \end{aligned} \tag{9}$$

Then, we can obtain the expected FCD for TOOF using (6). The delivery probability of B_j can be calculated using (2) and (6) as follows:

$$P_{TOOF} = \sum_{i=1}^{N_t} \left(\prod_{k=1}^{i-1} P_{NT,k} \right) (1 - P_{NT,i}) \mathbf{F}_{TEX}(T_l - E_{FCD,i}). \tag{10}$$

The expected FCD and delivery probability by using VOOF can be calculated in a similar way.

4) *Security and Privacy Issue*: The security issues are very important in smart grid since poor security would offset any cost effectiveness in Smart Grid. In vehicle-assisted SG data delivery mechanisms, the sensitive SG data might be exposed to the random vehicles, or modified by malicious vehicular users. In the literature, secure data forwarding schemes have been proposed for vehicular networks, which are proved to satisfy certain security requirements, e.g., data confidentiality, integrity, authentication and privacy preservation. In [37], a social-based privacy-preserving packet forwarding protocol for vehicular DTNs called SPRING is proposed in which RAPs deployed in intersections are used to forward packets among vehicles in a delay-tolerant manner in order to improve the delivery ratio and network reliability, while the privacy preservation can be achieved and most attacks, e.g., packet analysis attack, black (grey) hole attacks, and packet tracing attack can be resisted. In SPRING, the privacy preservation and attack resistance is achieved through a conditional privacy-preserving authentication (CPPA) technique, which is a group signature mechanism dedicated for vehicular communications. Similar schemes can be found in [38], [39]. These schemes can preserve the privacy and resist security attacks when the packets are forwarded to vehicles to store, carry, and forward. Therefore, the related methods and techniques can be utilized in our proposed vehicle-assisted data delivery method in order to achieve privacy preservation and secure data delivery in SG.

V. MODE SELECTION AND RESOURCE ALLOCATION

The forwarding schemes are proposed and analyzed based on vehicle arrival rate λ . In the proposed framework, there are two D2D transmission modes, i.e., M_W and M_C . Different modes with different λ can have different delivery performance and transmission costs. Based on the analysis of delivery probability in Section IV, a novel mode selection scheme is proposed to reduce the expected cost for the utility. Furthermore, a dynamic resource allocation scheme is introduced for DSs using M_C , in order to increase the total average delivery ratio and guarantee fairness among DSs.

A. Problem Formulation

1) *Mode Selection*: Note that M_D has the highest cost and poses a burden on the CN. Therefore, it is only used to transmit DBs which are not successfully delivered by the deadline. For D2D modes, i.e., M_W and M_C , they should be carefully selected. If M_W is used, DSs can forward the data to vehicles without any cost. However, due to the limited communication range, it is not that easy for DSs to find an optimal forwarder (as shown in Section IV). Therefore, the total delivery ratio could be low. On the other hand, if M_C is used, transmission cost is incurred when forwarding DBs to vehicles. Nevertheless, the total delivery ratio could be higher than that of M_W due to a larger communication range. As all undelivered DBs by the deadline will be transmitted using the most costly M_D , the mode selection should be considered to reduce the cost.

2) *Resource Allocation*: With the development of SG and the increasing popularity of smart meters and distributed generations, there would be a growing deployment of DSs which generate and transmit SG data. As a result, the DS density ρ could be very high. On the other hand, cellular resources are limited. For example, if LTE UL or downlink (DL) resources are reused by D2D communications, the number of D2D pairs which are allowed to transmit simultaneously can be calculated by $\frac{W_s}{W_b}$, where W_s is the system bandwidth and W_b is the size of a resource block allocated to a D2D pair [40]. Given a fixed amount of resources, the number of D2D pairs that can be supported is limited. In the literature, a resource spatial reuse scheme can be applied to support more D2D pairs. However, it is still possible that even within a DS cluster, the total resources are not enough to support all the D2D pairs, especially when ρ is high. Thus, how to efficiently allocate limited resources in such a dense scenario needs to be studied.

From (1), DSs which achieve higher delivery ratio will get more reward than others. This implies a fairness problem: some DSs are unsatisfied with the reward obtained, because they are required to conduct M_C transmissions as others (as a result of mode selection), but get less reward. As an alternative, the utility can reward the same amount to all DSs using M_C regardless of how much data they deliver. However, some DSs may refuse to transmit in order to save money. Thus, an intuitive solution is to dynamically allocate the resources to make each DS achieve a long-term average delivery ratio that is larger than a delivery ratio requirement $\bar{\Psi}$, and maximize $\bar{\Psi}$. By doing this, the fairness among DSs can be guaranteed, more SG data can be offloaded via D2D delivery, and the data transfer cost can be reduced.

Consider an RI, say the k -th RI, the delivery ratio of DBs generated in S_i can be expressed by

$$\Psi_i^k = \frac{\kappa_i^k}{n_{DB}} = \frac{\kappa_i^k}{\Delta t_g}, \tag{11}$$

where κ_i^k is the number of DBs that are generated in S_i within RI_k and successfully delivered before the end of RI_k by using D2D communications. Then, the long-term average

data delivery ratio Ψ_i can be calculated by

$$\Psi_i = \liminf_{K \rightarrow \infty} \frac{1}{K} \sum_{k=1}^K \Psi_i^k. \quad (12)$$

Let \mathcal{C}' denote the set of DSs using M_C in a cluster. Our objective is to design a resource allocation scheme η to

$$\max_{\eta} \quad \bar{\Psi}, \quad (13)$$

$$s.t. \quad \Psi_i \geq \bar{\Psi}, \quad \forall \mathbf{S}_i \in \mathcal{C}'. \quad (14)$$

The fairness can be guaranteed because if an arbitrary \mathbf{S}_i achieves a larger Ψ_i , it indicates that \mathbf{S}_i obtains too much resource, and thus $\bar{\Psi}$ is not maximized. To this end, a resource allocation scheme called fair delivery-ratio maximization resource allocation (FDMRA) is proposed to dynamically allocate LTE UL resources to DSs using M_C .

B. Mode Selection

With the knowledge of the delivery probability of DBs, we can obtain the expected cost of using M_W and M_C for an arbitrary DS, denoted by \mathbf{S}_i , respectively. Then, the D2D mode is determined for \mathbf{S}_i to reduced the total cost for the utility.

