Centralized Resource Allocation and Distributed Power Control for NOMA-Integrated NR V2X

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***Abstract*—The application of Non-Orthogonal Multiple Access (NOMA) technology to New Radio (NR) V2X can further reduce communication delay and improve the system capacity of the vehicular network. However, due to the high mobility of the vehicles, it is difficult for the base station to obtain the channel information between vehicles in real-time for resource allocation and vehicle transmission power control. To this end, we propose a two-stage scheme of centralized resource allocation and distributed power control to meet the requirement of the NR V2X Mode 1 while NOMA technology is employed in vehicle groups. Firstly, at the beginning of a transmission period, the base station allocates resources to vehicle groups. For this centralized manner, we propose a graph-based matching approach to allocate resources to improve system capacity. Then, each vehicle group controls and adjusts transmission power for NOMA communication in the period. For this distributed manner, we propose a non-cooperative game to control the power of the vehicle groups and then analyze the performance of the non-cooperative game. Afterward, we further put forward a cooperative game approach to control the power of the vehicle group while increase system capacity. Compared with the non-cooperative game, the proposed scheme can increase communication capacity by up to 5% and reduce transmission power consumption by 36%.**

***Index Terms*—Cooperative game, matching, non-cooperative game, NOMA, NR V2X, power control, resource allocation.**

I. Introduction

The rapid development of Intelligent Transportation Systems (ITS) requires vehicles to communicate with external things, e.g., traffic signals, pedestrians, more and more frequently, which makes vehicular communication technology acting as the mouth and ear of ITS becomes increasingly important [1]. The object of vehicular communication is to enable Vehicles-to-Everything (V2X) including Vehicle-to-Vehicle (V2V), Vehicle-to-Network/Infrastructure (V2N/I), and Vehicle-to-Pedestrian (V2P). Therefore, in order to adapt to the development of vehicular communication, various standardization groups have been working for years on specifications to define all aspects of connected vehicles, e.g., C-V2X supported by 3GPP and DSRC supported by IEEE. However, the existing V2X communication technology can only support safety applications that demand an end-to-end latency of around 100 milliseconds (msec) as long as the vehicular density is not very high [2]. As a consequence, to further satisfy more stringent V2X use-cases, 3GPP develops New Radio (NR) V2X in Release 16.

In Release 16, two sidelink modes are defined, i.e., Mode 1 and Mode 2. In Mode 1, the base station allocates resources to the vehicles in each transmission period within its coverage. Then, the vehicles directly communicate with each other by using the allocated resources. While in Mode 2, the vehicles choose their own resources and communicate with each other in the out-of-coverage scenarios. More advanced than C-V2X, Release 16 introduces feedback channel, unicast, and group-cast communication to enhance communication reliability and diversity [3]. However, in some scenarios that require high throughput and low latency, the NR V2X still confronts huge challenges [4], e.g., a vehicle transmits high-definition video to other vehicles at the same time.

One of the potential solutions is to apply the power domain Non-Orthogonal Multiple Access (NOMA) technology to V2X. This is because by using NOMA, multiple vehicles with different types of traffic requests can transmit concurrently on the same channel to improve spectrum efficiency and alleviate the congestion of data traffic by supporting massive connectivity [5]. With the continuous maturity of Successive Interference Cancellation (SIC) technology, NOMA can significantly improve spectral efficiency, support more user connections, and reduce the latency compared with traditional orthogonal multiple access (OMA).

By using NOMA, the system capacity can be extremely improved, however, if there is no favorable resource allocation mechanism, the performance will be discounted. Thus resource allocation is widely studied in different scenarios. For instance, Ashraf *et al.* [6], [7] propose quality-of-service-aware resource allocation schemes that incorporate the physical proximity and traffic demands of vehicles to reduce vehicle communication delay and power consumption. He *et al.* [8] propose a deep reinforcement learning framework to improve system throughput in the multi-carrier NOMA system. Xu *et al.* [9] investigate an optimization method to improve the system capacity in cognitive OFDM-NOMA systems. Budhiraja *et al.* [10] pro-

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pose a joint channel allocation and power control algorithm to increase system capacity in cognitive radio NOMA femtocell. Marcano *et al.* [11] analyze the capacity of 5G HetNets with hybrid multiple access where NOMA and OMA co-exist. In the scenarios where NOMA-based relaying networks, NOMA-based millimeter wave system, and NOMA-based edge computing system, the resource and power allocation are also investigated to improve the system throughput [12]–[18].

Considering the benefits of NOMA, most recently, it becomes a trend to employ NOMA in vehicular networks to support the high QoS requirements of V2X communications. In the basic research, modulation and coding technology are investigated in [19], [20]. The communication capacity is also analyzed in the NOMA-based V2X system [21]. In the vehicular broadcast system, Liu *et al.* [22] introduce NOMA to the broadcast and multicast communication of V2X, where the base station broadcasts information to RSU, and then RSU multicasts information to the vehicles in its communication range. Di *et al.* [23] employ NOMA to the V2X broadcast scenario where the vehicles broadcast their safety information to the neighborhood in each transmission period. In the NOMA-based V2X system, Zheng *et al.* [24] investigate a resource allocation problem for NOMA-enabled V2X communications to improve spectrum utilization while ensuring the fairness of vehicle communications. Zhao *et al.* [25] apply a convex optimization approach for resource allocation to increase system capacity. In [26], [27], interference hypergraph-based resource allocation approach is also proposed to optimize the system capacity.

Although these approaches can improve the system capacity, they need the base station to acquire and control the transmission power of the vehicles. As we know, in the V2X system, vehicles are moving at high speed, it is difficult for the base station to obtain the channel information between vehicles in real-time to control their transmission power. Even though the base station can perform real-time power control, it will consume a lot of computing resources and bandwidth. Therefore, it is difficult to use optimization approaches for resource allocation and power control in real-time. In Mode 1 of NR V2X, the base station first allocates resources in each transmission period, and then the vehicles transmit information on the allocated resource. The introduction of the feedback channel and group-cast also provides a foundation for the application of NOMA. Accordingly, in this paper, we apply NOMA in vehicle group communication to reduce information delay and increase communication capacity. We also consider that the density of vehicles in the network is high, and the channel of the base station adopts a resource-sharing method similar to D2D communication. Thus, we propose a two-stage scheme of centralized resource allocation and distributed power control to improve the system capacity and reduce power consumption. The main contributions of this paper are fourfold:

1) To satisfy the ultrahigh data rate and ultralow latency communication requirements in future V2X, in this paper, we propose to introduce NOMA in NR V2X, where NOMA is used for communication among members of the vehicle group and resource sharing based on spatial reuse for different groups are permitted. We employ a centralized resource allocation and distributed power control scheme to improve the system capacity and reduce power consumption.
2) In order to achieve effective and efficient resource allocation in the investigated NOMA-V2X networks, we construct a graph to model the interference scenario, in which the vertices denote the vehicle groups and the edges indicate the interference relationships. Then, we propose the graph-based matching algorithm for the base station to allocate resources. After that, the convergence of the algorithm is analyzed.
3) Besides, based on the allocated resources, we employ a distributed non-cooperative game for power control of the vehicle groups. Then, we prove that the game has an equilibrium point with each of the vehicle groups using its maximum power to transmit information. After that, we propose a greedy power allocation algorithm to distribute power to vehicles in the groups.
4) Based on the analysis of the non-cooperative game, we propose a distributed cooperative game approach to improve the system capacity and reduce power consumption. After that, we prove this game is a convex game and every player will participate in the cooperation. According to the characteristics of the game, a cooperative power adjustment algorithm is proposed. Simulations show that the application of the proposed method can significantly improve system capacity and reduce system power consumption.

