Resource Allocation for D2D-Based V2X Communication With Imperfect CSI

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***Abstract*—Different from the traditional device-to-device (D2D) communication, vehicle-to-everything (V2X) communication is characterized by the high mobility of vehicles, which introduces the fast variations of the channel state information (CSI) such that the accurate CSI is difficult to be obtained. Unlike other previous work which focuses on the perfect CSI, in this article, we investigate the joint power control and resource allocation problem for the D2D-based V2X communication in a more practical case where the CSI is imperfect. We aim at maximizing the sum ergodic capacity of all vehicular user equipments (VUEs) with imperfect CSI under the minimum signal-to-interference-plus-noise-ratio (SINR) requirements of cellular user equipments (CUEs) and the outage probability constraints of VUEs. We derive an approximate closed-form expression of VUE's ergodic capacity based on Jensen's inequality and propose a simple and efficient lower bound-based power control approach to solve the power control problem with low computational complexity. Based on the optimal power allocation results, we further propose an enhanced Gale–Shapley algorithm to solve the spectrum resource allocation problem, which is tailored to the scenario where each VUE can reuse spectrum resources of multiple CUEs but the resource of each CUE can be shared with one VUE at most and the maximum number of reuse CUEs for each VUE is limited by the maximum transmit power of the VUE. The numerical results verify the tightness of the proposed algorithm and demonstrate the proposed algorithm can enhance the sum ergodic capacity of VUEs efficiently and effectively.**

***Index Terms*—Device-to-device (D2D)-based Vehicle-to-Everything (V2X) communication, imperfect channel state information (CSI), one-to-many matching, power control, resource allocation.**

I. Introduction

A. Background

With the rapid development of wireless communication, sensing, and computing technologies, the transportation system is evolving toward an intelligent transportation system (ITS) which is more efficient, smarter, and safer ever before. An important facilitator for this evolution is the paradigm of V2X communication, which enables diverse connected vehicular communication, such as vehicle to network (V2N), vehicle to infrastructure (V2I), vehicle to vehicle (V2V), and vehicle to pedestrian (V2P) [1], [2]. The emerging Internet-of-Things (IoT) technologies are able to accelerate the realization of advanced V2X communication to improve the transportation experience and quality of life [3]. For example, the over-the-air function computation technology provides an effective solution to the data aggregation challenge of V2X communication with a large number of sensors [4], [5]. In particular, through the use of IoT, the knowledge of the surrounding environment of the vehicles can be gathered and shared with one another, thereby improving the driving situation awareness, degrading accident rates, reducing traffic congestion, decreasing environmental impacts, etc. [6]. V2X communication is useful and essential not just for the current transportation system [7] but also for the automated driving systems in the future [8].

In 2016, to improve road safety and traffic efficiency, D2D communication, which can facilitate the direct end-to-end proximity-based communication with no involvement of the evolved node B (eNB), was first proposed to support V2X communication by Third Generation Partnership Project (3GPP) Release 14 [2]. In recent years, D2D-based V2X communication is emerging as an essential application scenario for the fifth-generation mobile communication system due to its high reliability and low latency [9]. Different from the traditional D2D communication, D2D-based V2X communication is characterized by the high mobility of vehicles, which introduces the Doppler effect to the vehicular links. This leads to the fast channel state variations such that the accurate channel state information (CSI) of vehicular links is hard to obtain. To further improve the spectral efficiency, recently, underlay D2D-based V2X communication has attracted a lot of attention from both academia and industry. By reusing the spectrum resources of cellular user equipments (CUEs), underlay D2D-based V2X communication can improve the spectral efficiency. But it also introduces co-channel interference to cellular networks.

B. Related Work and Motivation

With appropriate power control and resource allocation methods, not only can the co-channel interference issues for underlay D2D-based V2X communication be mitigated effectively but also the spectrum/energy efficiency of the network

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can be improved dramatically. Chen *et al.* [10] introduced nonorthogonal multiple access (NOMA) in D2D-enabled V2X networks. By fixing the transmit power of users, they proposed an interference hypergraph-based resource allocation scheme and use the cluster coloring algorithm to solve the resource management problem of this scheme. To further improve the system performance, the approach of joint power control and channel allocation can be taken into account. Considering the maximum power consumption and maximum data transmission delay, Zheng *et al.* [11] studied how to maximize the energy efficiency of V2X communication by using the method of joint power control and resource allocation. Sun *et al.* [12] analyzed the latency and reliability requirements of vehicular links and proposed a separate resource block and power allocation algorithm for the communication scenario of one-to-one matching between vehicular user equipments (VUEs) and CUEs. Yang *et al.* [13] proposed a transfer actor–critic learning method to implement the intelligent resource management for D2D-enabled V2X communication such that the overall throughput of V2I links is maximized. Unlike the aforementioned work wherein only the scheduled resource allocation mode is taken into consideration, our previous work [14] takes into account both scheduled resource allocation mode and autonomous resource selection mode and addresses the problem of how to optimize resource allocation between these two modes for safety-related V2X communication.

The previous works discussed so far focus on V2X communication with perfect CSI. However, in the practical scenario, V2X communication is characterized by the high mobility of vehicles, which introduces the Doppler effect into the small-scale fading. Accordingly, the channel state varies fast and the accurate CSI is difficult to be obtained, especially for the links which are not connected to the eNB. Obviously, the high mobility of vehicles poses a challenge to V2X communication. Generally, for the low-speed D2D communication case, the Doppler effect is not noticeable, thereby being ignored. However, for the high-speed V2X communication, the generated Doppler effect has a significant influence on the small-scale fading of CSI and thereby causes the fast channel variations. In contrast, the large-scale fading of CSI is approximately constant in each transmission time interval (TTI). By taking this factor into consideration, some work only takes into account the large scale at eNB to simplify the system model [12], [14], [15]. Some research study the resource allocation problem under the statistical CSI [16]–[20]. However, the aforementioned works are not directly applicable in the context of V2X networks, since they do not take into consideration the main factor—the Doppler effect.

To make the scenario of V2X communication more accurate and practical, it is necessary to take into consideration the Doppler effect for the channel modeling of D2D-based V2X communication. This motivates us to investigate the resource allocation problem of D2D-based V2X communication on the imperfect CSI to track the fast variations of channel state caused by the Doppler effect. Even though Liang *et al.* [16] have investigated ways to improve the system throughput by joint spectrum and power allocation under the delayed CSI feedback and Doppler effect, the focus was solely on the communication scenario wherein the spectrum resource of each CUE can be reused by one VUE at most and each VUE can only be allowed to share one CUE's resource. Accordingly, the improvement in the system performance of V2X networks is limited in the model of [16].

Considering that VUEs and CUEs are two-sided disjoint sets, the resource allocation problem under imperfect CSI of the proposed scheme can be perfectly cast to the matching problem. By using the matching theory [21], not only can the overall system performance be improved but also the system stability can be guaranteed. In the recent past, the matching theory has been widely applied to solve diverse wireless resource allocation problems. Based on different co-channel interference scenarios, the matching relationship between VUEs and CUEs can be generally classified into three different groups.

1) *One-to-One Matching:* Under this scheme, the resource of each CUE is only reused by one VUE and each VUE is allowed to get access to one CUE's resource at most. In this case, each VUE is interfered by only one CUE and each CUE receives the interference signal from one VUE at most. This matching scheme has been widely studied [11]–[14], [21].
2) *One-to-Many Matching [22]:* In this article, we consider this scheme as the scenario where each VUE can get access to multiple CUEs' resources while each CUE allows only one VUE to share its resource. The interference scenario of this scheme is the same as the one-to-one matching scheme.
3) *Many-to-Many Matching [23]:* Under this scheme, the resource of each CUE can be shared with multiple VUEs while each VUE can reuse multiple CUEs' resources. In this case, each user including both CUEs and VUEs get interference signals from multiple other users, which results in the severe co-channel interference to both cellular and vehicular links.

Although the many-to-many matching scheme can enhance the system performance significantly by using proper power control and resource allocation methods, this scheme introduces severe co-channel interference to both cellular and vehicular links. However, as the primary user in the cellular network, CUEs must be shielded from the co-channel interference. If the resource of each CUE is shared with multiple VUEs as mentioned in the works of [10], [15], and [18]–[20], the welfare of CUEs will be degraded. Furthermore, the complex interference circumstance of the many-to-many matching scheme also leads to high computational complexity. In contrast, the one-to-one matching scheme can guarantee the Quality of Service (QoS) of both CUEs and VUEs with low complexity, but the enhancement of the overall system performance is limited under this scheme. To make a tradeoff between one-to-one and many-to-many matching schemes, in this article, we investigate the resource allocation problem of D2D-based V2X communication under the one-to-many matching scheme, in which each VUE can get access to multiple CUEs' resources while each CUE only allows one VUE to share its resource. This one-to-many scheme not just can improve the sum ergodic capacity of VUEs but also can guarantee the QoS of both CUEs and VUEs.