Assume that the maximum transmission range of M_W is d_W^m . We estimate the communication range of M_C through a simple path loss model:

$$\mathbf{P}_r = c\mathbf{P}_t d^{-\alpha}, \quad (15)$$

where d is the distance between D2D transmitter and receiver, c is the path-loss constant and α is the path-loss exponent, and \mathbf{P}_t and \mathbf{P}_r are D2D transmission and receive power using M_C , respectively. Assume that the target rate of the D2D pair to transmit DBs is r_{D2D} . Then, the target signal-to-interference-and-noise-ratio (SINR) at D2D receivers can be calculated by $SINR_{D2D} = 2^{\frac{r_{D2D}}{W_b}} - 1$. On the other hand, by the definition of SINR, we have

$$SINR_{D2D} = \frac{\mathbf{P}_r}{I_{0,i}}, \quad (16)$$

where $I_{0,i}$ is the maximum interference-plus-noise power that can be experienced by a D2D receiver within the cluster that \mathbf{S}_i belongs to, which is denoted by \mathbb{F}_i . Given the locations of all clusters, $I_{0,i}$ can be calculated by

$$I_{0,i} = \sum_{\mathbb{F}_j \neq \mathbb{F}_i} I_{j,i} + n_0, \quad (17)$$

where $I_{j,i}$ is the maximum interference from cluster \mathbb{F}_j to \mathbb{F}_i , and n_0 is the noise power. Since DSs in a cluster will not reuse the same resource, there is no interference from other D2D pairs in the same cluster. $I_{j,i}$ can be calculated by

$$I_{j,i} = c\mathbf{P}_{t,j}^{max} (d_{i,j}^{min})^{-\alpha}, \quad (18)$$

where $\mathbf{P}_{t,j}^{max}$ is maximum allowed transmission power of DSs using M_C in cluster \mathbb{F}_j , and $d_{i,j}^{min}$ is the minimum distance between cluster \mathbb{F}_j and \mathbb{F}_i . From (15) and (16), the D2D

communication range is given by

$$d = \left[\frac{I_0 (2^{\frac{r_{D2D}}{B}} - 1)}{c\mathbf{P}_t} \right]^{-\frac{1}{\alpha}}. \quad (19)$$

Finally, by substituting c , α , I_0 , and the maximum transmission power into (19), we can get the maximum expected D2D communication range of \mathbf{S}_i using M_C , which is denoted by $d_{i,C}^m$.

Then, we can estimate the expected cost for the utility when a DS uses M_W or M_C , by considering the expected D2D communication range of both modes. The expected cost of using M_W is

$$C_{U,W} = \left(1 - \frac{1}{n_{DB}} \sum_{k=1}^{n_{DB}} [P_d |\lambda(d_W^m), N_t(k)]\right) \cdot C_{DC}, \quad (20)$$

and the expected cost of using M_C can be calculated by (21),

where $[P_d |\lambda, N_t]$ is the delivery probability of an individual DB, given the vehicle arrival rate λ and the life time of this DB $T_l = N_t \Delta t_n$, which can be obtained from (10). $N_t(k)$ can be calculated by $N_t(k) = (T - (k-1)t_g) / \Delta t_n$. By comparison, the mode with less expected cost is then selected. The mode selection decision does not change with time, since λ is determined by D2D communication ranges, which are static for a DS through (19).

C. Cellular Resource Allocation

We consider a dense deployment of DSs in a specific cluster. Recall that \mathcal{C}' is the set of DSs using M_C in this cluster with $|\mathcal{C}'| = N_C$. The number of available resources (RBs) is M . To maximize $\bar{\Psi}$ while satisfying the constraint (14), we propose a novel resource allocation scheme called FDMRA by means of stochastic optimization theory [41].

We establish a virtual queue for each $\mathbf{S}_i \in \mathcal{C}'$. The queue dynamics are given by

$$Q_i(k+1) = Q_i(k) - \Psi_i^{k+1} + \bar{\Psi}, \quad (22)$$

where $Q_i(k)$ is the virtual queue backlog of \mathbf{S}_i in the k -th RI. Let $Q_i(0) = 0$ for all $\mathbf{S}_i \in \mathcal{C}'$. In (22), the arrival rate $\bar{\Psi}$ is the required long-term average delivery ratio, and the departure rate $\mathbb{E}[\Psi_i^k]$ is the actual delivery ratio in the k -th RI. Thus, the queue backlog $Q_i(k)$ indicates the information of whether \mathbf{S}_i satisfies the long-term average delivery ratio requirement $\bar{\Psi}$ by the end of the k -th RI. If $Q_i(k)$ is positive, it indicates that the delivery ratio of \mathbf{S}_i by the k -th RI is smaller than $\bar{\Psi}$, and vice versa.

Definition 1: $Q(k)$ is said to be *stable* if

$$\Pr \left\{ \limsup_{k \rightarrow \infty} \frac{Q(k)}{k} \leq 0 \right\} = 1, \quad (23)$$

which means $\forall \mathbf{S}_i \in \mathcal{C}'$, $\limsup_{k \rightarrow \infty} Q_i(k)/k \leq 0$ with probability one.

Lemma 1: Given the set \mathcal{C}' , the delivery ratio requirement (14) is satisfied if and only if $Q(k)$ is stable.

Proof: Using the law of telescoping sums to (22), we have

$$Q_i(k) - Q_i(0) = k\bar{\Psi} - \sum_{j=1}^k \Psi_i^j. \quad (24)$$

$$C_{U,C} = \frac{\gamma \mathcal{C}_C}{n_{DB}} \sum_{k=1}^{n_{DB}} [P_d | \lambda(d_{i,C}^m), N_t(k)] + \mathcal{C}_{DC} \left(1 - \frac{1}{n_{DB}} \sum_{k=1}^{n_{DB}} [P_d | \lambda(d_{i,C}^m), N_t(k)]\right). \quad (21)$$

With $Q_i(0) = 0$ and rearrangement of terms, we have

$$\limsup_{k \rightarrow \infty} \frac{Q_i(k)}{k} = \bar{\Psi} - \limsup_{k \rightarrow \infty} \frac{1}{k} \sum_{j=1}^k \Psi_i^j. \quad (25)$$

If $Q(k)$ is stable, with probability one, $\limsup_{k \rightarrow \infty} \frac{Q_i(k)}{k} \leq 0$ for all $S_i \in \mathbb{C}'$. Then, the following holds with probability one.

$$\limsup_{k \rightarrow \infty} \frac{1}{k} \sum_{j=1}^k \Psi_i^j \geq \bar{\Psi}, \quad \forall S_i \in \mathbb{C}'. \quad (26)$$

Therefore, the constraint (14) is satisfied. The **necessity** can be proved similarly. ■

Utilizing the concept of virtual queue, a resource allocation scheme called FDMRA is proposed.