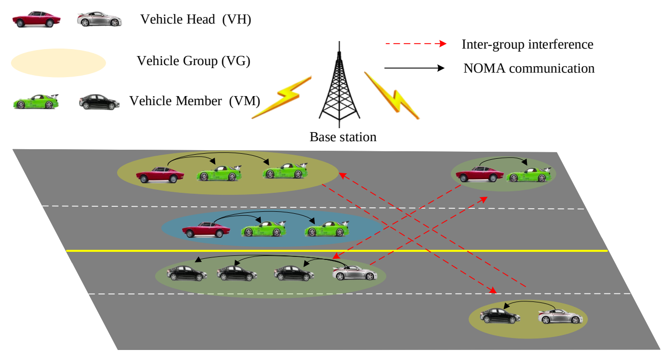

Fig. 1. NOMA-based vehicle group-cast communication.

The rest of this paper is organized as follows. After introducing the system model and the problem formulation in Section II, Centralized resource allocation is proposed and analyzed in Section III. After that, we present the decentralized power control and allocation for vehicle groups in Section IV. The proposed approach is evaluated in Section V. Section VI concludes this paper with future work.

II. System Model and Problem Formulation

A. Scenario Description

As illustrated in Fig. 1, we consider a typical NR V2X group-cast communication in a high-density vehicle scenario, where there are a single base station and a large number of vehicles in its coverage. All the vehicles are grouped to perform group-cast communication. In order to increase spectrum efficiency and reduce time delay, NOMA is applied to each vehicle group where the Vehicle Header (VH) can simultaneously communicate with Vehicle group Members (VM) for transmitting different information. There are N vehicle groups and each group has N_i vehicles, i is the index of the groups and j is the index of vehicles in each group, the set of groups is denoted by $\mathcal{N}$. We use V_{ij} to denote the vehicle j in i^{th} group and V_{i1} to denote the VH of group i. There are total M subchannels for the base station to allocate to vehicle groups, the index of the subchannel is k, and the set of subchannels is denoted by $\mathcal{M}$. For simplicity, we assume that the bandwidth of each subchannel is equal to B_w [28]. We consider vehicles are very dense and the number of groups is larger than the number of subchannels, i.e., $N > M$, so the subchannel needs to be reused by the groups as in [29].

In the NR V2X Mode 1, the subchannels used by vehicles are managed by the cellular network. We use $r_{ik} = 1$ to represent that the base station allocates subchannel k to the group i, while $r_{ik} = 0$ represents the subchannel k is not allocated to group i. The channel coefficient from the VH of group i to VM V_{ij} is h^i_{ij} and from another VH in group i' to VM V_{ij} is $h^{i'}_{ij}$. Based on the NOMA scheme, the VH of group i will send the superimposed signals $\sum_{j=2}^{N_i} \sqrt{p_{ij}} S_{ij}$ to the VMs in its group simultaneously. S_{ij} is the message sent from the VH to VM j in the group i. p_{ij} is the allocated power for vehicle j in group i. Therefore, the received signal of vehicle V_{ij} is expressed as

$$y_{ij} = r_{ik} h^i_{ij} \sum_{j=2}^{N_i} \sqrt{p_{ij}} S_{ij} + n_{ij} + \varphi_{ij}, \tag{1}$$

where $n_{ij} \sim \mathcal{CN}(0, 1)$ denotes the additive white Gaussian noise at vehicle V_{ij}. φ_{ij} is interference received by vehicle V_{ij} due to the subchannel being reused by other vehicle groups. Therefore, the interference can be denoted as

$$\varphi_{ij} = \sum_{i', i' \neq i} r_{i'k} h^{i'}_{ij} \sum_{j'=2}^{N_{i'}} \sqrt{p_{i'j'}} S_{i'j'}, \tag{2}$$

where i' represents a vehicle group except group i, j' represents a vehicle in group i'. $h^{i'}_{ij}$ is the channel coefficient between the VH of group i' and vehicle V_{ij} in group i. $S_{i'j'}$ is the message sent from VH of group i' to VM $V_{i'j'}$, $p_{i'j'}$ is the allocated power for $V_{i'j'}$ by the VH in group i', $N_{i'}$ is the number of vehicles in group i'.

In the equation (1), the channel coefficient h^i_{ij} can be defined as $h^i_{ij} = B \cdot c^i_{ij} \cdot \beta^i_{ij} \cdot (d^i_{ij})^{\alpha^i_{ij}}$, and the channel coefficient $h^{i'}_{ij}$ in equation (2) also has the same definition. In the definition, B is the constant power gain factor introduced by amplifier and antenna, c^i_{ij} is a complex Gaussian variable representing Rayleigh fading, β^i_{ij} follows log-normal distribution representing shadowing fading, d^i_{ij} is the distance between VH and VM j in group i, and α represents the pathloss exponent.

B. Serial Interference Cancellation Decoding

When the transmission rate for a vehicle is not larger than the corresponding achievable rate, SIC can be successfully carried out, which is each conflicting vehicle decodes the received signals in ascending order of channel gains [22]. When a vehicle V_{ij} decodes the superimposed signal, it first decodes the signal with the lowest channel gain while treating the other signals as noise. After that, it removes the decoded signal and decodes the signal with the second-lowest channel gains. When V_{ij} decodes its signal, it will treat the signals having higher channel gain as noise. We define the channel gain of channel from VH i to V_{ij} as $\gamma^i_{ij} = |h^i_{ij}|^2$. For the sake of generality, we assume that the channel gains of vehicles in group i are ordered as $\gamma^i_{i2} \leq \gamma^i_{i3} \leq \cdots \leq \gamma^i_{iN_i}$. In addition to intra-group interference, the vehicle V_{ij} will receive external interferences when other groups reuse this subchannel, so the achievable transmission rate for V_{ij} is

$$R_{ij} = B_w \log_2 \left(1 + \frac{r_{ik} p_{ij} \gamma^i_{ij}}{1 + r_{ik} \gamma^i_{i,j} \sum_{-j=j+1}^{N_i} p_{i,-j} + \chi_{ij}}\right), \tag{3}$$

where $-j$ denotes a vehicle which has channel gain higher that V_{ij} in group i, χ_{ij} is the total interference of the vehicle V_{ij} from the groups sharing the subchannel k, which can be denoted as

$$\chi_{ij} = \sum_{i', i' \neq i} r_{i'k} \gamma^{i'}_{ij} p_{i'1} \tag{4}$$

where $\gamma^{i'}_{ij}$ denotes the channel gains from VH of group i' to vehicle V_{ij}, $p_{i'1}$ is the total transmit power of VH in group i.

C. Problem Formulation

By using NOMA, different messages can be sent to different vehicles simultaneously in the vehicle group, which can significantly reduce time delay and improve the system capacity. However, due to the subchannel reusing between different groups, the total system capacity is affected by the subchannel allocation, and power control and allocation of each group. For the subchannel allocation, we consider that group i can occupy a subchannel, which is represented by a vector $\mathbf{r}_i = [r_{i1}, \ldots, r_{iM}]^T$, while the parameters $\{r_{i1}, \ldots, r_{iM}\}$ are 0 or 1. For the power control and allocation, the total power of VH is p_{i1} and it distributes the transmission power to the VMs in its group, so the power allocation vector of group i is $\mathbf{p}_i = [p_{i2}, \ldots, p_{iN_i}]^T$. We consider $G = \{\mathbf{r}_1, \ldots, \mathbf{r}_i, \ldots, \mathbf{r}_N\}$, $P = \{\mathbf{p}_1, \ldots, \mathbf{p}_i, \ldots, \mathbf{p}_N\}$. Therefore, optimizing the system capacity is to find the optimal parameters G and P. In addition to considering system capacity, we also need to consider the fairness of communication in each vehicle group. As we know that when maximizing system capacity, VH will allocate most of the power to VMs with high channel gains and allocate a small amount to VMs with low channel gains, which will lead to unfairness between different VMs. Therefore, in order to ensure fairness, the deviation of the communication rate between each VM should be constrained within a certain range. As a consequence, the problem of maximizing system capacity is expressed as