C. Contributions and Paper Organization

In this article, we investigate the joint power control and resource allocation problem for D2D-based V2X communication with imperfect CSI. The major contributions of this article are summarized as follows.

1) We base the resource allocation of D2D-based V2X communication on imperfect CSI, where the large-scale fading is given at eNB, but, the small-scale fading is estimated with an estimation error at eNB. We aim at maximizing the sum ergodic capacity of all VUEs under minimum signal-to-interference-plus-noise-ratio (SINR) requirements of CUEs and the reliability of vehicular links is guaranteed by maintaining the outage probability of received SINR below a small threshold. To improve the system performance of VUEs while guaranteeing the QoS of both CUEs and VUEs, we formulate the resource allocation optimization problem for a one-to-many matching D2D-based V2X communication scenario, where each VUE can share resources with multiple CUEs but each CUE only allows one VUE at most to reuse its resource.
2) We propose an approach of joint power control and resource allocation with low computational complexity to solve this optimization problem. In particular, we first derive the exact expression for the ergodic capacity of a single VUE over the imperfect CSI and use the heuristic simulated annealing (SA) algorithm to obtain an acceptable good power allocation result. However, due to the high iteration times, the SA algorithm is time consuming. To further reduce computing time and computational complexity, we then derive an approximate closed-form expression of the ergodic capacity by Jensen's inequality.
3) We propose a simple and efficient lower bound-based power control approach which can obtain the closed-form optimal power allocation result for the simplified approximate expression with low computational complexity. Based on these optimal power allocation results, the original optimization problem can be further altered to a one-to-many matching spectrum resource allocation problem. We then propose an enhanced Gale–Shapley (GS) algorithm to solve this problem, which is used to cater for the scenario where the maximum number of reuse CUEs for each VUE is limited by its maximum transmit power.

The remainder of this article is organized as follows. Section II illustrates the system model and channel model for the proposed scheme. Section III formulates the optimization problem of the system. Section IV presents the power control problem with imperfect CSI, describes the feasible region of admissible VUEs, and develops the proposed lower bound-based power control method. Section V illustrates the procedure of the proposed resource allocation algorithm. Section VI evaluates the system performance of the proposed algorithm by different numerical simulation results. In Section VII, we present a brief conclusion in which we summarize key contributions of this article.

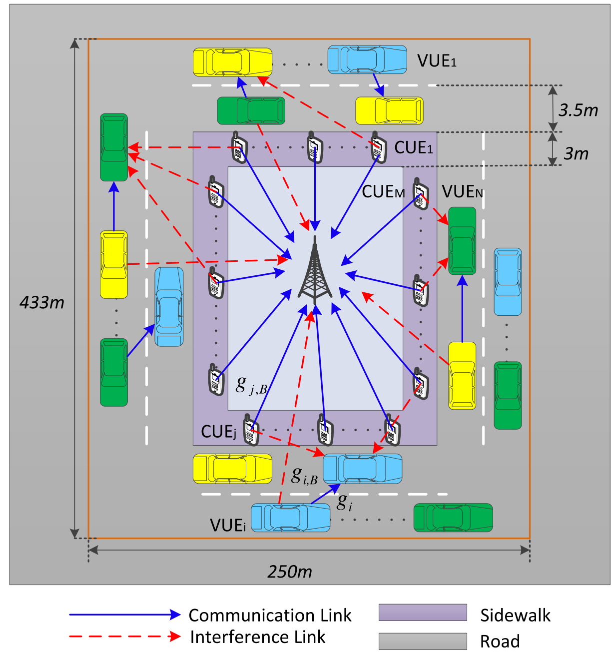


Fig. 1. System model of one-to-many matching V2X communication.

II. System Model

A. System Model of D2D-Based V2X Networks

The details of the proposed system model are shown in Fig. 1, where a multiuser OFDMA D2D-based V2X communication network is considered. In this system, all communication links are served by an eNB within its coverage area and VUEs have to reuse resources of CUEs due to the paucity of network resources. To effectively improve the data rates of VUEs, in this system model, for each VUE pair, V2X communication can be realized by reusing spectrum resources of multiple CUEs, such that the data rates of VUEs can reach as high as possible under the restriction of the maximum transmit power. Furthermore, in order to guarantee the QoS of CUEs, we assume that the resources allocated to CUEs are orthogonal from one to another and each CUE only allows one VUE at most to share its resource. Since the co-channel interference issues of uplink resources are better tackled than that of downlink one [12], we only consider the scenario where only the uplink cellular resources can be reused by VUEs.

The road configuration for D2D-based V2X communication is defined as an urban setting [2], where a single road grid with its center being eNB is considered. The total size of the road grid is 433 m × 250 m. The lane width is 3.5 m and the sidewalk width is 3 m. There are M traditional CUEs distributed uniformly in the cell and N VUE transmitters (VUTs) dropped at different points on lanes uniformly. The sets of CUEs and VUEs are defined as $\mathcal{C} = \{\mathrm{CUE}_1, \mathrm{CUE}_2, \ldots, \mathrm{CUE}_M\}$ and $\mathcal{V} = \{\mathrm{VUE}_1, \mathrm{VUE}_2, \ldots, \mathrm{VUE}_N\}$, respectively. We further assume that the speeds of all vehicles remain the same in all lanes. Since D2D-based V2X communication is proximity-based service, the clustered distribution model [14] is considered for each VUE pair to guarantee the reliable connection between VUT and VUE receiver (VUR). In this clustered model, VUR is distributed uniformly in a circle with the center of its corresponding VUT. To avoid the relative mobility between VUT and its VUR, we further assume that the movement direction and the vehicle speed are the same for each VUT and its VUR.

B. Channel Model

We assume that both cellular and vehicular links are independent block-fading channels, which imply the CSI can be approximately constant in each TTI [24]. Furthermore, to make the channel model more realistic, both large-scale fading and small-scale fading are taken into account in the proposed scheme. In this article, large-scale fading is caused by two major factors: 1) path loss and 2) shadow fading while the small-scale fading is introduced by the effect of multipath propagation. For example, g_i is defined as the channel gain between VUT i and its corresponding receiver, which can be expressed as [16]

$$g_i = |h_i|^2 L_i \tag{1}$$

where $L_i = G\zeta_i d_i^{-\alpha}$ represents the large-scale fading channel gain of VUE i, G is defined as the path loss constant, ζ_i is defined as the shadow fading gain with a log-normal distribution, α is defined as the path-loss exponent, d_i is defined as the distance from VUT i to its receiver, and h_i represents the small-scale fading effect. Similarly, the expressions of the interference channel gain from VUT i to eNB $g_{i,B}$, the channel gain between CUE j and eNB $g_{j,B}$, and the interference channel gain from CUE j to VUE i $g_{i,j}$ can be obtained.

Since the large-scale fading effect can be approximately considered constant in each TTI, we assume that the information of large-scale fading of all communication links can be perfectly obtained at eNB. However, with respect to the small-scale fading, for different communication situations, we have different assumptions. Considering the links $g_{j,B}$ and $g_{i,B}$ connected to the eNB directly as shown in Fig. 1, we assume that the information of the small-scale fading of these two links can be accurately obtained at eNB. Furthermore, we also assume eNB can obtain the perfect knowledge of g_i of VUE pair i. There are two main reasons for this assumption. One is that there is no relative movement between VUT and its corresponding receiver, which means the Doppler effect can be ignored for this case. The other is that the channel information of each VUE pair is already reported to eNB in the process of the D2D discovery stage before D2D communication was established [25]. We further assume that the perfect small-scale fading information h for the aforementioned situations is independent and identically distributed (i.i.d) according to $\mathcal{CN}(0, 1)$.