Fair delivery-ratio maximization resource allocation: In the beginning of each RI (RI_k), the queue backlog $Q(k)$ of each DS in \mathbb{C}' is announced to the eNB by the utility. The queue backlogs are decreasingly ordered so that $Q_1(k) \geq Q_2(k) \geq \dots \geq Q_N(k)$. In each slot within RI_k (slot is defined in TOOF in Section IV), RBs are allocated to DSs in \mathbb{C}' which have the largest $Q(k)$ and find an optimal forwarder.

Definition 2: A resource allocation scheme η is called a *max-weight* allocation scheme if it maximizes

$$\sum_{i=1}^{N_c} [Q_i(k)]^+ \cdot \Psi_i^k(\eta), \quad (27)$$

where $\Psi_i^k(\eta)$ is the actual delivery ratio of S_i in k -th RI under the allocation scheme η .

Lemma 2: FDMRA is a max-weight allocation scheme. With FDMRA and $\bar{\Psi} < \mathbb{E}[\Psi(\eta_{FDMRA})]$, $Q(k)$ is stable, where $\mathbb{E}[\Psi(\eta_{FDMRA})]$ is the expected delivery ratio for each DS.

Proof: We define a non-negative *Lyapunov function* $L(Q(k))$ as follows.

$$L(Q(k)) \triangleq \frac{1}{2} \sum_{i \in \mathbb{C}'} ([Q_i(k)]^+)^2. \quad (28)$$

Thus,

$$\begin{aligned} & L(Q(k+1)) - L(Q(k)) \\ &= \frac{1}{2} \sum_{i \in \mathbb{C}'} (([Q_i(k+1)]^+)^2 - ([Q_i(k)]^+)^2) \\ &\leq \frac{1}{2} \sum_{i \in \mathbb{C}'} (([Q_i(k)]^+ - \Psi_i^{k+1}(\eta) + \bar{\Psi})^2 - ([Q_i(k)]^+)^2) \\ &= \frac{1}{2} \sum_{i \in \mathbb{C}'} ((\Psi_i^{k+1}(\eta) - \bar{\Psi})^2 - 2[Q_i(k)]^+(\Psi_i^{k+1}(\eta) - \bar{\Psi})). \end{aligned} \quad (29)$$

Define the *Lyapunov drift* by

$$\Delta(Q(k)) \triangleq \mathbb{E}[L(Q(k+1)) - L(Q(k)) | Q(k)]. \quad (30)$$

Therefore, we have (31), where B is constant so that

$$\frac{1}{2} \sum_{i \in \mathbb{C}'} \mathbb{E}[(\Psi_i^{k+1}(\eta) - \bar{\Psi})^2 | Q(k)] \leq B,$$

since both $\Psi_i^{k+1}(\eta)$ and $\bar{\Psi}$ can be upper bounded by 1. A resource allocation which maximizes

$$\sum_{i \in \mathbb{C}'} [Q_i(k)]^+ + \mathbb{E}[\Psi_i^{k+1}(\eta) | Q(k)] \quad (32)$$

is needed to minimize $\Delta(Q(k))$, which is called a max-weight allocation. The proposed FDMRA scheme is a max-weight allocation since it guarantees that at any time, the resources are allocated to those DSs which have the largest $Q(k)$. In other words, with FDMRA applied, DSs with larger $Q(k)$ can obtain higher delivery ratio Ψ_i^k , which in turn maximizes (32). Thus, we have (33), where η^* is a non max-weight resource allocation scheme. Substituting (33) into (31) yields:

$$\begin{aligned} & \Delta(Q(k)) \\ &\leq B + \sum_{i \in \mathbb{C}'} [Q_i(k)]^+ \bar{\Psi} - \sum_{i \in \mathbb{C}'} [Q_i(k)]^+ \mathbb{E}[\Psi_i^{k+1}(\eta_{FDMRA}) | Q(k)] \\ &= B - \sum_{i \in \mathbb{C}'} [Q_i(k)]^+ (\mathbb{E}[\Psi_i^{k+1}(\eta_{FDMRA}) | Q(k)] - \bar{\Psi}) \\ &= B - \sum_{i \in \mathbb{C}'} [Q_i(k)]^+ \epsilon \end{aligned} \quad (34)$$

where $\epsilon = \mathbb{E}[\Psi_i^{k+1}(\eta_{FDMRA})] - \bar{\Psi} > 0$ is the difference between the expected delivery ratio using FDMRA and the required delivery ratio. By utilizing FDMRA, cellular resources are evenly allocated to each $S_i \in \mathbb{C}'$ from the long-term perspective. Thus, we have $\mathbb{E}[\Psi_i^k(\eta_{FDMRA})] = \mathbb{E}[\Psi(\eta_{FDMRA})]$, $\forall S_i \in \mathbb{C}'$. Therefore, with

$$\epsilon = \mathbb{E}[\Psi(\eta_{FDMRA})] - \bar{\Psi}, \quad (35)$$

and taking expectation, $\mathbb{E}[\Delta(Q(k))]$ is upper bounded:

$$\mathbb{E}[\Delta(Q(k))] \leq B - \epsilon \sum_{i \in \mathbb{C}'} \mathbb{E}[[Q_i(k)]^+] \quad (36)$$

Using the definition of $\Delta(Q(k))$ in (30), we have

$$\begin{aligned} \mathbb{E}[\Delta(Q(k))] &= \mathbb{E}[\mathbb{E}[L(Q(k+1)) - L(Q(k)) | Q(k)]] \\ &= \mathbb{E}[L(Q(k+1))] - \mathbb{E}[L(Q(k))] \end{aligned} \quad (37)$$

Substituting (37) into (36) and doing telescoping sums over $k \in \{1, 2, \dots, K-1\}$ yields:

$$\mathbb{E}[L(Q(K))] - \mathbb{E}[L(Q(0))] \leq BK - \epsilon \sum_{k=1}^{K-1} \sum_{i \in \mathbb{C}'} \mathbb{E}[[Q_i(k)]^+] \quad (38)$$