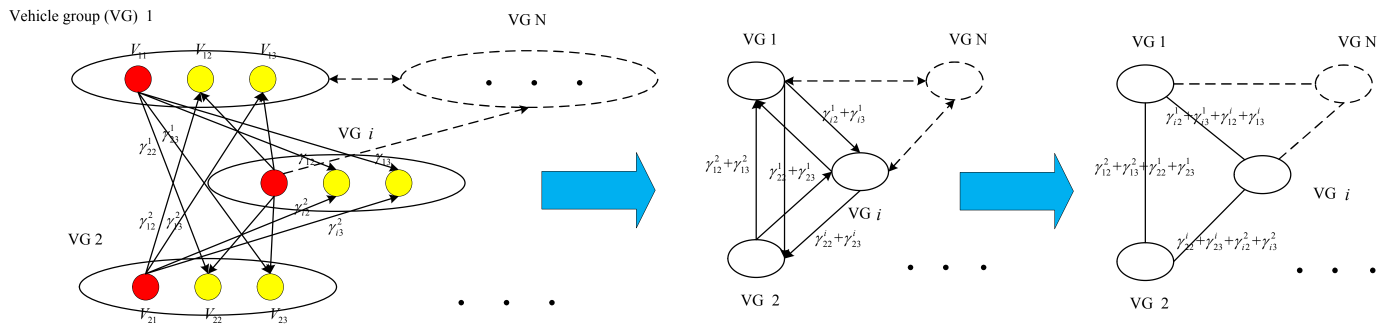

Fig. 2. Interference channel gains between vehicle groups.

$$\max_{G,P} \quad \sum_k \sum_i \sum_{j,j\neq 1} R_{ij} \tag{5}$$

$$\text{s.t.} \quad p_{i1} = \sum_{j=2}^{N_i} p_{ij}, \quad 1 \leq i \leq N, \tag{5a}$$

$$0 \leq p_{i1} \leq p_{max}, \quad 1 \leq i \leq N, \tag{5b}$$

$$\sum_k r_{ik} = 1, \quad 1 \leq i \leq N, 1 \leq k \leq M, \tag{5c}$$

$$\sum_i r_{ik} \leq q_{max}, \quad 1 \leq i \leq N, 1 \leq k \leq M, \tag{5d}$$

$$max\{R_{i2}, \cdots, R_{iN_i}\} - min\{R_{i2}, \cdots, R_{iN_i}\} \leq \Delta R, \; 1 \leq i \leq N, \tag{5e}$$

$$R_{min} \leq R_{ij}, \quad 1 \leq i \leq N, j \neq 1. \tag{5f}$$

The constraint (5a) denotes that the VH allocates transmission power to the VMs in its group. The power of VH has the maximum value p_{max} as shown in constraint (5b). In the system, each group is allowed to allocate one subchannel that is shown in constraint (5c). The constraint (5d) indicates that there are at most q_{max} vehicle groups sharing a channel. The constraint (5e) indicates that the deviation of the maximum transmission rate and the minimum rate of VMs in each group is less than ΔR to guarantee the transmission rate of each vehicle is as fair as possible. The constraint (5f) denotes that the minimum transmission rate for each VM is R_{min}.

The equation (5) represents that the base station allocates resources to vehicle groups and controls the transmission power of the vehicles to maximize the system capacity. However, the vehicles are moving at high speed, it is challenging for the base station to obtain the channel information between vehicles in real-time to control their transmission power. Therefore, it is difficult to optimize the equation (5) in a centralized manner. In NR V2X Mode 1, the base station allocates subchannels to the vehicles in each transmission period, and then the vehicles use the assigned subchannel to communicate with each other [4]. Thus, according to this feature, we can solve the equation (5) in steps. Firstly, the base station allocates resources to each group at the beginning of a period. Then, each vehicle group performs power control and allocation to maximize the system capacity. We consider this solution is suitable for the practical application of NOMA-based NR V2X. Accordingly, equation (5) can be solved in a centralized resource allocation and distributed power control scheme.

III. Centralized Resource Allocation

In each transmission period, the base station dispatches subchannels to each vehicle group first, then the group performs power control and allocation. Therefore, at the very beginning of a period before the resource allocation, the base station cannot obtain the transmit power of each group, so we can assume that each VH uses its maximum transmit power p_{max} and the power allocation to each VM is fixed as in [26], [27]. When constraints (5a) (5e) (5f) are satisfied, the optimization equation (5) can be changed as

$$\max_{G} \quad \sum_k \sum_i \sum_{j,j\neq 1} R_{ij} \tag{6}$$

$$\text{s.t.} \quad \sum_k r_{ik} = 1, \quad 1 \leq i \leq N, 1 \leq k \leq M, \tag{6a}$$

$$\sum_i r_{ik} \leq q_{max}, \quad 1 \leq i \leq N, 1 \leq k \leq M. \tag{6b}$$

The object of the equation (6) is to optimize the subchannel allocation to maximize the system capacity. It is a non-convex optimization problem due to the existence of the interference term in the objective function [25]. Since the complexity of the exhaustive method increases exponentially with the number of groups and subchannels, to describe the subchannel allocation, we consider it as a many-to-one matching process between the sets of vehicle groups and subchannels.

From the equation (3), we know that when the power allocation p_{ij}, $p_{i,-j}$ is fixed and the subchannel k is allocated to group i, i.e., $r_{ik} = 1$, then R_{ij} has only one variable χ_{ij}. So we can get

$$\frac{dR_{ij}}{d\chi_{ij}} = \frac{B_w}{(1+\frac{p_{ij}\gamma_{ij}}{1+\gamma_{i,-j}\sum_{-j\in S_i} p_{i,-j}+\chi_{ij}})\ln 2} \cdot \frac{-p_{ij}\gamma_{ij}}{(1+\gamma_{i,-j}\sum_{-j\in S_i} p_{i,-j}+\chi_{ij})^2} < 0. \tag{7}$$

R_{ij} is a monotonously decreasing function about χ_{ij}, obtaining the minimum value of χ_{ij} can achieve the maximum value of R_{ij}.

From equations (3) and (4), we know that when $p_{i'1}$ is equal to q_{max}, R_{ij} is a function of $r_{i'k}\gamma_{ij}^{i'}$. For $\gamma_{ij}^{i'}$ is channel gain, to maximize R_{ij} is to minimize $r_{i'k}\gamma_{ij}^{i'}$, so the equation (6) can be represented that how to allocate resources to minimize interference. Therefore, we can use graph-based theory to find M groups to occupy the subchannels first, and then use matching theory to allocate resources.

A. Graph-based matching approach

In order to find the optimal resource allocation, we first allocate M subchannels to M groups that are least likely to share subchannels. From the equation (7), we know when the interference χ_{ij} is maximum, the R_{ij} is minimum, while the interference χ_{ij} depends on the interference channel gain. So the largest interference channel gain will lead to the smallest transmission rate R_{ij}. We use graph theory to represent the interference between vehicle groups as shown in Fig. 2, in which each group is regarded as a vertex, the sum of the channel gains between the groups is considered to be an edge. So we can use a complete graph to represent the channel gain of the system. The two vertices with the shortest side length are the least likely to share a subchannel, because huge interference will cause the two groups to have the lowest transmission rate. Therefore, we first allocate two subchannels to the two groups. Then, we will find the next vertex with the shortest distance to the vehicle groups occupying the subchannels and allocate a subchannel to the group, until we allocated M resources to M groups that are least likely to share subchannels.