With respect to the interference link $g_{i,j}$ from CUE transmitter j to VUR i, which is given as

$$g_{i,j} = \left|h_{i,j}\right|^2 L_{i,j}. \tag{2}$$

Different from the traditional D2D communication, where the knowledge of $g_{i,j}$ can be perfectly obtained at eNB, for V2X communication, the fast relative movement between CUE transmitter j and VUR i leads to an imperfect CSI of $g_{i,j}$. In particular, eNB can only achieve the accurate knowledge of large-scale fading $L_{i,j}$ of vehicular links while the small-scale fading $h_{i,j}$ is greatly influenced by the Doppler shift caused by the high mobility of vehicles. Furthermore, $g_{i,j}$ is reported to eNB periodically with a feedback latency T. In this case, as described in Lemma 1 of the work in [26], eNB is only able to achieve an estimated channel gain $\tilde{h}_{i,j}$ of the small-scale fading and the distribution of estimation error $e_{i,j}$. Therefore, we model the small-scale fading channel estimation of $h_{i,j}$ by using the first-order Gauss–Markov process [27] in each TTI as follows:

$$h_{i,j} = \epsilon\tilde{h}_{i,j} + \sqrt{1-\epsilon^2}e_{i,j} \tag{3}$$

we assume that the estimated channel gain $\tilde{h}_{i,j}$ is i.i.d and subject to $\mathcal{CN}(0, 1)$ such that $|\tilde{h}_{i,j}|^2$ has the exponential distibution with unit mean. Furthermore, $e_{i,j}$ is also i.i.d as $\mathcal{CN}(0, 1)$ and independent and uncorrelated of $\tilde{h}_{i,j}$. The coefficient ϵ $(0 < \epsilon < 1)$ quantifies the channel correlation between the two consecutive time slots and we assume that time correlation coefficient ϵ is same for all VUEs. According to the Jakes statistical model for the fading channel [28], ϵ is given as

$$\epsilon = J_0(2\pi f_D T) \tag{4}$$

where J_0 is the zero-order Bessel function of the first kind. $f_D = vf_c/c$ is the maximum Doppler frequency, where v indicates the vehicle speed, f_c indicates the carrier frequency, and $c = 3\times10^8$ m/s. T is a period feedback latency. Generally, both transmitter and receiver can know the accurate ϵ.

Based on the aforementioned discussion, when VUE i share the same resource with CUE j, considering the co-channel interference, the received signal by VUR i is given as follows:

$$y_{i,j} = \sqrt{p_{i,j}^V L_i}h_i s_i + \sqrt{p^C L_{i,j}}h_{i,j}s_{i,j}^C + n \tag{5}$$

the corresponding SINR $\xi_{i,j}^V$ of VUE i is expressed as

$$\begin{aligned}\xi_{i,j}^V &= \frac{p_{i,j}^V g_i}{p_{i,j}^C g_{i,j} + \sigma^2}\\ &= \frac{p_{i,j}^V g_i}{p_{i,j}^C L_{i,j}\left(\epsilon^2\left|\tilde{h}_{i,j}\right|^2 + \left(1-\epsilon^2\right)\left|e_{i,j}\right|^2\right) + \sigma^2}\end{aligned} \tag{6}$$

and the SINR of reuse CUE j is given as

$$\xi_{i,j}^C = \frac{p^C g_{j,B}}{p_{i,j}^V g_{i,B} + \sigma^2} \tag{7}$$

where $y_{i,j}$ is the received signal at VUE i which shares resource with CUE j. s_i is the transmitted signal from VUT i. $s_{i,j}^C$ is the transmitted interference signal from CUE j to VUR i. We further assume that $E[|s_{i,j}^C|^2] = 1$ [28]. $p_{i,j}^V$ is the transmit power of VUE i. p^C is the transmit power of CUE j. n is the Guassian noise with zero mean and variance σ^2, i.e., $n \sim \mathcal{CN}(0, \sigma^2)$, where σ^2 is the noise power spectral density [28].

III. Problem Formulation

Our objective is to maximize the sum ergodic capacity of all VUEs under imperfect CSI while guaranteeing the QoS of both CUEs and VUEs. To make a significant improvement in the sum ergodic capacity of all VUEs, the proposed scheme is designed for the scenario where each VUE can reuse spectrum resources of multiple CUEs and the number of reuse CUEs of each VUE is restricted by its maximum transmit power. Furthermore, to shield CUEs from the severe co-channel interference and guarantee the SINR requirements of CUEs, in the proposed scheme, each CUE only allows one VUE to share its resource and the transmit power of CUEs is fixed with their maximum transmit power, i.e., $p^C = P^C_{\max}$. The mathematical formula of the resource allocation problem for the proposed D2D-based V2X communication scheme is given as

$$\left(\mathbf{x}^*, \mathbf{p}^{\mathbf{V}^*}\right) = \underset{\mathbf{x},\mathbf{p}}{\operatorname{argmax}} \sum_{i=1}^{N}\sum_{j=1}^{M} x_{i,j} E\left[\log_2\left(1+\xi^V_{i,j}\right)\right] \tag{8}$$

$$\text{subject to} \sum_{i=1}^{N} x_{i,j} \le 1, x_{i,j} \in \{0,1\} \quad \forall j \tag{8a}$$

$$\sum_{j=1}^{M} x_{i,j} p^V_{i,j} \le P^V_{\max} \quad \forall i \tag{8b}$$

$$\Pr\left\{\xi^V_{i,j} \le \xi^V_{\min}\right\} \le p_0 \quad \forall i \tag{8c}$$

$$\xi^C_{i,j} \ge \xi^C_{\min} \quad \forall j \tag{8d}$$

where $\mathbf{x}$ is defined as an $N \times M$ channel allocation matrix for D2D-based V2X communication. If VUE i reuse the resource of CUE j, $x_{i,j} = 1$; otherwise, $x_{i,j} = 0$. $\mathbf{p}^{\mathbf{V}}$ is the transmit power matrix of VUEs. $P^V_{\max}$ is the maximum transmit power of VUEs. $\xi^C_{\min}$ and $\xi^V_{\min}$ are the minimum SINR thresholds of CUEs and VUEs, respectively. $\Pr\{\cdot\}$ defines the probability of the input and p_0 defines the acceptable outage probability.

Constraint (8a) restricts that each CUE's resource can only be shared with one VUE at most. Constraint (8b) indicates that each VUE can reuse multiple CUEs' resources, but the sum of the transmit power of each VUE is limited to its maximum transmit power. Constraints (8c) and (8d) are used to guarantee the QoS requirements of VUEs and CUEs, respectively. As shown in (2)–(4), due to the fast channel variations caused by the Doppler effect, the CSI of the interference link $g_{i,j}$ of VUEs is imperfect. Accordingly, we can only obtain a statistical SINR of VUEs shown in (6). In this case, we introduce the outage probability constraint (8c) to guarantee the reliability of vehicular links. In contrast, since $g_{i,B}$ and $g_{j,B}$ of CUEs in (7) can be perfectly obtained at eNB, we use a minimum SINR threshold $\xi^C_{\min}$ to guarantee the QoS of cellular links.

The original problem in (8) is a mixed-integer nonlinear program (MINLP) problem for which an optimal solution is hard to obtain. Therefore, we divide this problem into two subproblems: 1) the power control problem and 2) one-to-many matching channel allocation problem. We first derive the exact expression for the ergodic capacity of a single VUE over the imperfect CSI. To reduce the complexity, we then derive an approximate closed-form expression of the ergodic capacity by Jensen's inequality and propose a simple and efficient lower bound-based power control approach to obtain closed-form optimal power allocation results. Based on these power allocation results, we then proposed an enhanced GS algorithm to solve the one-to-many matching channel allocation problem of the proposed scheme where the maximum number of CUEs which can be reused by each VUE is determined by VUE's maximum transmit power.

IV. Power Control With Imperfect CSI

In this section, we will discuss how to find the optimal transmit power of a single VUE and its reuse CUE to maximize the VUE's achievable data rate under imperfect CSI. In particular, we first derive the exact expression for the ergodic capacity of a single VUE over the imperfect CSI. Based on this expression, we then use the heuristic SA algorithm to obtain an acceptably good power allocation result. However, due to the high iteration times, the SA heuristic algorithm is time consuming. To further reduce computing time and complexity, we then propose an approximate closed-form expression of the ergodic capacity with low computational complexity by Jensen's inequality.

When VUE pair i shares the resource with CUE j, VUT i introduces the interference signal to eNB while CUE j sends the interference signal to VUR with imperfect CSI. In this case, we use the constraints of the minimum SINR threshold and outage probability to guarantee the QoS of CUEs and VUEs, respectively. The optimization problem of the ergodic capacity of a single VUE can be formulated as follows:

$$p^{V*}_{i,j} = \underset{p^V_{i,j}}{\operatorname{argmax}} \left\{E\left\{\log_2\left(1+\frac{B_1}{B_2+B_3X}\right)\right\}\right\} \tag{9}$$

$$\text{subject to} \quad 0 \le p^V_{i,j} \le P^V_{\max} \quad \forall i \tag{9a}$$

$$\Pr\left\{\xi^V_{i,j} \le \xi^V_{\min}\right\} \le p_0 \quad \forall i \tag{9b}$$

$$\xi^C_{i,j} = \frac{p^C g_{j,B}}{p^V_{i,j} g_{i,B} + \sigma^2} \ge \xi^C_{\min} \quad \forall j \tag{9c}$$

where $B_1 = p^V_{i,j} g_i$, $B_2 = p^C_{i,j} L_{i,j} \epsilon^2 |\tilde{h}_{i,j}|^2 + \sigma^2$, and $B_3 = p^C_{i,j} L_{i,j}(1-\epsilon^2)$. $X = |e_{i,j}|^2$ is an exponential random variable with unit mean, i.e., $X \sim \exp(1)$.