By taking a lim sup and using the fact that $\mathbb{E}[L(Q(K))] \geq 0$

$$\begin{aligned} \Delta(\mathbf{Q}(k)) &= \frac{1}{2} \sum_{i \in \mathcal{C}'} \mathbb{E}[(\Psi_i^{k+1}(\eta) - \bar{\Psi})^2 | \mathbf{Q}(k)] - \sum_{i \in \mathcal{C}'} \mathbb{E}[[Q_i(k)]^+ (\Psi_i^{k+1}(\eta) - \bar{\Psi}) | \mathbf{Q}(k)] \\ &\leq B + \sum_{i \in \mathcal{C}'} [Q_i(k)]^+ \bar{\Psi} - \sum_{i \in \mathcal{C}'} [Q_i(k)]^+ \mathbb{E}[\Psi_i^{k+1}(\eta) | \mathbf{Q}(k)]. \end{aligned} \quad (31)$$

$$\sum_{i \in \mathcal{C}'} [Q_i(k)]^+ \mathbb{E}[\Psi_i^{k+1}(\eta_{FDMRA}) | \mathbf{Q}(k)] \geq \sum_{i \in \mathcal{C}'} [Q_i(k)]^+ \mathbb{E}[\Psi_i^{k+1}(\eta^*) | \mathbf{Q}(k)], \quad (33)$$

and $\mathbb{E}[L(\mathbf{Q}(0))] = 0$, we have

$$\limsup_{K \rightarrow \infty} \frac{1}{K} \sum_{k=1}^{K-1} \sum_{i \in \mathcal{C}'} \mathbb{E}[[Q_i(k)]^+] \leq \frac{B}{\epsilon} \quad (39)$$

Thus, all queues are stable, and the long-term average backlog is upper bounded by $\frac{B}{\epsilon}$.

Theorem 1: By applying FDMRA, the constraint (14) is satisfied, and the optimization target $\bar{\Psi} = \mathbb{E}[\Psi(\eta_{FDMRA})] - \epsilon$, where ϵ is a positive number.

From Lemma 1 and 2, Theorem 1 can be easily proved. Theorem 1 indicates that by using FDMRA, each DS can achieve the long-term average delivery ratio that is larger than $\bar{\Psi}$, which is upper bounded by and arbitrarily close to $\mathbb{E}[\Psi(\eta_{FDMRA})]$. The derivation of $\mathbb{E}[\Psi(\eta_{FDMRA})]$ is given in Appendix.

VI. PERFORMANCE EVALUATION

In this section, we conduct simulations to evaluate the performance of the proposed offloading framework. An urban scenario is considered with LTE coverage and randomly deployed RAPs. We employ event-driven simulation, where events include DB generation, request, and vehicle arrival at DSs and contact with RAPs. Simulation parameters are listed in Table III.

The performance of the proposed optimal forwarding schemes are shown in Fig. 5. The effect of λ and μ is studied. Simulation and analytical results of FCD are shown in Fig. 5(a) and 5(b). In Fig. 5(a), the impact of the vehicle arrival rate λ is presented. The increase of λ reduces the time for DSs to wait for the eligible D2D receiver, and thus the FCD is reduced. In Fig. 5(b), the impact of mean meeting time $\frac{1}{\mu}$ is shown. A small value of $\frac{1}{\mu}$ indicates that the value of T_{vd} is small, which leads to a small value of FCD. The reason for that VOOF achieves smaller FCD than TOOF is that in TOOF, vehicle arrivals within a time slot are considered as arrivals at the beginning of the time slot to simplify the scheme. Moreover, it is shown that the theoretical and simulation result match each other, which validates the analysis. The overall delivery ratio of DBs within an RI is shown in Fig. 5(c) and 5(d). We compare the delivery ratio of using TOOF and VOOF with that of a simple scheme called best effort (BE), in which the first vehicle with $T_{vd} < t_{req} - t_f$ is selected. BE is to guarantee that vehicles carrying DBs can contact at least one RAP before the request time. However, BE fails to consider T_{EX} , and achieves the lowest delivery ratio among the three.

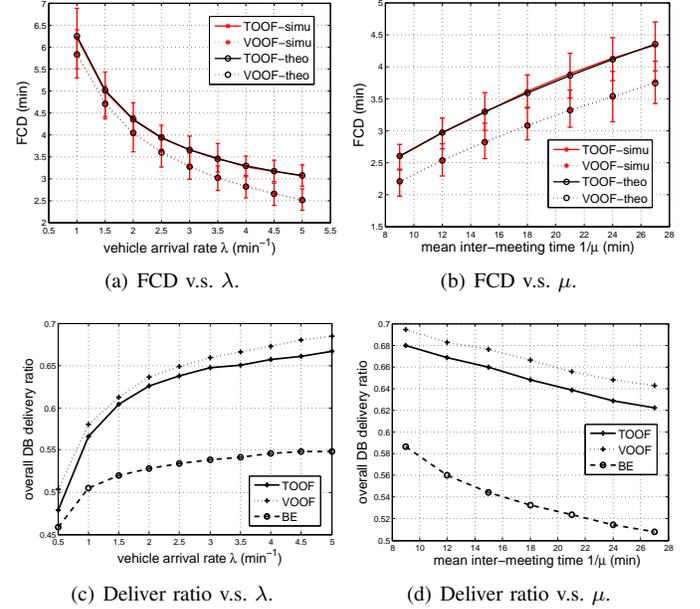


Figure 5. Performance of optimal forwarding scheme

The performance of the mode selection scheme is shown in Fig. 6, where \mathcal{C}_C is set to 1. Fig. 6(a) gives the percentage of DSs which select M_C with respect to the direct cellular communication cost \mathcal{C}_{DC} and reward parameter γ . It can be seen that with the increase of \mathcal{C}_{DC} , the number of DSs selecting M_C increases, because with larger \mathcal{C}_{DC} , the increase of delivery ratio will save more cost. The percentage decreases with the increase of reward parameter γ . This is because the utility pays more for rewarding DSs using M_C . Fig. 6(b) shows the average cost for the utility with the appropriate mode selected for each DS. The cost of the proposed scheme is compared with that of the case in which only M_W is utilized for D2D communications. It can be seen that the proposed mode selection scheme can achieve a lower average cost.