After allocating the corresponding subchannels to the M groups, we use the matching approach to distribute the remaining $N-M$ groups. Since there are already M vehicle groups occupying all the subchannels, the matching is equivalent to matching the remaining groups with the allocated resource groups. However, the number of remaining groups may be large and there may be more than two groups occupying the same subchannel, so these groups will affect each other. Thus, different from traditional matching, this matching has peer influence which is called the matching with peer effects. Next, we first give the definition of this matching, and then analyze the matching and propose a solution. We use Φ to denote the set of remaining groups and give the definition of matching as

Definition 1. *A matching ψ is a function from the set $\mathcal{M} \cup \Phi$ into the set of all subsets of $\mathcal{M} \cup \Phi$, such that 1) $\psi(k) \subseteq \Phi$ and $\psi(i_r) \subseteq \mathcal{M}$, i_r is the index of the remaining groups $1 \leq i_r \leq N-M$; 2) $|\psi(i_r)| = 1$, $\forall i_r \in \Phi$; 3) $0 \leq |\psi(k)| \leq q_{max} - 1$, $\forall k \in \mathcal{M}$.*

In the definition, the remaining group must be allocated a subchannel for transmission, so the number of matching from the group i_r to the resource set $\mathcal{M}$ should satisfy $|\psi(i_r)| = 1$, $\forall i_r \in \Phi$. There may be multiple groups sharing the subchannel with the group already occupying it, thus $0 \leq |\psi(k)| \leq q_{max} - 1$, $\forall k \in \mathcal{M}$, where q_{max} represents that the maximum number for the groups sharing a resource as in constrain (6b). When matching the vehicle groups, we should not only consider increasing the system capacity but also improve the utility of each group at the same time. The utility of each vehicle group is expressed as

$$u_i = \sum_{j=2}^{N_i} R_{ij}. \tag{8}$$

During the matching operation, the M groups that have allocated resources do not change their choice, while the remaining groups will find the optimal match with them. Due to the mutual interference between peers in this matching, we use the swap matching approach to exchange the subchannels used by the vehicle groups to increase the system capacity. The concept of swap matching is defined as

$$\psi_{i_r}^{i'_r} : \{(k, i_r), (k', i'_r)\} \rightarrow \{(k, i'_r), (k', i_r)\}, \tag{9}$$

which means groups i_r and i'_r swap subchannels while keeping the match of other groups unchanged. It is worth noting that i'_r maybe a hole, in this case, equation (9) means the group i_r uses subchannel k' instead of subchannel k. To improve the system capacity, we also need to consider the increase in group utility when performing swap matching. Therefore, we give the feasible condition for group exchange, i.e., swap-feasible pair, as follows

Definition 2. *(i_r, i'_r) is a swap-feasible pair iff $\exists i_r \in \Phi$, $u_{i_r}(\psi_{i_r}^{i'_r}) > u_{i_r}(\psi)$ and $\forall i_r \in \Phi$, $u_{i_r}(\psi_{i_r}^{i'_r}) \geq u_{i_r}(\psi)$.*

Note that the above definition implies that if two groups are swap-feasible pair, they must satisfy 2 conditions: (1) the utility of all groups after the exchange is not lower than the original utility; (2) there is at least one group whose utility is higher than the original utility. When there is no swap-feasible pair in the system, the system reaches stability [30]. Next, we will propose a graph-based matching algorithm to optimize the transmission rate of the system.

B. Resource allocation algorithm and the convergence analysis

In order to optimize subchannel allocation for the vehicle groups, we propose a graph-based matching algorithm in **Algorithm** 1. In the algorithm, we use graph-based theory to find the M vehicle groups that are least likely to share subchannels to occupy M sub-channels respectively and then use the swap matching approach to match the remaining groups to the corresponding subchannels. The algorithm is divided into three stages, in the first stage, we find the two groups with the shortest side and then let them occupy the two subchannels. After that, we sequentially calculate the groups with the shortest distance to vertices occupying the subchannels and let them occupy reminding subchannels. Until M resources are occupied by M groups. In the second stage, we continue to allocate subchannels to the remaining groups based on the length of the side. After that, we adopt the swap matching method, in which every remaining vertex i_r performs swap matching to improve the utility, i.e. when the matching is a swap-feasible pair, we update the subchannel allocation scheme Q until the matching is two-sided exchange-stable. Then, the output is the final subchannel allocation scheme.

In the proposed matching approach, the number of vehicle groups is limited and the maximum number of groups that can

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Algorithm 1: Graph-based matching algorithm for resource allocation

Input: Number of vehicle groups N, number of vehicles in each group N_i, number of subchannels M, location of all vehicles.
Output: Resource block allocation scheme Q.

Calculate the length of all sides of the complete graph;
Sort side length from small to large;
Select the two vertices with the shortest side length and allocate them with two subchannels respectively;
for $k = 3 : M$ **do**
  Find the vertex with the shortest distance from the vertex of occupied resources, then put this vertex into resource k;
end for
The vertices are matched according to the length of the side between the vertices, and the matching list $Q = \{q_1, \cdots, q_M\}$ is recorded;
while *Swap-feasible pair exists* **do**
  for $k = 1 : M$ **do**
    The remaining vertices i_r using subchannel k are exchanged with the remaining vertices i'_r using other subchannels;
    Calculate the utility of the exchanged groups;
    if (i_r, i'_r) *is a swap-feasible pair* **then**
      Update the matching list Q;
    end if
  end for
end while
The final matching list Q is the optimal resource allocation scheme.

be allocated to each subchannel is restricted, which indicates that the number of potential swap operations is finite. From the **definition 2**, we know that when the system has swap-feasible pairs, the system capacity can be further improved. If there is no exchange feasible pair in the system, the system capacity cannot continue to increase, and then the algorithm converges.

IV. Distributed power control and allocation

After subchannel allocation, we introduce two distributed approaches to resolve power control and allocation. Firstly, the non-cooperative game is used to improve the system capacity, and then we analyze the non-cooperative game and propose a cooperative game approach to further enhance the system performance.

After the subchannels are assigned, some groups may share the same subchannel. Since different subchannels are orthogonal, these groups applying different subchannels do not interfere with each other. However, the groups sharing the same subchannel should control and allocate their transmission power to maximize system capacity. Then, the optimization equation (5) can be rewritten as

$$\max_{P} \quad \sum_{k} \Big(\sum_{i} \sum_{j, j \neq 1} R_{ij}^{k} \Big) \tag{10}$$

$$\text{s.t.} \quad p_i = p_{i1} = \sum_{j=2}^{N_i} p_{ij}, \quad 1 \leq i \leq N, \tag{10a}$$

$$0 \leq p_i \leq p_{max}, \quad 1 \leq i \leq N, \tag{10b}$$

$$max\{R_{i2}, \cdots, R_{iN_i}\} - min\{R_{i2}, \cdots, R_{iN_i}\} \leq \Delta R,$$
$$1 \leq i \leq N, \tag{10c}$$

$$R_{min} \leq R_{ij}, \quad 1 \leq i \leq N, j \neq 1. \tag{10d}$$

in the equation (10), R_{ij}^{k} is the transmission rate of vehicle V_{ij} occupying the subchannel k. Since there is no interference between groups using different subchannels, the optimization equation (10) can be divided into independent subchannels for distributed optimization as follows

$$\max_{P} \quad \sum_{k} \Big(\sum_{i} \sum_{j, j \neq 1} R_{ij}^{k} \Big) = \sum_{k} \max_{P_k} \quad \sum_{i} \sum_{j, j \neq 1} R_{ij}^{k}, \tag{11}$$

where P_k is power control and distribution variables of groups using subchannel k.

A. Distributed non-cooperative game

Although the optimization problem (10) can be decomposed into k optimization problems as the equation (11), there is no control node to perform the optimization for the groups sharing the same subchannel. So we can turn each optimization into a non-cooperative game that each group maximizes its own transmission rate, thus the equation (11) can be regarded as k game problems. In each game, we first consider there is no information exchange between groups sharing a subchannel, so the game is a non-cooperative game with incomplete information, the utility of group i sharing resource k can be denoted as

$$\max_{\mathbf{P}_i} \quad \sum_{j, j \neq 1} R_{ij}^{k} \tag{12}$$

$$\text{s.t.} \quad p_{i1} = \sum_{j=2}^{N_i} p_{ij}, \tag{12a}$$

$$0 \leq p_{i1} \leq p_{max}, \tag{12b}$$

$$max\{R_{i2}, \cdots, R_{iN_i}\} - min\{R_{i2}, \cdots, R_{iN_i}\} \leq \Delta R,$$
$$1 \leq i \leq N, \tag{12c}$$

$$R_{min} \leq R_{ij}, \quad 1 \leq i \leq N, j \neq 1. \tag{12d}$$

In the game, we first consider there are s groups sharing the subchannel k. So this game is a s players game. Each VH can increase or decrease its transmit power and then allocate the power to the VMs in the group, so the actions of VH in group i are $\{p_{i2}, \ldots, p_{iN_i}\}$, the utility of the group i is $u_i^k = \sum_{j, j \neq 1} R_{ij}^k$. Then, we should consider if each of the games has a Nash equilibrium and how to achieve the equilibrium.