A. Feasible Region for Admissible VUEs

According to constraints (9a)–(9c), the feasible region $\mathcal{F}^V_{i,j}$ of (9) can be decomposed into two cases shown as follows. The proof of the feasible region can be found in Appendix B.

Case 1: If $P_2 \le P^V_{\max}$, the feasible region of (9) is given as

$$\mathcal{F}^V_{\text{case1}} = \left\{p^V_{i,j} \in \mathcal{F}^V_{i,j} : P_1 \le p^V_{i,j} \le P_2\right\} \tag{10}$$

Case 2: If $P^V_{\max} \le P_2$, the feasible region of (9) is derived as

$$\mathcal{F}^V_{\text{case2}} = \left\{p^V_{i,j} \in \mathcal{F}^V_{i,j} : P_1 \le p^V_{i,j} \le P^V_{\max}\right\} \tag{11}$$

where

$$P_1 = \frac{(B_2 - B_3 \ln p_0)\xi^V_{\min}}{g_i} \tag{12}$$

$$P_2 = \frac{p^C g_{j,B} - \xi_{\min}^C \sigma^2}{g_{i,B}}. \quad (13)$$

B. SA-Based Power Control

To solve the optimization problem in (9), it is necessary to derive an exact expression for the ergodic capacity of VUE i and find the optimal power allocation solution in its feasible region. Due to the imperfect CSI of the interference link $g_{i,j}$ from CUE j to VUR i, we first start by deriving the exact expression of the ergodic capacity shown in (9). Based on Lemma 2 proved in [29], we can obtain the following lemma.

Lemma 1: For $X \sim \exp(\alpha)$ it holds that

$$E[\ln(1 + PX)] = \phi(P\alpha) \quad (14)$$

where $\phi(x) = e^{1/x}E_1(1/x)$, $E_1(x) = \int_x^\infty (1/t)e^{-t}dt$, $x > 0$.

As explained in Appendix A, when VUE i reuses the resource of CUE j, the exact expression for the ergodic capacity of VUE i can be calculated as the following equation:

$$E\left\{\log_2\left(1 + \frac{B_1}{B_2 + B_3X}\right)\right\} = \log 2\left(1 + \frac{B_1}{B_2}\right) + \frac{\phi\left(\frac{B_3}{B_1+B_2}\right)}{\ln 2} - \frac{\phi\left(\frac{B_3}{B_2}\right)}{\ln 2}. \quad (15)$$

By substituting (15) in (9), we find that (9) is hard to solve because it is a nonlinear optimization problem and involved with exponential integral functions which is not closed form. Furthermore, due to the randomness of UEs locations, it is difficult to certify whether (15) is convex with variable $p_{i,j}^V$ in the feasible region. Hence, the optimal transmit power of VUEs cannot be obtained directly.

The heuristic SA algorithm proposed by Kirkpatrick *et al.* [30] can obtain an acceptable good solution to the nonlinear bound-constrained optimization problem. This method uses a probabilistic technique to approximate the global optimum of a given objective function which may have several local minima [31]. It works by modeling the physical process of heating metal until it melts and then cooling it slowly to form a crystallization with minimal energy. Therefore, the SA algorithm can be used to obtain an acceptable optimum of (9). Algorithm 1 gives a brief description of the outer cooling loop and SA-based power control method. The procedure of the basic SA algorithm can be depicted as iterative and evolutionary and includes two loops: 1) an outer cooling loop and 2) a nested inner thermal equilibrium loop. The outer cooling loop cools the temperature down until the minimum temperature is reached and the search is stopped. With a given temperature, the inner thermal equilibrium loop stops when it achieves thermal equilibrium, which implies either the threshold of the maximum number of iterations possible is reached or an acceptable optimal solution has been found.

As shown in Algorithm 1, we find that the convergence of the SA algorithm is determined by the following critical parameters. For the outer loop, there are the initial temperature $\text{Temp}_{\max}$, the final freezing temperature $\text{Temp}_{\min}$, and the cooling ratio η. For the inner loop, there is the maximum number of iteration length L for each given temperature [32]. If we assume that the final freezing temperature $\text{Temp}_{\min} = 1$, we can obtain the computational complexity of the outer loop is $O(\log(\text{Temp}_{\max}))$ [33]. Furthermore, for each given temperature, the inner loop is executed $O(L)$. Therefore, the computational complexity of SA is $O(L \times \log(\text{Temp}_{\max}))$.

Algorithm 1 SA-Based Power Control

Set $Temp_{\max}$ as the initial temperature, $Temp_{\min}$ final freezing temperature, $Temp$ the current temperature and η the cooling ratio, $0 < \eta < 1$;
For the thermal equilibrium loop, set L as the maximum number of iterations and μ and $\mu_{\max}$ as the positive integers;
Based on the feasible region of shown in the Section IV-A, generate a random p_0^V as an initial solution $p_{i,j}^V$ of equation (15);
Set $Temp = Temp_{\max}$, $p_{i,j}^V = p_0^V$ and $\mu = 0$;
while $Temp > Temp_{\min}$ **do**
  for $i = 1 : L$ **do**
    Substitute $p_{i,j}^V$ into equation (15), calculate its corresponding ergodic capacity r_{old};
    Generate a random neighbouring solution p^V by making a small perturbation to $p_{i,j}^V$, and compute the new solution's ergodic capacity r_{new};
    Compare the new solution's ergodic capacity (r_{new}) with the old one (r_{old}):
    if $r_{\text{new}} > r_{\text{old}}$ **then**
      Accept the new solution;
      Set $p_{i,j}^V = p^V$, $\mu = 0$;
    else if $r_{\text{new}} < r_{\text{old}}$ **then**
      Accept the new solution with a certain probability, which helps the algorithm to explore more possible global solutions instead of being trapped in local maxima;
      Set $p_{i,j}^V = p^V$, $\mu = \mu + 1$;
    end if
    if $\mu > \mu_{\max}$ **then**
      Set the optimal transmit power $p_{i,j}^{V*} = p_{i,j}^V$;
      A near-optimal solution is found. Stop the thermal equilibrium loop;
    end if
  end for
  The algorithm systematically lowers the temperature by setting $Temp = \eta Temp$;
end while
Obtain $p_{i,j}^{V*}$.

C. Lower Bound-Based Power Control

Apparently, the globally optimal solution cannot be guaranteed by the SA algorithm. Besides, the performance of the SA algorithm depends on the initial parameters of both outer and inner loops. Furthermore, directly finding an acceptably good solution to (9) by the SA heuristic algorithm is time consuming when the time of the iteration is high and the number of users is large. Therefore, it is necessary to develop an alternative algorithm with lower complexity and higher reliability.

Considering that the exact expression shown in (15) for the ergodic capacity of a single VUE contains the exponential integral function, to make (15) tractable, in this section, we consider an approximate closed-form expression of the achievable capacity to simplify (15) such that the computational complexity can be reduced. Notice that the ergodic capacity in (15) is convex with X, which is proved as follows. Similar to [34] and [35], we can derive an approximate closed-form expression of the ergodic capacity by Jensen's inequality.

Lemma 2: Closed-form expression (lower bound) of the ergodic capacity in (15) is expressed as

$$E\left\{\log_2\left(1+\frac{B_1}{B_2+B_3X}\right)\right\} \geq \log_2\left(1+\frac{B_1}{B_2+B_3E[X]}\right) = \log_2\left(1+\frac{B_1}{B_2+B_3}\right). \quad (16)$$

Proof:

$$f(X)=\log_2\left(1+\frac{B_1}{B_2+B_3X}\right). \quad (17)$$

By differentiating $f(X)$ with respect to X, we have its corresponding second derivative

$$\frac{\partial^2 f}{\partial X^2}=\frac{B_1B_3^2(B_1+2(B_2+B_3X))}{(B_2+B_3X)^2(B_1+B_2+B_3X)^2\ln 2}>0. \quad (18)$$

As shown in (18), the value of the second derivative is larger than 0. Therefore, we can conclude that $f(X)$ is convex with X. The proof is concluded. ∎

Obviously, the lower bound function (16) is much simpler than the original optimization function (15). To obtain a low-complexity power allocation method, we then focus on maximizing the lower bound function of the ergodic capacity to obtain the optimal power allocation

$$p_{i,j}^{V*}=\underset{p_{i,j}^V}{\operatorname{argmax}}\left\{\log_2\left(1+\frac{p_{i,j}^V g_i}{B_2+B_3}\right)\right\}. \quad (19)$$

Since the logarithm function shown in (19) monotonically increases with respect to $p_{i,j}^V$, the maximum value of the objective function of (19) can be reached at maximum $p_{i,j}^{V*}$ based on the feasible region of (10) and (11), which is shown as

$$p_{i,j}^{V*}=\begin{cases}P_2, & \text{if } P_2<P_{\max}^V\\ P_{\max}^V, & \text{if } P_2\geq P_{\max}^V.\end{cases} \quad (20)$$

The computational complexity of the proposed lower bound method is $O(1)$, which reduces the system computational complexity significantly when compared to the SA algorithm.