The performance of the proposed FDMRA scheme is shown in Fig. 7. In Fig. 7(a), the average vehicle arrival rate λ is set to 1 per minute, and the long-term (over 70 hours) average delivery ratio of each DS and the theoretical delivery ratio of FDMRA ($\mathbb{E}[\Psi(\eta_{FDMRA})]$) are compared. It can be seen that DSs achieve almost the same long-term average delivery ratio, which demonstrates fairness of FDMRA. Moreover, the long-term average delivery ratios of DSs are close to theoretical result $\mathbb{E}[\Psi(\eta_{FDMRA})]$, which validates our analysis. The

Table III
SIMULATION PARAMETERS.

Parameter	Value	Parameter	Value
Radius of the cell	2 km	M_W D2D communication range	100 m
Maximum UE transmission power	33 dBm	Noise power density	-174 dBm/Hz
Maximum system bandwidth	5 MHz	Size of data block	10 kB
Resource block	180 kHz	Request interval	30 min
Path loss of M_C	$38+54\log_{10}(d[km])$	Generation interval	2 min

delivery ratios decrease with the increase of DS density ρ and the decrease of the number of RB M . This is because a large number of DSs in a cluster or a small number of RBs will make the resource scarcity problem more severe. Fig. 7(b) shows the relationship between the delivery ratios and the average vehicle arrival rate λ , when M is set to 10. With the increase of λ , the delivery ratios also increase because DSs can easily find an optimal vehicle to forward DBs.

The overall performance of the proposed D2D based offloading scheme is shown in Fig. 8, where \mathcal{C}_{DC} , \mathcal{C}_C and γ are set to 7, 1, and 1.3 respectively. Clusters are randomly located in the cell. We compare the proposed offloading framework with two schemes in which only M_W is used, and both M_W and M_C are used without cellular resource spatial reuse within a cell. It can be seen in Fig. 8(a) that by using the proposed offloading scheme, about 49% to 58% SG data can be offloaded from the CN, according to different DS densities. Compared with the other two schemes (on average data offloading percentage of 25% and 8%, respectively), the proposed framework can efficiently offload the CN. Fig. 8(b) shows the total saved cost for the utility. By offloading more, less data is transmitted using M_D , which in turn reduces more cost for the utility, especially when ρ is high.

VII. CONCLUSION

In this paper, we have developed a vehicle-assisted offloading framework for SG delay-tolerant applications through D2D communications. We have first proposed two optimal forwarding schemes for DSs to optimally select a vehicle to forward SG data. Then, we have designed a mode selection scheme and a resource allocation scheme called FDMRA to minimize the expected cost and maximize the data delivery ratio, respectively. Simulation results have validated the performance of the proposed forwarding, mode selection, and resource allocation schemes, and demonstrated that the proposed framework can offload up to 58% SG data from the CN, guarantee the fairness among DSs, and save much cost for the utility, especially when DS density is high. Our future work will consider the differentiation of SG applications in the data offloading framework.

APPENDIX

A. Calculation of expected delivery ratio in FDMRA

We calculate the expected delivery ratio for DSs in an RI using M_C and FDMRA. For simplicity, it is considered that the maximum transmission powers \mathbf{P}_i are the same for DSs

within the same cluster. Thus, by (19), D2D communication ranges for DSs in a cluster are the same, so are the vehicle arrival rates λ . We focus on the expected delivery ratio when TOOF is used, while the case in which VOOOF is employed is similar. Because the case $N \leq M$ is trivial, we consider the case $N > M$, where the number of resources is smaller than that of potential D2D pairs.

Recall that if a DS can have the resource and forward DBs whenever it wants to, the expected delivery ratio of DBs in the DS within an RI is

$$\mathbb{E}[P_{RI}] = \frac{T}{t_g} \sum_{T_l} \sum_{i=1}^{N_t(T_l)} \left(\prod_{k=1}^{i-1} P_{NT,k} \right) (1 - P_{NT,i}) \cdot \mathbf{F}_{TEX}(T_l - E_{FCD,i}), \quad (40)$$

where $T_l \in \{T, T - t_g, T - 2t_g, \dots, t_g, 0\}$ is the life time DBs, and $N_t(T_l) = \lfloor \frac{T_l}{t_g} \rfloor$. Thus, in an RI, the M DSs with the largest queue backlog $Q(k)$ (we denote this set of DSs by \mathcal{C}_M) will all achieve an expected delivery ratio $\mathbb{E}[P_{RI}]$ because FDMRA will allocate an RB to these DSs whenever they find an optimal vehicle to forward data. However, in each slot, not all DSs in \mathcal{C}_M can find an optimal forwarder due to the optimal forwarding rules described in Section IV. Thus, DSs in $\mathcal{C}' \setminus \mathcal{C}_M$ may be allocated with RBs when they have DBs to forward.

Consider a DB with life time T_l . Note that each DS in \mathcal{C}' generates a DB at the same time and the number of such DBs is N . In a time slot k , the probability P_o that a DS will find an optimal forwarder is given by $P_o = 1 - P_{NT,k}$, where $P_{NT,k}$ can be calculated by (7). In the first time slot, in expect $M P_o$ RBs are allocated to DSs in \mathcal{C}_M . Thus, the expected number of DBs in $\mathcal{C}' \setminus \mathcal{C}_M$ which are forwarded in slot #1 is

$$n_f^1 = \min\{M(1 - P_o), (N - M)P_o\}. \quad (41)$$

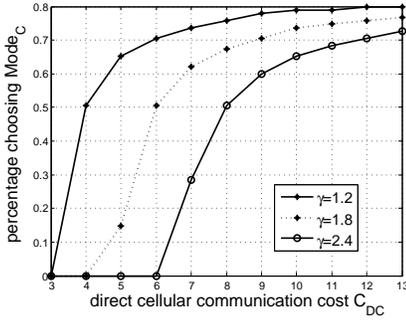
Therefore, in the second slot, the number of DBs to be forwarded in \mathcal{C}_M is $M(1 - P_o)$. We have the expected number of DBs in $\mathcal{C}' \setminus \mathcal{C}_M$ which are forwarded in slot #2:

$$n_f^2 = \min\{M - M(1 - P_o)P_o, [N - M - n_f^1]^+ P_o\}. \quad (42)$$

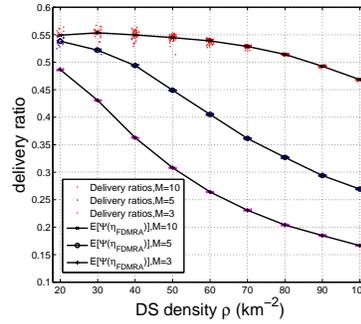
Similarly, in slot #s,

$$n_f^s = \min\{M - M(1 - P_o)^{s-1} P_o, [N - M - \sum_{i=1}^{s-1} n_f^i]^+ P_o\}. \quad (43)$$