Lemma 1. *The function* max u_i^k is an increasing function of p_{i1}, under the optimal power allocation.

Proof: We consider a group which has 3 vehicles including 1 VH and 2 VMs and the optimal allocation is p_{i2}, p_{i3}. When VH has an increment Δp on p_{i1}, $p_{i1} + \Delta p \leq p_{max}$ and all the Δp is allocated to the 2^{th} VM, the utility of group is

$$u_i^k(p + \Delta p) - u_i^k(p) = B_w \log_2 \Big(1 + \frac{(p_{i2} + \Delta p)\gamma_{i2}}{1 + \gamma_{i2} p_{i3} + \chi_{i2}}\Big) +$$

$$B_w \log_2(1+\frac{p_{i3}\gamma_3}{1+\chi_{i3}}) - B_w \log_2(1+\frac{p_{i2}\gamma_{i2}}{1+\gamma_{i2}p_{i3}+\chi_{i2}}) - B_w \log_2(1+\frac{p_{i3}\gamma_3}{1+\chi_{i3}}) > 0. \quad (13)$$

Under the optimal allocation of the power $p_{i1}+\Delta p$

$$\left[\max_{\mathbf{p}_i} \quad u_i^k(p_{i1}+\Delta p)\right] > u_i^k(p_{i1}+\Delta p). \quad (14)$$

In (13), we know that $u_i^k(p+\Delta p) - u_i^k(p) > 0$ under the optimal allocation is p_{i2}, p_{i3}. So

$$\left[\max_{\mathbf{p}_i} \quad u_i^k(p_{i1}+\Delta p)\right] > \left[\max_{\mathbf{p}_i} \quad u_i^k(p_{i1})\right] \quad (15)$$

Accordingly, when the group has more vehicles, the function max u_i^k is still an increasing function, **Lemma** 1 is proved. □

Theorem 1. *The utility u_i^k is a descending and concave function of p_{-i}^k, where the p_{-i}^k is the transmit power of any other VHs sharing subchannel k.*

Proof: We first consider there are $s-1$ groups sharing subchannel k with group i, and the group i has 1 VH and 2 VMs. The transmit power of other VHs are $\{p_1,\ldots,p_{s-1}\}$.

$$\begin{aligned}\frac{\partial u_i^k}{\partial p_1^k} =& B_w \frac{E}{(E+p_{i2}^k\gamma_{i2}^i)\ln 2} \cdot \frac{-p_{i2}^k\gamma_{i2}^i\gamma_{i2}^1}{E^2} \\ &+ B_w \frac{F}{(F+p_{i3}^k\gamma_{i3}^i)\ln 2} \cdot \frac{-p_{i3}^k\gamma_{i3}^i\gamma_{i3}^1}{F^2} < 0, \end{aligned} \quad (16)$$

where $E = 1+p_{i3}\gamma_{i2}^i + \sum_{d=1}^{s-1} p_d^k\gamma_{i2}^d$, $F = 1+\sum_{d=1}^{s-1} p_d^k\gamma_{i3}^d$. For p_1^k can be any transmission power of other VHs, so u_i^k is descending function about p_{-i}^k.

$$\begin{aligned}\frac{\partial^2 u_i^k}{\partial (p_1^k)^2} =& \frac{-B_w(p_{i2}^k\gamma_{i2}^i\gamma_{i2}^1)^2}{(E+p_{i2}^k\gamma_{i2}^i)^2E^2(\ln 2)^2} + \frac{B_w 2p_{i2}^k\gamma_{i2}^i(\gamma_{i2}^1)^2}{(E+p_{i2}^k\gamma_{i2}^i)E^2(\ln 2)^2} \\ & \frac{-B_w(p_{i3}^k\gamma_{i3}^i\gamma_{i3}^1)^2}{(F+p_{i3}^k\gamma_{i3}^i)^2F^2(\ln 2)^2} + \frac{B_W 2p_{i3}^k\gamma_{i3}^i(\gamma_{i3}^1)^2}{(F+p_{i3}^k\gamma_{i3}^i)F^2(\ln 2)^2} \\ =& \frac{2Ep_{i2}^k\gamma_{i2}^i(\gamma_{i2}^1)^2 + (p_{i2}^k\gamma_{i2}^i\gamma_{i2}^1)^2}{(E+p_{i2}^k\gamma_{i2}^i)^2E^2(\ln 2)^2} + \\ & \frac{2Fp_{i3}^k\gamma_{i3}^i(\gamma_{i3}^1)^2 + (p_{i3}^k\gamma_{i3}^i\gamma_{i3}^1)^2}{(F+p_{i3}^k\gamma_{i3}^i)^2F^2(\ln 2)^2} > 0 \end{aligned} \quad (17)$$

When the group has more than 2 VMs, the above calculation is still satisfied. For p_1^k can be any transmission power of other VHs, so u_i^k is concave function about p_{-i}^k, **Theorem** 1 is proved. □

From **Lemma** 1 we prove **Theorem** 2 that the game has Nash equilibrium.

Theorem 2. *The game has Nash equilibrium and the equilibrium strategy is that each VH transmits the maximum power.*

Proof: From **Lemma** 1 we know that the equation (12) is a increase function of p_{i1}. So in the s players non-cooperative game, when the transmit power of other $s-1$ VHs remains unchanged, the utility of player i will achieve its maximum value when $p_{i1} = p_{max}$. The dominant strategy of player i is p_{max}. Similarly, the dominant strategy of other players is p_{max}, therefore, the dominant strategy equilibrium of this game is that each player uses its maximum power. When the players are in this equilibrium, no player can change its action to improve the utility, so the dominant strategy equilibrium is a Nash equilibrium. This game has a Nash equilibrium. □

From **Theorem** 1, we know that the equation (12) is a descending and concave function of p_{-i}^k. When p_{-i}^k increases, the utility of player $-i$ increases, however, the utility of the other players decreases. Since the utility of player i is also an increasing function of p_i^k when all users use the maximum transmit power, the system capacity may not reach the maximum, so the Nash equilibrium cannot guarantee the maximum system utility.

According to **Theorem** 2, when each VH transmits its maximum power, the game will achieve the Nash equilibrium. After that, the VH in each group needs to allocate power to each vehicle to maximize the utility of its group. The optimization equation of each group is

$$\max_{\mathbf{p}_i} \quad \sum_{j,j\neq 1} R_{ij}^k \quad (18)$$

$$\begin{aligned} \text{s.t.} \quad & p_{i1} = \sum_{j=2}^{N_i} p_{ij}, \quad 1 \le i \le N, & (18a) \\ & p_{i1} = p_{max}, \quad 1 \le i \le N, & (18b) \\ & max\{R_{i2},\cdots,R_{iN_i}\} - min\{R_{i2},\cdots,R_{iN_i}\} \le \Delta R, & \\ & 1 \le i \le N, & (18c) \\ & R_{min} \le R_{ij}, \quad 1 \le i \le N, j \ne 1. & (18d) \end{aligned}$$

Due to the existence of external interference, the equation (18) is a non-convex function of $\mathbf{p}_i$. To solve this problem we propose a greedy power allocation algorithm to maximize the transmission rate, in which the power p_{max} is divided into multiple equal parts p [28] and the greedy method is used. The proposed algorithm is shown in **Algorithm** 2.

Algorithm 2: Greedy power allocation algorithm

Input: Number of vehicles in the i^{th} group N_i, maximum transmission power of VH p_{max}, deviation of transmission rate between VMs ΔR, the minimum transmission rate of the vehicles R_{min}.