V. Proposed Resource Allocation Algorithm

By leveraging the lower bound-based power control method proposed in Section IV, we can evaluate the closed-form optimal power allocation result for all possible combinations of VUEs and CUEs. By substituting these power allocation results into the original optimization problem (8), the resource allocation problem can be simplified into a spectrum resource allocation problem which is a 0-1 integer programming problem with only one variable $\mathbf{x}$

$$\mathbf{x}^*=\underset{\mathbf{x}}{\operatorname{argmax}}\left\{\sum_{i=1}^{N}\sum_{j=1}^{M}x_{i,j}\log_2\left(1+\frac{p_{i,j}^{V*}g_i}{B_2+B_3}\right)\right\} \quad (21)$$

$$\text{subject to } \sum_{i=1}^{N}x_{i,j}\leq 1,\ x_{i,j}\in\{0,1\}\quad \forall j \quad (21a)$$

$$\sum_{j=1}^{M}x_{i,j}p_{i,j}^V\leq P_{\max}^V\quad \forall i. \quad (21b)$$

In this article, we assume that each VUE pair can reuse resources of multiple CUEs such that the data rate of each VUE can reach as high as possible under its maximum transmit power constraint. Furthermore, to guarantee the QoS of CUEs, we assume that each CUE's resource can be shared with one VUE at most. Considering VUEs and CUEs as two disjoint sets, the spectrum resource allocation problem in (21) can be regarded as a one-to-many two-sided matching problem.

A. One-to-Many Two-Sided Matching Algorithm Design

The college admissions problem is a one-to-many matching problem, in which a number of students apply to a number of colleges and one college can recruit a fixed number of students with a certain quota while one student can be admitted by only one college. How to design a one-to-many matching mechanism to maximize the welfare of both students and colleges is a very challenging task. Gale and Shapley [36] have already designed a stable one-to-many matching mechanism by which both students and colleges get matched in such a way that no such pair exists in which a student A of the first matched set which prefers some given college B of another matched set over the college to which A is already matched and *vice versa*. This method is called the GS algorithm. Note that in the proposed scheme, as shown in constraints (21a) and (21b), a VUE can get access to resources of multiple CUEs under its constraint of the maximum transmit power while each CUE's resource can be reused by only one VUE. This is in accordance with a one-to-many matching in the matching theory.

Inspired by the college admission problem, we propose an enhanced GS algorithm which is tailored to the one-to-many matching resource allocation problem of the proposed scheme. Different from the traditional GS algorithm [22] where one college can recruit a fixed number of students with a certain quota, to facilitate the practical application in V2X communication, as shown in constraint (21b), the proposed one-to-many matching algorithm takes into account the maximum transmit power of VUEs to limit the number of CUEs which can be reused by each VUE. For each VUE, the one-to-many matching resource allocation problem with the limitation of its maximum transmit power is formulated as

$$\mathbf{x_i}^*=\underset{\mathbf{x_i}}{\operatorname{argmax}}\left\{\sum_{j=1}^{M}x_{i,j}\log_2\left(1+\frac{p_{i,j}^{V*}g_i}{B_2+B_3}\right)\right\} \quad (22)$$

$$\text{subject to } \sum_{j=1}^{M}x_{i,j}p_{i,j}^V\leq P_{\max}^V\quad \forall i,\ x_{i,j}\in\{0,1\}. \quad (22a)$$

Equation (22) is a 0-1 integer programming problem which can be solved by the well-known branch-and-bound algorithm [37]. By solving the problem in (22), we can obtain the optimal reuse CUEs for each VUE.

B. Utility Matrix and Preference List Establishment

One key advantage of the matching theory is to establish a suitable preference list which can tackle the complex and heterogeneous QoS requirements of matching players in two distinct sets. The goal of the proposed one-to-many matching algorithm is to match CUEs set $\mathcal{C}$ to VUEs set $\mathcal{V}$ such that the sum ergodic capacity of all VUEs can be maximized under the constraint of maximum transmit power of VUEs. Therefore, we define a utility function matrix $\mathcal{U}$ that evaluates the optimal capacity of the approximation expression for all possible combinations of VUEs and CUEs to measure the preference of both VUEs set and CUEs set. Considering that there are N VUEs and M CUEs, the size of the $\mathcal{U}$ is $N \times M$

$$\mathcal{U} = \begin{pmatrix} u_{1,1} & u_{1,2} & \cdots & u_{1,M} \\ u_{2,1} & u_{2,2} & \cdots & u_{2,M} \\ \vdots & \vdots & \ddots & \vdots \\ u_{N,1} & u_{N,2} & \cdots & u_{N,M} \end{pmatrix}. \tag{23}$$

Based on the optimal power allocation results discussed in Section IV-C, we can obtain the utility function $u_{i,j}$: if VUE i is admissible to get access to the resource of CUE j, $u_{i,j}$ can be calculated by (9); otherwise, $u_{i,j} = 0$. The utility function matrix $\mathcal{U}$ provides the preference framework for the two-sided VUEs set and CUEs set. Based on the individual preferences of VUEs and CUEs, the proposed one-to-many algorithm can provide a stable and optimal matching between VUEs and CUEs. The stable matching for the proposed scheme is defined as follows.

Definition 1: A matching is stable if there are no two CUEs j and j' which are reused by VUEs i and i', respectively, such that $u_{i,j'} > u_{i,j}$ and $u_{i,j'} > u_{i',j'}$, which means VUE i prefers CUE j' and CUE j' prefers VUE i.

C. Proposed Resource Allocation Algorithm

The specific details of the proposed algorithm are presented in Algorithm 2, which is illustrated as follows. *Step 1:* Each CUE ranks the VUEs in the descending order of its preference value, ignoring the VUEs which are not admissible. Likewise, each VUE ranks the CUEs in order of its preference eliminating those CUEs which cannot be accessed under the constraints of (9a)–(9c). *Step 2:* Each CUE makes an offer to its highest ranked VUE. *Step 3:* Among the applicants, each VUE picks up the q highest ranked CUEs under its maximum transmit power restriction by using the optimal solution $\mathbf{x_i^*}$ of (22) and put them on the waitlist. The rest of the applicants are rejected. *Step 4:* The rejected CUEs are assigned to their next highest ranked VUEs. *Step 5:* The VUE then reranks CUEs among all applicants and those who are on the waitlist. Repeat steps 3–5 and the procedure will be stopped until all CUEs are either matched to VUEs or have proposed to all VUEs on their preference list.

Algorithm 2 Proposed Resource Allocation Algorithm

```
Define C_UM as the set of unmatched CUEs;
Define Pro_j as the proposition vector of CUE j, where
  if CUE j proposes to VUE i, Pro_{i,j} = 0; otherwise
  Pro_{i,j} = 1;
Calculate the optimal power allocation of VUEs by using
  the lower bound-based power control method discussed in
  Section IV-C;
Establish the preference list of CUEs and VUEs by
  matching matrix U;
while C_UM ≠ ∅ and Pro_j ≠ ∅ do
  Choose any CUE j from C_UM;
  CUE j makes an offer to its highest ranked VUE i;
  Pro_{i,j} = 0;
  Among the applicants, VUE i picks up the q highest
    ranked CUEs under its maximum transmit power
    restriction by using the optimal solution x_i^* of (22) and
    puts them on the waitlist. The rest of the applicants are
    rejected;
  if CUE j is selected by VUE i then
    Remove CUE j from C_UM;
  end if
  for all m ∈ M do
    if VUE i does not chooose CUE m then
      Add CUE m into C_UM;
    end if
  end for
end while
Obtain the optimal one-to-many matching matrix x^*.
```

VI. Performance Analysis

A. Scenarios and Parameters

In this section, we configure an urban road scenario for V2X communication as described in 3GPP TR 36.885 [2], where the path-loss model for VUEs is the WINNER+B1 Manhattan grid layout (note that the antenna height is 1.5 m) and the path-loss model for CUEs is set as the macrocell propagation model of the urban area. Considering the different data traffic requirements of CUEs, in the proposed scheme, the spectrum resources are randomly allocated to CUEs. The major parameters used for the proposed scheme are summarized in Table I [2], [16], [38].