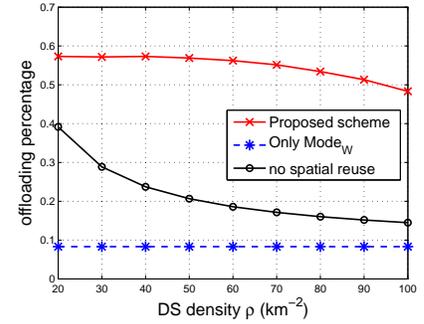
Based on the analysis in Section IV-D3, the expected number out of the $N - M$ DBs in $\mathcal{C}' \setminus \mathcal{C}_M$ which can be successfully



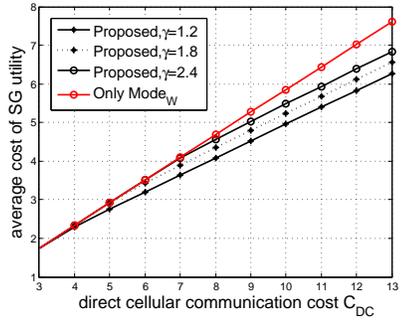
(a) Mode selection results.



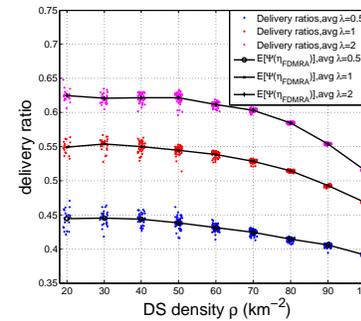
(a) Delivery ratio w.r.t. RB number.



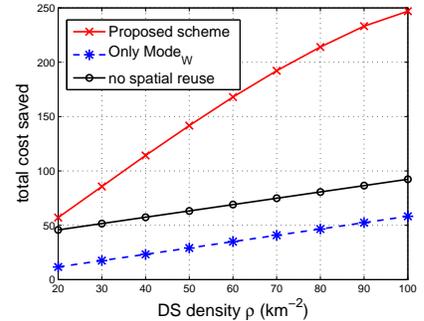
(a) Overall offloading performance.



(b) Average cost for the utility.



(b) Delivery ratio w.r.t. average λ .



(b) Overall amount of saved cost.

Figure 6. Performance of mode selection scheme.

Figure 7. Performance of FDMRA.

Figure 8. Overall performance.

delivered to UCC is

$$n_d(T_l) = \sum_{i=1}^{N_t(T_l)} n_f^i F_{TEX}(T_l - E_{FCD,i}), \quad (44)$$

where $E_{FCD,i}$ can be calculated by (9). Thus, the number of DBs which are generated in DSs in $\mathbb{C} \setminus \mathbb{C}_M$ and successfully delivered to UCC within a whole RI is

$$n_{d,RI} = \sum_{T_l} n_d(T_l) = \sum_{T_l} \sum_{i=1}^{N_t(T_l)} n_f^i F_{TEX}(T_l - E_{FCD,i}), \quad (45)$$

where $T_l \in \{T, T - t_g, T - 2t_g, \dots, t_g, 0\}$. Finally, the expected delivery ratio for a DS in an RI is

$$\mathbb{E}[\Psi(\eta_{FDMRA})] = \frac{MTE[P_{RI}] + n_{d,RI}}{N \frac{T}{t_g}} = \frac{M}{N} \mathbb{E}[P_{RI}] + \frac{t_g n_{d,RI}}{NT}. \quad (46)$$

REFERENCES

- [1] H. Farhangi, "The Path of the Smart Grid," *IEEE Power and Energy Magazine*, vol. 8, no. 1, pp. 18–28, 2010.
- [2] M. Fouda, Z. Fadlullah, N. Kato, R. Lu, and X. Shen, "A lightweight message authentication scheme for smart grid communications," *IEEE Trans. on Smart Grid*, vol. 2, no. 4, pp. 675–685, 2011.
- [3] P. Nyeng and J. Ostergaard, "Information and communications systems for control-by-price of distributed energy resources and flexible demand," *IEEE Trans. on Smart Grid*, vol. 2, no. 2, pp. 334–341, 2011.
- [4] R. Yu, Y. Zhang, S. Gjessing, C. Yuen, S. Xie, and M. Guizani, "Cognitive radio based hierarchical communications infrastructure for smart grid," *IEEE Network*, vol. 25, no. 5, pp. 6–14, 2011.
- [5] Y. V. Makarov, C. Loutan, J. Ma, and P. de Mello, "Operational impacts of wind generation on california power systems," *IEEE Trans. on Power Systems*, vol. 24, no. 2, pp. 1039–1050, 2009.
- [6] "Application domain partitioning for smart grid security." [Online]. Available: <http://www.triliantinc.com/de/education/upcoming-webinar-application-domain-partitioning-for-smart-grid-security>
- [7] S. Galli, A. Scaglione, and Z. Wang, "For the grid and through the grid: The role of power line communications in the smart grid," *Proceedings of the IEEE*, vol. 99, no. 6, pp. 998–1027, 2011.
- [8] G. Deconinck, "An evaluation of two-way communication means for advanced metering in flanders (belgium)," in *Proc. of IEEE IMTC*, Victoria, Canada, May 2008.
- [9] Z. Alliance, "Smart energy profile 2." [Online]. Available: <http://www.zigbee.org/Standards/ZigBeeSmartEnergy/SmartEnergyProfile2.aspx>
- [10] H. Liang, B. J. Choi, A. Abdrabou, W. Zhuang, and X. Shen, "Decentralized economic dispatch in microgrids via heterogeneous wireless networks," *IEEE J. Selected Areas in Communications*, vol. 30, no. 6, pp. 1061–1074, 2012.
- [11] Cisco, "Cisco visual networking index: Global mobile data traffic forecast update." [Online]. Available: http://www.cisco.com/en/US/solutions/collateral/ns341/ns525/ns537/ns705/ns827/white_paper_c11-520862.html
- [12] N. Golrezaei, A. F. Molisch, and A. G. Dimakis, "Base-station assisted Device-to-Device communications for high-throughput wireless video networks," in *Proc. of IEEE ICC*, Ottawa, Canada, Jun 2012.
- [13] K. Lee, J. Lee, Y. Yi, I. Rhee, and S. Chong, "Mobile data offloading: How much can wifi deliver?" *IEEE/ACM Trans. on Networking*, vol. 21, no. 2, pp. 536–550, 2013.
- [14] L. Lei, Z. Zhong, C. Lin, and X. Shen, "Operator controlled Device-to-Device communications in LTE-advanced networks," *IEEE Wireless Communications*, vol. 19, no. 3, pp. 96–104, 2012.
- [15] J. Zhao and G. Cao, "VADD: Vehicle-assisted data delivery in vehicular ad hoc networks," *IEEE Trans. on Vehicular Technology*, vol. 57, no. 3, pp. 1910–1922, 2008.
- [16] "KPMG's global automotive executive survey." [Online]. Available: <http://www.kpmg.com/GE/en/IssuesAndInsights/ArticlesPublications/Documents/Global-automotive-executive-survey-2012.pdf>
- [17] J. Eriksson, H. Balakrishnan, and S. Madden, "Cabernet: vehicular content delivery using WiFi," in *Proc. of ACM MobiCom*, San Francisco, USA, September 2008.
- [18] V. Bychkovsky, B. Hull, A. Miu, H. Balakrishnan, and S. Madden, "A measurement study of vehicular internet access using in situ Wi-Fi