Output: Power allocation scheme $\mathbf{p}_i$, the transmission rate of each group.

```
Assign a power p to each VM;
Calculate the transmission rate of each VM;
for i = N_i : p_max/p do
    for j = 2 : N_i do
        Calculate the transfer rate of VM j+1, when the
        power p is allocated to it;
        if the constrain (18c) and (18d) is satisfied then
            Calculate the total transmission rate of the
            group according to (18);
        end if
    end for
    Find the maximum group transmission rate, allocate
    the power p to the corresponding VM.
end for
```

In **Algorithm** 2, for each calculation, we always allocate the

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power p to the VM that can maximize the group transmission rate under the constrain (18c) and (18d). After allocating the power p_{max}, we can optimize the transmission rate for each group. By using the non-cooperative game, each vehicle group can obtain the optimal action without negotiation. However, from the previous analysis, we know that when this game is employed, the system cannot guarantee the maximum communication capacity, so in the next section, we propose a cooperative game to further improve system capacity.

B. Distributed cooperative game

From **Theorem 2**, we know that by using the non-cooperative game, the VH in each group will use its maximum power to transmit information, which can not ensure that the system has the optimal capacity. If these groups can cooperate with each other, they can further enhance system performance. Therefore, a cooperative coalition game is proposed to improve the system capacity. In the game, each group can cooperate with one or more groups to improve the coalition utility, so the set of players sharing the resource k is $\mathcal{N}^k = \{1, \ldots, N^k\}$. In the coalition game, we consider S^k to represent a coalition, while $N^k - S^k$ is the other coalition. If a group in the S^k joins the other coalition the system utility increases, it will leave this coalition and join the other coalition. Groups in the same coalition cooperate with each other, while different coalitions are competitive relationships. When the transmission power of one coalition rises, the interference of other coalitions will increase, and the utility of other coalitions will decrease. Therefore, we can conclude that the characteristic function of the game f is expressed as

$$f(S^k) = \max_{\mathbf{P}_i, i\in S^k} \min_{\mathbf{P}_{-i}, -i\in(N^k - S^k)} \sum_{i_k\in S^k}\sum_{j_k} R_{ij}^k. \tag{19}$$

This characteristic function indicates that the coalitions compete with each other to maximize their own utility, i.e., in this game, the players in $N^k - S^k$ will take the action to increase its transmission power and it also increases interference to reduce the utility S^k, while the players in S^k take the action to maximize the coalition utility. So the coalition game is expressed as $(\mathcal{N}^k, f)$.

A group in the game can leave or join a coalition, so it is important to find the number of coalitions in the game and the distribution of vehicle groups in each coalition. To determine these, we will give the definition of the convex game and then prove this coalition game is a convex game.

Definition 3. *For a coalition game $(\mathcal{N}, f)$, if any two coalitions S and B, $S \bigcup B = \mathcal{N}$, $S \bigcap B = \emptyset$, $f(S) + f(B) \leq f(S \cup B)$, the game $(\mathcal{N}, f)$ is a convex game.*

After giving the definition, we prove this game is a convex game.

Theorem 3. *The coalition game $(\mathcal{N}^k, f)$ of improving the system capacity is a convex game.*

Proof: We consider any two coalitions in the game S^k and B^k, $S^k \bigcup B^k = \mathcal{N}^k$, $S^k \bigcap B^k = \emptyset$.

$$f(S^k) = \max_{\mathbf{P}_i, i\in S^k} \min_{\mathbf{P}_{-i}, -i\in B^k} \sum_{i\in S^k}\sum_{j} R_{ij}^k. \tag{20}$$

From **Theorem 1**, we know that the function u_i^k is a descending and concave function of p_{-i}^k, so when all VHs $-i \in B^k$ use their maximum transmit power, the function u_i^k obtains its minimal value. While the $f(S^k)$ is the sum of u_i^k in the set S^k, so

$$f(S^k) = \max_{\substack{\mathbf{P}_i, i\in S^k \\ \mathbf{P}_{-i} = \mathbf{P}_{-i,max}, -i\in B^k}} \sum_{i\in S^k}\sum_{j} R_{ij}^k, \tag{21}$$

where $\mathbf{P}_{-i,max}$ indicates that all the VH in the set B^k use their maximum transmission power. So

$$f(S^k) \leq \max_{\mathbf{P}_i, i\in S^k} \sum_{i\in S^k}\sum_{j} R_{ij}^k. \tag{22}$$

Similarly,

$$f(B^k) \leq \max_{\mathbf{P}_i, i\in B^k} \sum_{i\in B^k}\sum_{j} R_{ij}^k. \tag{23}$$

We know in equation (22) and (23), $\mathbf{P}_{-i}$ can be any value in the domain, so

$$\begin{aligned}
&\max_{\mathbf{P}_i, i\in S^k} \sum_{i\in S^k}\sum_{j} R_{ij}^k + \max_{\mathbf{P}_i, i\in B^k} \sum_{i\in B^k}\sum_{j} R_{ij}^k \\
&\leq \max_{\mathbf{P}_i, i\in (S^k+B^k)} \sum_{i\in S^k}\sum_{j} R_{ij}^k \\
&= \max_{\mathbf{P}_i, i\in (S^k+B^k)} \min \sum_{i\in S^k}\sum_{j} R_{ij}^k \\
&= f(S^k + B^k).
\end{aligned} \tag{24}$$

$$f(S^k) + f(B^k) \leq f(S^k \cup B^k). \tag{25}$$

This coalition game is a convex game □

From **Theorem 3**, we know the coalition game is a convex game, so when all groups are merged, the coalition will obtain its maximum utility. Thence, the coalition game is expressed as

$$\max_{P_k} \sum_{i\in\mathcal{N}^k}\sum_{j, j\neq 1} R_{ij}^k \tag{26}$$

$$\text{s.t.} \quad p_{i1} = \sum_{j=2}^{N_i} p_{ij}, \tag{26a}$$

$$0 \leq p_{i1} \leq p_{max}, \tag{26b}$$

$$max\{R_{i2}, \cdots, R_{iN_i}\} - min\{R_{i2}, \cdots, R_{iN_i}\} \leq \Delta R. \tag{26c}$$

$$R_{min} \leq R_{ij}, \quad 1 \leq i \leq N, j \neq 1. \tag{26e}$$

According to the analysis of the **Theorem 2**, we know that when each group employs its maximum transmit power, the system capacity may not reach the maximum value. Therefore, to maximize the system capacity, each group can first adopt the maximum transmission power and then reduce its transmit power. Specifically, the groups in the coalition determine a group that needs to reduce the transmission power through negotiation, and then the group reduces its transmission power. After that, the groups conduct the next negotiations until the system capacity can no longer be increased. Accordingly, we propose the cooperative power adjustment algorithm in **Algorithm 3**.

Algorithm 3: Cooperative power adjustment algorithm

Input: N_i, p_{max}, R_{min}, ΔR, termination condition ϵ.
Output: Power allocation scheme of each group $\mathbf{p}_i$ sharing subchannel k, the communication capacity of the k^{th} subchannel u^k.

Each group uses its maximum transmission power;
Calculate the maximum communication capacity of the k^{th} subchannel u^k;
repeat
  for $i = 1 : card(\mathcal{N}^k)$ **do**
    VH in group i tries to reduce a unit power p ;
    Calculate the optimal power allocation for each group;
    Calculate the communication capacity of subchannel k ;
  end for
  Find the group that can maximize the communication capacity, reduce its transmission power of p, while keeping the transmission power of other groups unchanged;
  Calculate the communication capacity of the k^{th} subchannel $u^{k'}$;
  $u^{k''}= u^{k'}$, $u^{k'}=u^k$;
until $u^{k''} - u^{k'} \leq \epsilon$;

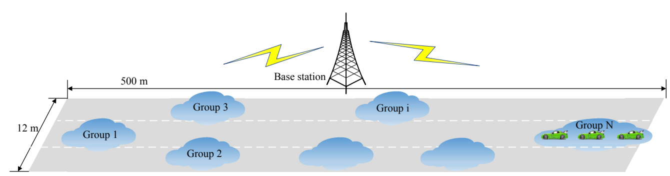

Fig. 3. Communication scenario of the freeway.