We present the numerical results of different algorithms and parameters to evaluate the system performance of the proposed algorithm in terms of the sum ergodic capacity of all VUEs and the sum ergodic capacity of the overall network which includes all VUEs and CUEs, respectively. Here, the sum ergodic capacity of all VUEs is calculated by the following equation:

$$T_{\mathrm{SUM}}^{V} = \sum_{i=1}^{N}\sum_{j=1}^{M} x_{i,j} E\left[\log_2\left(1 + \xi_{i,j}^{V}\right)\right]. \tag{24}$$

In contrast, the overall network is composed of all VUEs and CUEs. In particular, in the proposed scheme, some CUEs' resources are reused by VUEs while the rest of CUEs work

TABLE I
SIMULATION PARAMETERS

Parameter	Value
Cell radius, R	500 m
VUE pair distrance, r	$20-100$ m
Carrier frequency	2 GHz
Uplink Bandwidth	10 MHz
Noise spectral density	-174 dBm/Hz
Path-loss model for CUEs	$128.1+37.6\log(d[\text{km}])$
Multiple-path fading	Unit mean
Shadowing standard deviation	8 dB (CUEs), 4 dB (VUEs)
SINR threshold of CUEs, ξ^C_{min}	$5-15$ dB
SINR threshold of VUEs, ξ^V_{min}	10 dB
Reliability for VUEs, p_0	10^{-3}
Channel feedback latency, T	0.5 ms
Maximum power of CUEs, P^C_{max}	23 dBm
Maximum power of VUEs, P^V_{max}	19-26 dBm
The number of CUEs, M	5,8
The number of VUEs, N	1-8
The absolute vehicle speed	60km/h

in the vacant resources. In this case, the sum capacity $T^{\text{CR}}_{\text{SUM}}$ of reuse CUEs can be expressed as

$$T^{\text{CR}}_{\text{SUM}}=\sum_{j=1}^{M}\sum_{i=1}^{N}x_{i,j}\log_2\left(1+\frac{P^C_{\max}g_{j,B}}{p^V_{i,j}g_{i,B}+\sigma^2}\right). \tag{25}$$

The sum capacity $T^{\text{CV}}_{\text{SUM}}$ of CUEs working in the vacant resources can be expressed as

$$T^{\text{CV}}_{\text{SUM}}=\sum_{j=1}^{M}\left(1-\sum_{i=1}^{N}x_{i,j}\right)\log_2\left(1+\frac{P^C_{\max}g_{j,B}}{\sigma^2}\right). \tag{26}$$

Based on the above consideration, the sum ergodic capacity T_{SUM} of the overall network is given as

$$T_{\text{SUM}}=T^{V}_{\text{SUM}}+T^{\text{CR}}_{\text{SUM}}+T^{\text{CV}}_{\text{SUM}}. \tag{27}$$

To verify the tightness of the proposed algorithm, we compare the performance of the SA-based one-to-many (SA-O2M) matching algorithm which is expected to achieve an acceptably good solution to the original optimization problem (8), and the proposed algorithm which can be used to obtain a suboptimal system performance. The main difference between the SA-O2M matching algorithm and the proposed algorithm is that to solve the power control problem, SA-O2M adopts the heuristic SA method to obtain an acceptable optimal power allocation to the exact expression of the ergodic capacity of the VUE. In contrast, the proposed algorithm applies the lower bound-based power control method to obtain a closed-form optimal solution to the approximate expression of the ergodic capacity. To further evaluate the performance of the proposed algorithm, we also simulate the numerical results of the one-to-one matching algorithm proposed in [16]. The algorithm proposed in [16] is developed by the joint spectrum and power allocation under the delayed CSI feedback and is designed for the one-to-one matching communication scenario where each CUE's resource can be reused by one VUE at most and each VUE can only be allowed to get access to one CUE's resource.

Since the SA-O2M matching algorithm is time consuming as the number of users increases, for the simulation, both the number of VUEs and CUEs is limited to less than 10. Parameter r is defined as the radius of the D2D-based V2X clustered model, which is equal to the maximum communication distance between VUT and VUR. We further assume the radius r to be the same for all VUE pairs. For each VUE pair, since the VUR is distributed uniformly in the circle, the locations of VURs are different for different VUE pairs and the communication distance for each VUE pair is also different. Therefore, for simulation, we change communication distances for all VUE pairs by changing r.

B. Impact of Different Parameters on the System Performance

Fig. 2 compares the system performance of different algorithms against different distance r. As shown in Fig. 2, as r increases, both the sum ergodic capacity of all VUEs [Fig. 2(a)] and the sum ergodic capacity of the overall network [Fig. 2(b)] decrease gradually. This is because the increase in r introduces a large path loss to the vehicular link which results in the decrease in the capacity of VUEs. Accordingly, the reuse gain introduced by VUEs is also degraded. Hence, the sum capacity of the overall network also decreases with an increase in r.

Fig. 2(a) illustrates the sum ergodic capacity of all VUEs against various r. As shown in the figure, the proposed algorithm achieves the best performance among all three algorithms, which demonstrates that, when compared to the SA-O2M algorithm, the proposed algorithm not only has a lower computational complexity but also performs better. Furthermore, the performance of both the proposed algorithm and SA-O2M algorithm outperforms algorithm in [16] dramatically. The main reason for this is that, by using the proposed algorithm and SA-O2M algorithm, each VUE is able to reuse multiple CUEs' resources which can introduce high reuse gains, especially when the networks have enough available cellular resources. However, the system model in [16] only allows one VUE to share the resource with one CUE at most, which limits the improvement in the sum capacity of all VUEs.

Fig. 2(b) compares the sum ergodic capacity of overall network against various r. From this figure, we can observe that when compared to the pure cellular network, D2D-based V2X communication can enhance the sum ergodic capacity of the overall network dramatically. This demonstrates that by leveraging the proximity service-D2D technology, V2X communication can bring high reuse gains to the conventional cellular network. We can also see that the sum capacity of the overall network is higher than the sum capacity of all VUEs. This is reasonable because the overall network includes not just VUEs but also CUEs. It is also very interesting that when compared to Fig. 2(a), the difference gap between the proposed algorithm and algorithm in [16] is reduced obviously. The main reason for this is that the number of reuse CUEs in the model of [16] is less than that of the proposed scheme. Consequently, the sum capacity of all CUEs in the model

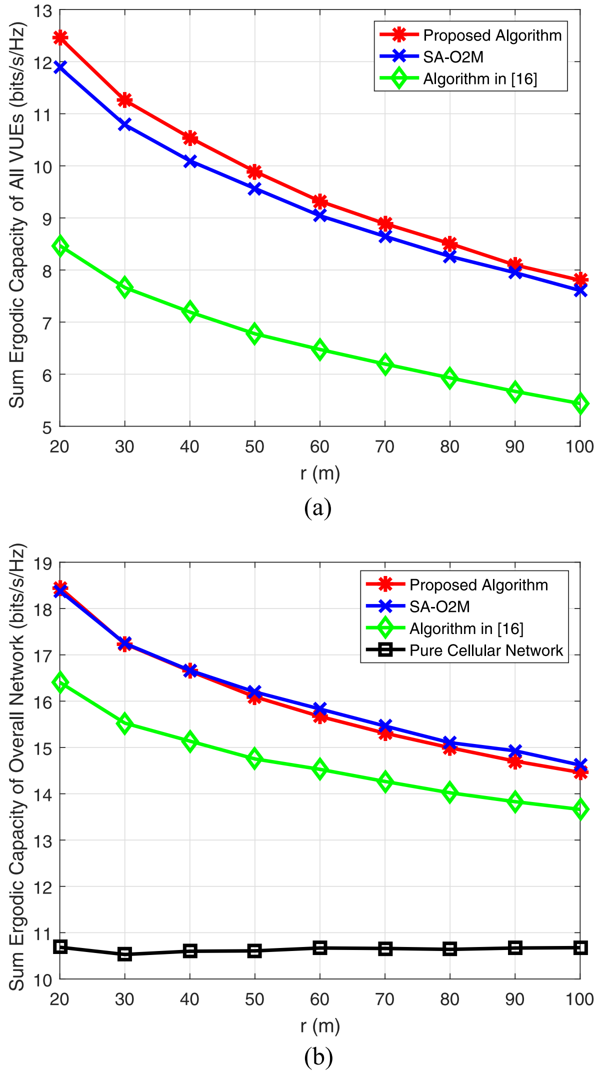


Fig. 2. System performance with different distance r, where $P_{\max}^C = P_{\max}^V =$ 23 dBm, $M = 8$, $N = 4$, and $\xi_{\min}^C = 10$ dB. (a) Sum ergodic capacity of all VUEs against various r. (b) Sum ergodic capacity of overall network against various r.

of [16] is larger than that of the proposed scheme. Hence, the difference gap between the proposed algorithm and algorithm in [16] becomes smaller when compared to Fig. 2(a).