networks,” in *Proc. of ACM MobiCom*, Los Angeles, USA, September 2006.

- [19] N. Cheng, N. Lu, N. Zhang, X. Shen, and J. Mark, “Vehicular WiFi offloading: Challenges and solutions,” *Elsevier Vehicular Communications*, vol. 1, no. 1, pp. 13–21, 2014.
- [20] “High density and high concentrations of cars.” [Online]. Available: <http://www.planetizen.com/node/45622>
- [21] “Seemless Wi-Fi offload: from vision to reality.” [Online]. Available: <http://www.enterprisechannelsmea.com/FileManagerImages/12047.pdf>
- [22] S. Hakola, T. Chen, J. Lehtomaki, and T. Koskela, “Device-to-Device (D2D) communication in cellular network-performance analysis of optimum and practical communication mode selection,” in *Proc. of IEEE WCNC*, Sydney, Australia, Apr 2010.
- [23] M. Jung, K. Hwang, and S. Choi, “Joint mode selection and power allocation scheme for power-efficient Device-to-Device (D2D) communication,” in *Proc. of IEEE VTC*, Yokohama, Japan, May 2012.
- [24] K. Akkarajitsakul, P. Phunchongharn, E. Hossain, and V. K. Bhargava, “Mode selection for energy-efficient D2D communications in LTE-advanced networks: A coalitional game approach,” in *Proc. of IEEE ICCS*, Omaha, USA, June 2012.
- [25] C.-H. Yu, K. Doppler, C. B. Ribeiro, and O. Tirkkonen, “Resource sharing optimization for Device-to-Device communication underlying cellular networks,” *IEEE Trans. on Wireless Communications*, vol. 10, no. 8, pp. 2752–2763, 2011.
- [26] P. Cheng, L. Deng, H. Yu, Y. Xu, and H. Wang, “Resource allocation for cognitive networks with D2D communication: An evolutionary approach,” in *Proc. of IEEE WCNC*, Paris, France, Apr 2012.
- [27] A.-H. Tsai, L.-C. Wang, J.-H. Huang, and T.-M. Lin, “Intelligent resource management for Device-to-Device (D2D) communications in heterogeneous networks,” in *Proc. of IEEE WPMC*, Taipei, Taiwan, Sep 2012.
- [28] D. Niyato and P. Wang, “Optimization of the mobile router and traffic sources in vehicular delay-tolerant network,” *IEEE Trans. on Vehicular Technology*, vol. 58, no. 9, pp. 5095–5104, 2009.
- [29] N. Lu, T. Luan, M. Wang, X. Shen, and F. Bai, “Bounds of asymptotic performance limits of social-proximity vehicular networks,” *IEEE/ACM Trans. on Networking*, vol. 22, no. 3, pp. 812–825, 2014.
- [30] J. Ott and D. Kutscher, “Drive-thru Internet: IEEE 802.11 b for Automobile,” in *Proceedings of IEEE INFOCOM*, Hong Kong, China, March 2004.
- [31] W. L. Tan, W. C. Lau, O. Yue, and T. H. Hui, “Analytical models and performance evaluation of drive-thru internet systems,” *IEEE J. Selected Areas in Communications*, vol. 29, no. 1, pp. 207–222, 2011.
- [32] X. Ma, R. Yin, G. Yu, and Z. Zhang, “A distributed relay selection method for relay assisted Device-to-Device communication system,” in *Proc. of IEEE PIMRC*, Sydney, Australia, Sep 2012.
- [33] “Interview with dave bassett.” [Online]. Available: <http://smartgrid.ieee.org/questions-and-answers/>
- [34] T. Luan, L. Cai, J. Chen, X. Shen, and F. Bai, “Engineering a distributed infrastructure for large-scale cost-effective content dissemination over urban vehicular networks,” *IEEE Trans. on Vehicular Technology*, vol. 63, no. 3, pp. 1419–1435, 2014.
- [35] G. Peškir, A. Shiryayev, and A. Shiryayev, *Optimal stopping and free-boundary problems*. Birkhauser, 2006, vol. 10.
- [36] “Optimal Stopping and Applications.” [Online]. Available: <http://www.math.ucla.edu/~tom/Stopping/Contents.html>
- [37] R. Lu, X. Lin, and X. Shen, “Spring: A social-based privacy-preserving packet forwarding protocol for vehicular delay tolerant networks,” in *Proc. of IEEE INFOCOM*, 2010, pp. 1–9.
- [38] X. Lin, R. Lu, X. Liang, and X. Shen, “Stap: A social-tier-assisted packet forwarding protocol for achieving receiver-location privacy preservation in vanets,” in *Proc. of IEEE INFOCOM*, 2011, pp. 2147–2155.
- [39] K. Zhang, X. Liang, R. Lu, and X. Shen, “Vslp: Voronoi-socialspot-aided packet forwarding protocol with receiver location privacy in msns,” in *Proc. of IEEE GLOBECOM*, Anaheim, USA, Dec 2012.
- [40] “LTE resource guide.” [Online]. Available: http://www.anritsu.com/en-GB/Media-Room/Newsletters/files/anritsu_lte_guide.pdf
- [41] M. J. Neely, “Stochastic network optimization with application to communication and queueing systems,” *Synthesis Lectures on Communication Networks*, vol. 3, no. 1, pp. 1–211, 2010.



offloading.