V. Performance Evaluation

In this section, we consider a freeway scenario including a single base station with a radius of 500 m. The base station is located at the center of this topology with a carrier frequency of 2 GHz. The road is one-way with 3 lanes and the width of each lane is 4 meters [31]. The schematic diagram is shown in Fig. 3. We consider each vehicle group has three vehicles, one VH and two VMs. The VH communicates with two VMs at the same time by using NOMA and each VM uses SIC to receive information. The maximum deviation of the communication rate between VMs is 0.5 $Mbps$, i.e., $\Delta R = 0.5Mbps$. The average inter-vehicle distance in the same lane is $2.5s \times v$, the distribution of vehicles follows the Poisson point process. Major simulation parameters are listed in Table I, which is based on the case specified in 3GPP TR 36.885 [32]. We consider that the base station has 5 subchannels and each subchannel has 2 resource blocks.

A. Characteristics of the algorithms

In the paper, the base station first employs a centralized allocation approach to assign subchannels to vehicle groups. Then, each vehicle group performs distributed power control and allocation to maximize system capacity. We first consider the characteristic of these algorithms. Fig. 4 demonstrates the convergence of **Algorithm 1**, which shows the cumulative distribution of system capacity. The algorithm is divided into three stages, which are graph-based resource occupation, greedy resource allocation, and swap matching. From Fig. 4, we can see the cumulative distribution is increasing in the first stage, i.e., the first 5 matchings. This is because at this stage the base station allocates 5 subchannels to the 5 closest vehicle groups and they do not interfere with each other. The second stage is different for a different number of vehicle groups. When the number of groups is 11, the second stage is 5-11 of the horizontal axis and the second stage is 5-20 for 20 groups. In the second stage, the cumulative distribution of system capacity increases first and then decreases. This is because the greedy algorithm is used, i.e., the vehicle groups with small interference are matched first, and then groups with large interference are matched. Therefore, when the interference of the system gradually increases, the system capacity decreases. In the last stage, the swap matching approach is used, we can see that the capacity of the system increases when each swap is performed. Until there are no exchangeable groups in the system, the algorithm converges to the optimal capacity.

From the analysis of **Theorem 1** and **Theorem 2**, we know that the non-cooperative game approach cannot guarantee the maximum capacity of the system. So we apply a cooperative

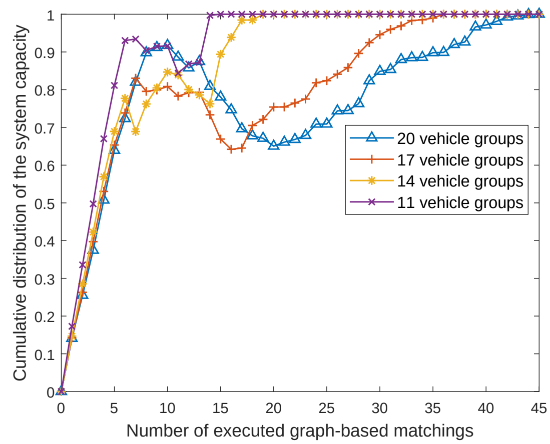

Fig. 4. The convergence of the graph-based matching algorithm.

TABLE I
SIMULATION PARAMETERS

Parameter	Value
Peak power of each VH per sub-channel p_{max}	23 dBm
Carrier center frequency	2 GHz
Power spectral density of noise	-174 dBm/Hz
Channel model	UMi model [33]
Number of vehicle groups N	[5, 20]
Resource block	180 kHz
Fast fading	Rayleigh fading
Shadow fading	Log-normal
Vehicle speed	[30, 60]
Radius of cell	500m

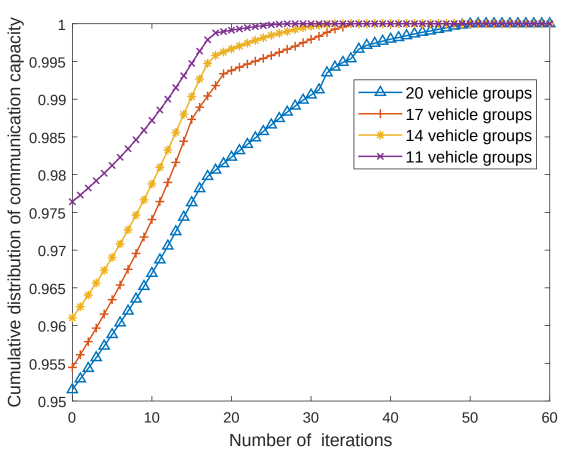

Fig. 5. Convergence of cooperative power adjustment algorithm in terms of system capacity.

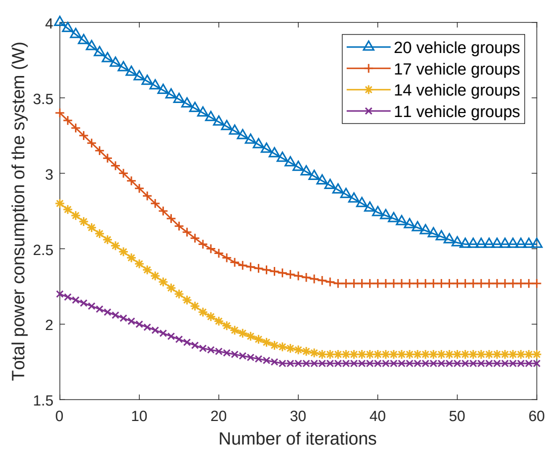

Fig. 6. Convergence of cooperative power adjustment algorithm in terms of power consumption.

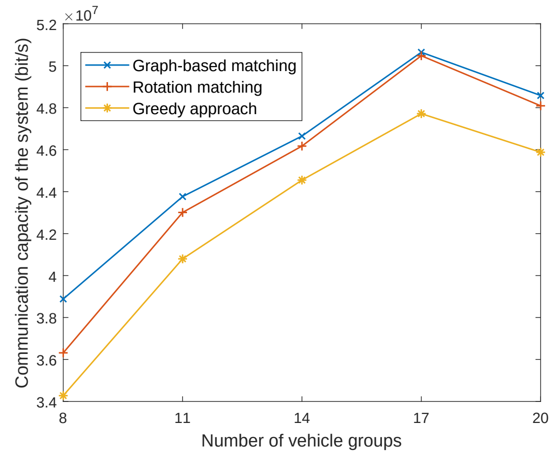

Fig. 7. Comparison of system capacity under different matching approaches.

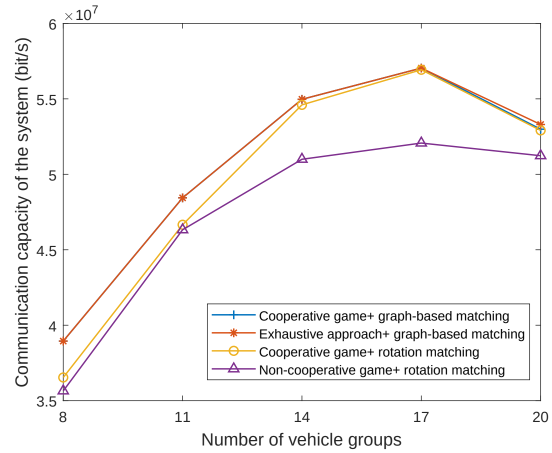

Fig. 8. Comparison of system capacity under different approaches.

game approach and propose the cooperative power adjustment algorithm to solve the game. The convergence of the algorithm is shown in Fig. 5. At the beginning of **Algorithm 3**, each VH uses its maximum power, and then the VHs sharing the same subchannel cooperate with each other to reduce transmission power to increase system capacity. As we can see from Fig. 5, at the beginning of the algorithm, when there are a small number of groups in the system, the cumulative distribution of the system capacity is high. This is because, with a small number of groups, there is less mutual interference in the system. When the number of groups increases, the interference between groups increases, and the cumulative distribution of the system capacity decreases. With the iteration of the algorithm, the interference between the vehicle groups gradually decreases, so the system capacity continues to increase. When the difference between the two iterations is less than the termination condition, the algorithm reaches stability. In Fig. 5, the system capacity is greater than that of the initial after convergence, we can conclude that the cooperative game approach can increase the communication capacity by up to 5% compared to non-cooperative games.