Fig. 3 evaluates the system performance of different algorithms under different communication scenarios where the number of VUE pairs can be any case (less than, equal to, or greater than the number of CUEs). The parameters are set as $P_{\max}^C = P_{\max}^V = 23$ dBm, $M = 5$, $r = 20$ m, $\xi_{\min}^C = 10$ dB. It can be observed that the sum ergodic capacity of the network experiences a noticeable increase with the increase in the number of VUE pairs. As the number of VUE pairs increases, the number of admissible VUEs also increases. Consequently, the sum capacity of the system goes up. We can also see that when the number of VUE pairs is larger than that of CUEs, the gap between all three algorithms becomes small. This is because when the number of VUE pairs is large enough, the paucity of cellular resources makes each VUE can only get access to one CUE's resource such that the sum capacity of all VUEs can be maximized. In this case, all three algorithms perform similar performances.

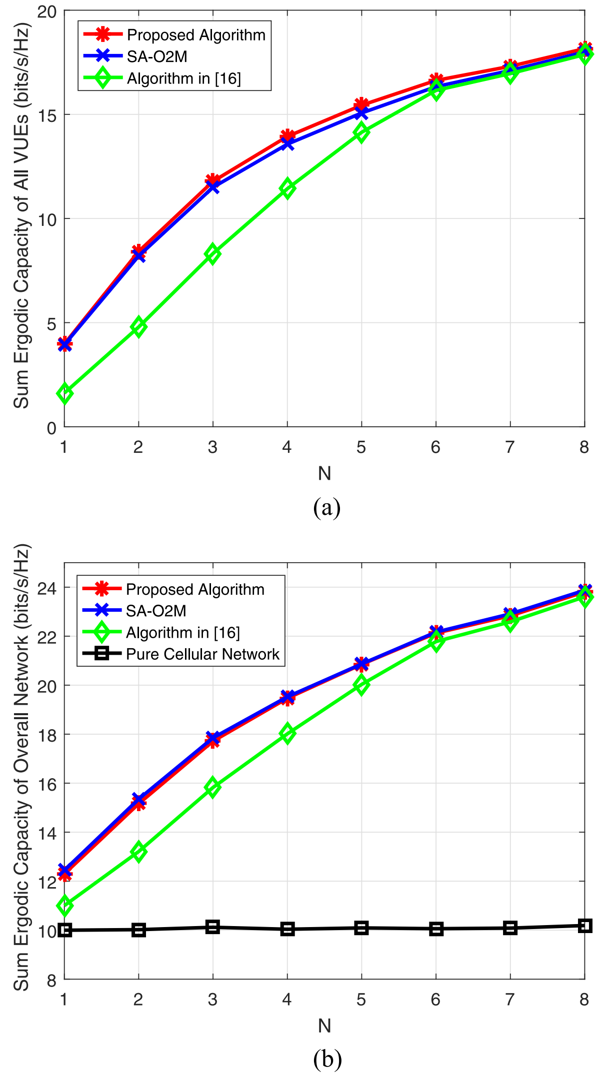
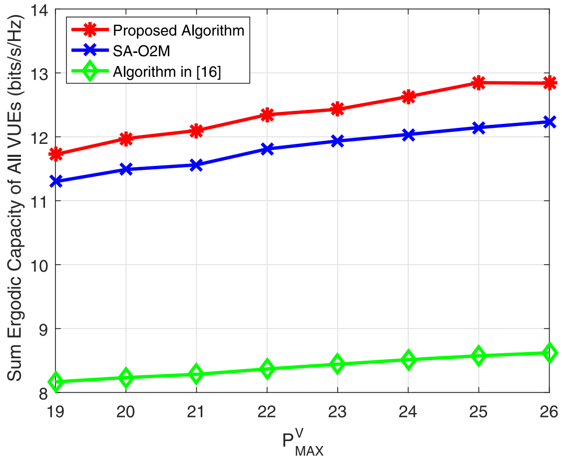


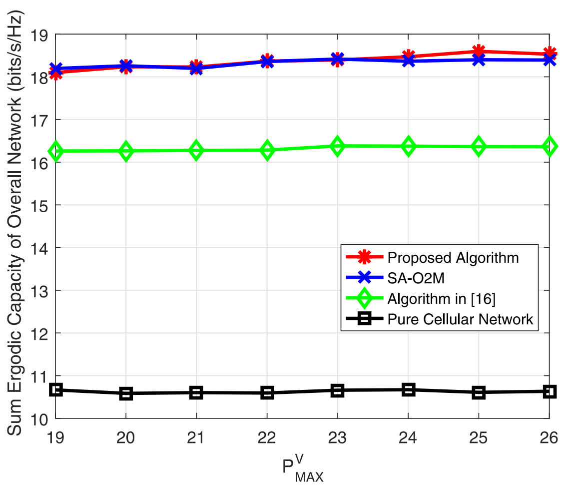
Fig. 3. System performance with different number of VUE pairs N, where $P_{\max}^C = P_{\max}^V = 23$ dBm, $M = 5$, $r = 20$ m, $\xi_{\min}^C = 10$ dB. (a) Sum ergodic capacity of all VUEs versus increasing N. (b) Sum ergodic capacity of overall network versus increasing N.

Fig. 3(a) compares the sum ergodic capacity of all VUEs for different algorithms with the increasing number of VUE pairs N. As observed from the figure, when the number of VUE pair is not greater than 2 and there are enough cellular resources, VUEs have big probabilities to get access to the cellular links with better CSI. In this case, the performance of the proposed algorithm and SA-O2M algorithm is quite similar. As the number of VUE pairs keeps rising, we can further find that the proposed algorithm has a better performance than the other two algorithms. Fig. 3(b) presents the sum ergodic capacity of the overall network for the different number of VUE pairs. As we can see, the sum capacity of the overall network of the proposed algorithm and SA-O2M algorithm is very close and both of their performances are greater than that of Algorithm in [16].

Fig. 4 elaborates the effect of the maximum transmit power of VUEs $P_{\max}^V$ on the system performance by using different algorithms, where $P_{\max}^C = 23$ dBm, $M = 8$, $N = 4$, $r = 20$ m, $\xi_{\min}^C = 10$ dB. From Fig. 4(a), we can observe that the sum ergodic capacity of all VUEs has an obvious increase with

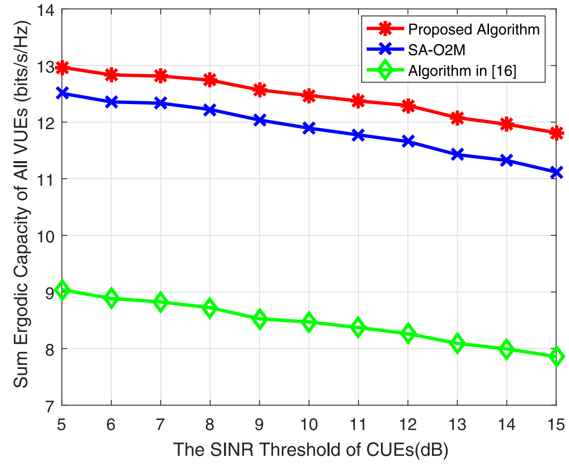


(a)

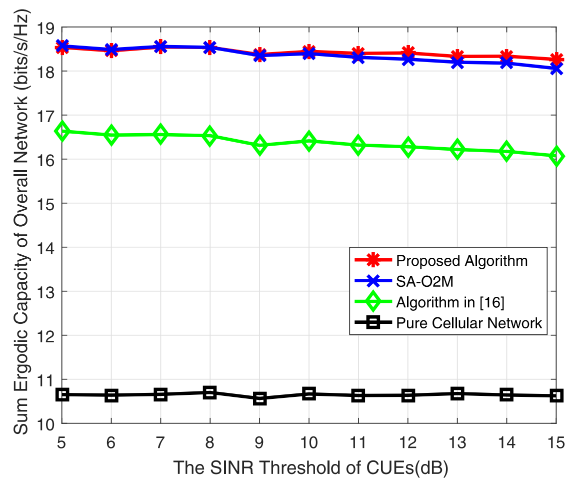


(b)

Fig. 4. System performance with maximum transmit power of VUEs $P^V_{\max}$, where $P^C_{\max} = 23$ dBm, $M = 8$, $N = 4$, $r = 20$ m, $\xi^C_{\min} = 10$ dB. (a) Sum ergodic capacity of all VUEs for different $P^V_{\max}$. (b) Sum ergodic capacity of overall network for different $P^V_{\max}$.