Nan Cheng (S'13) is currently a Ph.D. candidate in the department of Electrical and Computer Engineering, the University of Waterloo, Waterloo, ON, Canada. He received his B.S. degree and M.S. degree from Tongji University, China, in 2009 and 2012, respectively. Since 2012, he has been a research assistant in the Broadband Communication Research group in ECE Department, the University of Waterloo. His research interests include vehicular communication networks, cognitive radio networks, resource allocation in smart grid, and cellular traffic



Mobile Radio Communications.

Ning Lu (S'12) received the B.Sc. and M.Sc. degrees from Tongji University, Shanghai, China, in 2007 and 2010, respectively. He is currently working toward the Ph.D. degree with the Department of Electrical and Computer Engineering, University of Waterloo, Waterloo, ON, Canada. His current research interests include capacity and delay analysis, media access control, and routing protocol design for vehicular networks. Mr. Lu served as a Technical Program Committee Member for IEEE 2012 International Symposium on Personal, Indoor, and



Ning Zhang (S'12) received the B.Sc. degree from Beijing Jiaotong University and the M.Sc. degree from Beijing University of Posts and Telecommunications, Beijing, China, in 2007 and 2010, respectively. He is currently working toward the Ph.D. degree with the Department of Electrical and Computer Engineering, University of Waterloo, Waterloo, ON, Canada. His current research interests include cooperative networking, cognitive radio networks, physical layer security, and vehicular networks.



Tingting Yang (M'13) received the B.Sc. and Ph.D. degrees from Dalian Maritime University, China, in 2004 and 2010, respectively. She is currently an associate professor at Navigation College of Dalian Maritime University, China. Since September 2012, she has been a visiting scholar at the Broadband Communications Research (BBRC) Lab at the Department of Electrical and Computer Engineering, University of Waterloo, Canada. Her research interests are in the areas of maritime wideband communication networks, DTN networks, green wireless communication. She serves as the associate Editor-in-Chief of the IET Communications, as well as the advisory editor for SpringerPlus. She also serves as a TPC Member for IEEE ICC'14 & ICC'15 Conference, IEEE SmartGridComm'14 Symposium and IEEE ScalCom'14 Conference.



Xuemin (Sherman) Shen (IEEE M'97-SM'02-F'09) received the B.Sc.(1982) degree from Dalian Maritime University (China) and the M.Sc. (1987) and Ph.D. degrees (1990) from Rutgers University, New Jersey (USA), all in electrical engineering.

He is a Professor and University Research Chair, Department of Electrical and Computer Engineering, University of Waterloo, Canada. He was the Associate Chair for Graduate Studies from 2004 to 2008. Dr. Shen's research focuses on resource management in interconnected wireless/wired networks, wireless

network security, wireless body area networks, vehicular ad hoc and sensor networks. He is a co-author/editor of six books, and has published many papers and book chapters in wireless communications and networks, control and filtering. Dr. Shen served as the Technical Program Committee Chair for IEEE VTC'10 Fall, the Symposia Chair for IEEE ICC'10, the Tutorial Chair for IEEE VTC'11 Spring and IEEE ICC'08, the Technical Program Committee Chair for IEEE Globecom'07, the General Co-Chair for Chinacom'07 and QShine'06, the Chair for IEEE Communications Society Technical Committee on Wireless Communications, and P2P Communications and Networking. He also serves/served as the Editor-in-Chief for IEEE Network, Peer-to-Peer Networking and Application, and IET Communications; a Founding Area Editor for IEEE Transactions on Wireless Communications; an Associate Editor for IEEE Transactions on Vehicular Technology, Computer Networks, and ACM/Wireless Networks; and the Guest Editor for IEEE JSAC, IEEE Wireless Communications, IEEE Communications Magazine, and ACM Mobile Networks and Applications.

Dr. Shen is a registered Professional Engineer of Ontario, Canada, an IEEE Fellow, a Fellow of the Canadian Academy of Engineering, a Fellow of Engineering Institute of Canada, and a Distinguished Lecturer of IEEE Vehicular Technology Society and Communications Society.



Jon W. Mark (M'62-SM'80-F'88-LF'03) received the Ph.D. degree in electrical engineering from McMaster University in 1970. In September 1970 he joined the Department of Electrical and Computer Engineering, University of Waterloo, Waterloo, Ontario, where he is currently a Distinguished Professor Emeritus. He served as the Department Chairman during the period July 1984-June 1990. In 1996 he established the Center for Wireless Communications (CWC) at the University of Waterloo and is currently serving as its founding Director. Dr. Mark had been

on sabbatical leave at the following places: IBM Thomas J. Watson Research Center, Yorktown Heights, NY, as a Visiting Research Scientist (1976-77); AT&T Bell Laboratories, Murray Hill, NJ, as a Resident Consultant (1982-83); Laboratoire MASI, Universit  Pierre et Marie Curie, Paris France, as an Invited Professor (1990-91); and Department of Electrical Engineering, National University of Singapore, as a Visiting Professor (1994-95). He has previously worked in the areas of adaptive equalization, image and video coding, spread spectrum communications, computer communication networks, ATM switch design and traffic management. His current research interests are in broadband wireless communications, resource and mobility management, and cross domain interworking.

Dr. Mark is a Life Fellow of IEEE and a Fellow of the Canadian Academy of Engineering. He is the recipient of the 2000 Canadian Award for Telecommunications Research and the 2000 Award of Merit of the Education Foundation of the Federation of Chinese Canadian Professionals. He was an editor of IEEE TRANSACTIONS ON COMMUNICATIONS (1983-1990), a member of the Inter-Society Steering Committee of the IEEE/ACM TRANSACTIONS ON NETWORKING (1992-2003), a member of the IEEE Communications Society Awards Committee (1995-1998), an editor of Wireless Networks (1993-2004), and an associate editor of Telecommunication Systems (1994-2004).