In Fig. 6, it is shown that the convergence of the **Algorithm 3** on the other hand. To be more intuitive, we use W instead of dBm to represent the sum of the power consumption of all vehicle groups. At the beginning of the algorithm each VH uses its maximum power, so the power consumption of the system is at its maximum. With the iteration of the algorithm, the power consumption of the system gradually decreases. At the same time, the capacity of the system gradually increases as shown in Fig. 5. After the algorithm reaches stability, the power consumption of the system also decreases to the minimum. From Fig. 6, we can also see that the cooperative game approach can reduce transmission energy consumption by 36 % compared with the non-cooperative game.

B. Performance comparison

In order to evaluate the performance of the proposed graph-based matching algorithm, we compared the proposed algorithm with a greedy algorithm and rotation matching algorithm in [23]. Fig. 7 shows the comparison of the communication capacity of the system by using the non-cooperative game. We can see that when the number of vehicle groups gradually increases, the system capacity of the proposed algorithm is

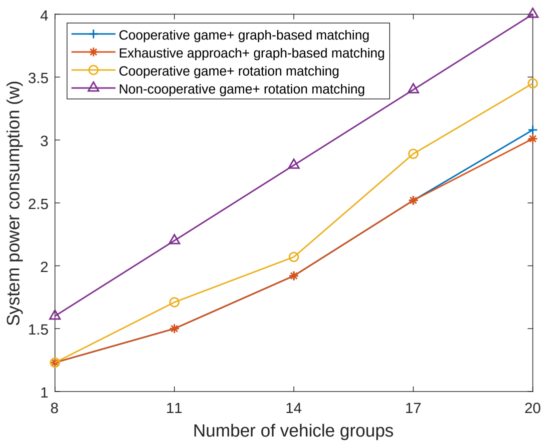

Fig. 9. Comparison of system power consumption under different cooperative approaches.

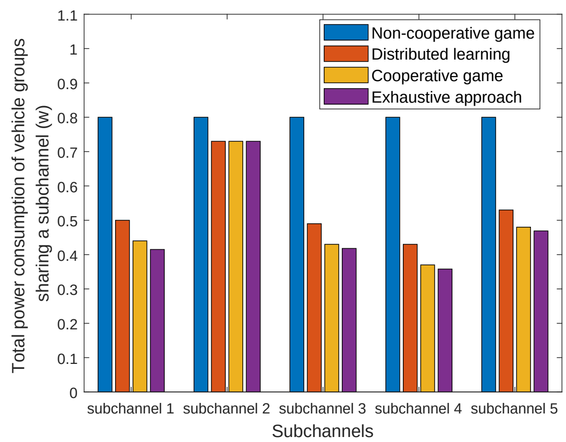

Fig. 11. Total power consumption of vehicle groups sharing a subchannel.

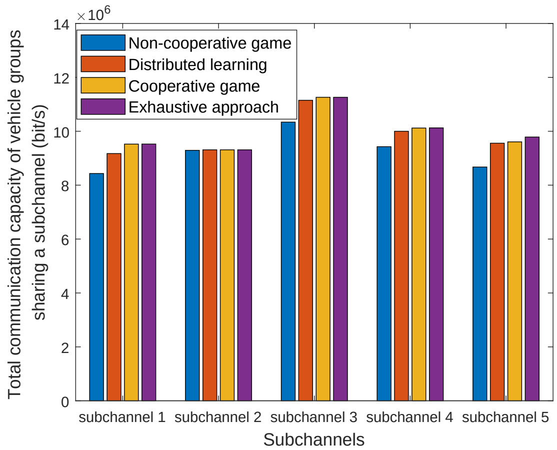

Fig. 10. Total communication capacity of vehicle groups sharing a subchannel.

always higher than the greedy algorithm. This is because the greedy algorithm always finds the local optimal point, while the proposed algorithm by using the matching approach can further improve the system capacity. The system capacity of the proposed approach is also higher than the rotation matching algorithm, since the former not only considers the vehicle group for swap matching, but also considers moving a vehicle group to other subchannels for matching, and the latter only considers the vehicle group for swap matching. From Fig. 7, we can conclude that as the number of vehicle groups increases, the system capacity may decrease. This is because when the number of subchannels is constant, more vehicle groups will bring greater interference.

To comprehensively evaluate the proposed approach, we compare the non-cooperative game, cooperative game, and exhaustive algorithm. Fig. 8 illustrates that the comparison of system capacity under different approaches. We can see that compared with the non-cooperative game, the cooperative game can further improve system capacity. This is because by using the non-cooperative game, each VH uses its maximum power, while by using the cooperative game the VHs will reduce transmit power to decrease system interference. From Fig. 8, we also can conclude that the system capacity obtained from the cooperative game is close to that obtained from the exhaustive method.

Fig. 9 demonstrates the comparison of the system power consumption. We can see that by using the non-cooperative game, each VH uses its maximum transmit power, so the power consumption increases linearly with the number of vehicle groups. The power consumption obtained from the cooperative game is lower than the non-cooperative game approach. This is because by using the cooperative game approach the VHs can cooperate with each other to reduce transmission power for decreasing mutual interference and increasing system capacity. We also can see that from the cooperative game approach, the power consumption of the system is close to that by using the exhaustive method.

Fig. 10 shows the total communication capacity of the vehicle groups sharing a subchannel when there are 20 vehicle groups in the system. We compare the proposed approach with a non-cooperative game, distributed learning algorithm in [34], and exhaustive approach. We can see that the capacity of the subchannels obtained from the cooperative game is higher than that by using the non-cooperative game and distributed learning algorithm in most cases. Thus the proposed approach can almost improve the capacity of each subchannel and can approximate the capacity getting from the exhaustive approach.

Fig. 11 illustrates the total power consumption of the vehicle groups sharing each subchannel. When using the non-cooperative game, each vehicle group uses its maximum transmission power, so the power consumption is the highest. When the distributed learning algorithm is used, each vehicle group will reduce the transmission power to increase the communication capacity, but when the same number of negotiations is used, its power consumption is higher than the proposed cooperative game method. We can also obtain the conclusion that when the cooperative game approach is applied, the power consumption of vehicle groups is close to the exhaustive approach.

Although the cooperative game can increase system capacity and reduce system energy consumption compared to the non-cooperative game, it requires multiple negotiations between vehicle groups. For example, in Fig. 5, when there are 17 vehicle groups in the system, the system requires approximately 30 iterations to converge to the maximum capacity, which means it needs about 30 negotiations between the vehicle groups. As a consequence, if the vehicle groups cannot negotiate with each other, they can adopt the non-cooperative game method to increase the capacity. If the vehicles can only perform a small number of negotiations, by using the cooperative game, the system can still increase communication capacity and reduce power consumption. In practical applications, the number of negotiations between vehicle groups can be determined according to the actual scenarios.

VI. Conclusion and Future Works

In this paper, we propose a novel approach to improve the system capacity and reduce the energy consumption of NOMA-integrated NR V2X, i.e., the centralized resource allocation and distributed power control approach. For the centralized resource allocation, the graph-based matching is proposed to improve the system capacity, and then the convergence is proved. For the distributed power control, we first analyze the non-cooperative game and prove it has Nash equilibrium. Then, we propose a cooperative game approach to improve system capacity and reduce power consumption. Simulations show that compared with non-cooperative games, the cooperative game can increase communication capacity by up to 5% and reduce transmission power consumption by 36%. In future work, we will comprehensively consider the reliability and system capacity of the NOMA-integrated NR V2X.

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