(a)



(b)

Fig. 5. System performance with different SINR threshold of CUEs, $\xi^C_{\min}$, where $P^C_{\max} = P^V_{\max} = 23$ dBm, $M = 8$, $N = 4$, $r = 20$ m. (a) Sum ergodic capacity of all VUEs for different $\xi^C_{\min}$. (b) Sum ergodic capacity of overall network for different $\xi^C_{\min}$.

the increasing $P^V_{\max}$. However, the sum capacity of the overall network experiences a slight increase. This occurs because the high transmit power of VUEs brings high data rates for vehicular links, but it also introduces high co-channel interference to the cellular links, which reduces the capacity of the reuse CUEs. Furthermore, as we can see, when the VUE communication distance is not big, such as $r = 20$ m, and there are adequate available cellular resources for V2X communication, such as $M = 8$ and $N = 4$, the proposed algorithm has an excellent performance which outperforms other two algorithms significantly.

Fig. 5 depicts the performance degradation in the system capacity with the rise in the SINR threshold of CUEs $\xi^C_{\min}$. Fig. 5(a) shows that the increasing $\xi^C_{\min}$ brings about a gradual reduction in the sum ergodic capacity of all VUEs. In general, the low $\xi^C_{\min}$ values indicate that the SINR constraints of CUEs are easily satisfied. In this case, VUEs can get permission to reuse CUEs' resources easily. Accordingly, the number of admissible VUEs is large such that the sum ergodic capacity of VUEs is high. However, the big $\xi^C_{\min}$ values make it difficult for CUEs to satisfy their SINR requirements, which requires VUEs to transmit their data with a very low transmit power. But, this leads to the degradation in the number of admissible VUEs because a lot of VUEs cannot meet their own QoS requirements with the low transmit power. Accordingly, the sum ergodic capacity of VUEs decreases when the SINR threshold of CUEs is high. When compared to Fig. 5(a), Fig. 5(b) presents that the sum ergodic capacity of the overall network is degraded slightly with the increase in $\xi^C_{\min}$. The main reason for this is that, due to the increase in the SINR threshold of CUEs, the number of admissible VUEs decreases leading to the reduction in the number of reuse CUEs. As a result, the sum capacity of all CUEs increases. Furthermore, since the decrease rate of the sum capacity of all VUEs is bigger than the increase rate of the sum capacity of all CUEs in the network, the overall system experiences a slight decrease.

In this article, our goal aims at maximizing the sum ergodic capacity of all VUEs. The proposed algorithm can effectively and efficiently realize our goal when compared to other existing algorithms, which has been demonstrated in Figs. 2(a), 3(a), 4(a), and 5(a). In contrast, from Figs. 2(b), 3(b), 4(b), and 5(b), we can further observe that the proposed algorithm and the SA-O2M algorithm have very close system performance in terms of the sum ergodic capacity of the overall network. The main reason for this is that to improve the performance of VUEs, the cost of the proposed algorithm is to reduce the welfare of CUEs due to the co-channel interference issues. In contrast, since the performance enhancement of VUEs by using the SA-O2M algorithm is not good as that of the proposed algorithm, to some extent, the welfare of CUEs can be guaranteed better by using the SA-O2M algorithm. Furthermore, the sum ergodic capacity of the overall network is influenced by both VUEs and CUEs. Therefore, it is reasonable that the proposed algorithm and the SA-O2M algorithm have similar system performances in terms of the overall network.

VII. Conclusion

In this article, we have studied the joint power control and spectrum resource allocation problem for D2D-based V2X communication with imperfect CSI. To track the fast channel variations of vehicular links incurred due to the high mobility of vehicles, we have considered the Doppler effect into the small-scale fading of vehicular links. Our objective is to maximize the sum ergodic capacity of all VUEs under imperfect CSI while satisfying the QoS requirements of both vehicular and cellular links. We have derived the exact expression for the ergodic capacity of a single VUE over the imperfect CSI and solved its power control problem by using the heuristic SA algorithm. To reduce the computational complexity, we have simplified the exact expression of the ergodic capacity to an approximate closed-form expression based on Jensen's inequality and solved it by the proposed lower bound-based power control approach with low computational complexity. Furthermore, to improve the system performance of VUEs while guaranteeing the QoS of CUEs, in the proposed scheme, each VUE can reuse spectrum resources of multiple CUEs while the resource of each CUE can be shared with one VUE at most. To solve the spectrum resource allocation problem of this scheme, we have proposed an enhanced GS algorithm which is tailored to the scenario where the number of reuse CUEs of each VUE is restricted by its maximum transmit power. Numerical results verify the tightness of the proposed algorithm and demonstrate the validity and effectiveness of the proposed algorithm in terms of the improvement of the system performance of the V2X communication network. In future work, we aim to develop a more complicated resource allocation scheme which includes not just channel resource allocation but also considers time resource allocation.

Appendix A
Ergodic Rate of Single VUE

The ergodic capacity of a single VUE can be expressed as

$$
\begin{aligned}
E\left[\log_2\left(1+\xi_{i,j}^V\right)\right] &= \frac{E\left\{\ln\left(1+\frac{B_1}{B_2+B_3X}\right)\right\}}{\ln 2} \\
&= \frac{E\left\{\ln\left(\frac{B_1+B_2+B_3X}{B_2+B_3X}\right)\right\}}{\ln 2} \\
&= \frac{E\{\ln(B_1+B_2+B_3X)-\ln(B_2+B_3X)\}}{\ln 2} \\
&= \frac{E\left\{\ln\left((B_1+B_2)\left(1+\frac{B_3X}{B_1+B_2}\right)\right)\right\}}{\ln 2} \\
&\quad - \frac{E\left\{\ln\left(B_2\left(1+\frac{B_3X}{B_2}\right)\right)\right\}}{\ln 2} \\
&= \frac{E\left\{\ln\left(\frac{(B_1+B_2)}{B_2}\right)\right\}}{\ln 2} + \frac{E\left\{\ln\left(1+\frac{B_3X}{B_1+B_2}\right)\right\}}{\ln 2} \\
&\quad - \frac{E\left\{\ln\left(1+\frac{B_3X}{B_2}\right)\right\}}{\ln 2}
\end{aligned} \tag{28}
$$

where $X \sim \exp(1)$. Based on Lemma 1, the ergodic capacity of VUE i in (28) is given as

$$
\begin{aligned}
E\left[\log_2\left(1+\xi_{i,j}^V\right)\right] &= \log 2\left(\frac{(B_1+B_2)}{B_2}\right) + \frac{\phi\left(\frac{B_3}{B_1+B_2}\right)}{\ln 2} \\
&\quad - \frac{\phi\left(\frac{B_3}{B_2}\right)}{\ln 2}.
\end{aligned} \tag{29}
$$

Appendix B
Proof of the Feasible Region of (9)

By substituting the PDF of X into the outage probability constraint of (9b), we can get the feasible power region of the outage probability as

$$
\begin{aligned}
\Pr\left\{\xi_{i,j}^V \le \xi_{\min}^V\right\} &= \Pr\left\{\frac{B_1}{B_2+B_3X} \le \xi_{\min}^V\right\} \\
&= 1-\Pr\left\{X \le \frac{B_1-B_2\xi_{\min}^V}{B_3\xi_{\min}^V}\right\} \\
&= 1-\int_0^{\frac{B_1-B_2\xi_{\min}^V}{B_3\xi_{\min}^V}} e^{-x}dx \\
&= \exp\left(-\frac{B_1-B_2\xi_{\min}^V}{B_3\xi_{\min}^V}\right) \le p_0.
\end{aligned} \tag{30}
$$

Then, we have the equivalent result of the inequality function in (30) as

$$
\begin{aligned}
&-\frac{B_1-B_2\xi_{\min}^V}{B_3\xi_{\min}^V} \le \ln p_0 \\
&\qquad \Rightarrow \frac{p_{i,j}^V g_i - B_2\xi_{\min}^V}{B_3\xi_{\min}^V} \ge -\ln p_0 \\
&\qquad \Rightarrow p_{i,j}^V \ge \frac{(B_2-B_3\ln p_0)\xi_{\min}^V}{g_i} = P_1.
\end{aligned} \tag{31}
$$

Furthermore, since $0 \le p_0 \le 1$, we can obtain $\ln p_0 \le 0$ such that $[((B_2-B_3\ln p_0)\xi_{\min}^V)/g_i] > 0$. Hence, by combining constraints (9a) and (9b), we can obtain

$$
\left\{P_1 \le p_{i,j}^V \le P_{\max}^V\right\}. \tag{32}
$$

In order to satisfy the minimum SINR requirement of reuse CUE j, the transmit power of VUE i is also limited by constraint (9c)

$$\frac{p^C g_{j,B}}{p_{i,j}^V g_{i,B} + \sigma^2} \geq \xi_{\min}^C$$

$$\Rightarrow p_{i,j}^V \leq \frac{p^C g_{j,B} - \xi_{\min}^C \sigma^2}{g_{i,B} \xi_{\min}^C} = P_2 \qquad (33)$$

which concludes the proof.

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