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Multiobjective Optimization of Uplink NOMA-Enabled Vehicle-to-Infrastructure Communication

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ABSTRACT Vehicular communication is gradually evolving from the rudimentary data exchange techniques to innovative, efficient, and large-scale communication platform. The future vehicular networks aim to offer new services and achieve massive connectivity with the aid of advanced wireless communication techniques. In this regard, one of the emerging paradigms is non-orthogonal multiple access (NOMA) which holds the promise to meet the resource-intensive demands of future networks. Due to this reason, the applications of NOMA are being investigated by the researcher of academia and industry alike. This article aims to build on the state-of-the-art by providing a novel multiobjective optimization framework for vehicle-to-infrastructure (V2I) communications. Specifically, this work aims to improve upon the sum-rate and energy efficiency of uplink NOMA-enabled V2I communications. The formulated problem is based on the tradeoff between sum-rate and total transmit power while maintaining the quality of service (QoS) requirements of the network. To provide a reliable solution, a multiobjective optimization framework has been proposed by applying the weighted-sum method and handle joint metrics of sum-rate maximization and total transmit power minimization. Extensive simulations have been performed to validate the superiority of the proposed framework against conventional benchmark techniques. The results clearly indicate that the proposed framework is feasible for NOMA-enabled V2I communication and can be scaled up for practical implementation.

INDEX TERMS Non-orthogonal multiple access, multiobjective optimization, QoS, vehicular communication.

I. INTRODUCTION

Recent years have seen tremendous growth in terms of research interest in vehicular communications [1]. This is partly due to the fascination of the research community with autonomous vehicles and utility in road safety applications. To materialize the concept of the fully autonomous transportation system, it is deemed necessary to build an efficient and reliable communication network among vehicles and other roadside entities. For these realizations, there generally exist two distinct communication regimes, i.e., dedicated short-range communications (DSRC) and cellular vehicular (C-V2X) communications [2]. Both regimes have been proven to be useful under different circumstances and communication requirements. The DSRC approach for vehicular communication is useful for enabling connectivity in

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ad-hoc vehicular networks, whereas, the C-V2X communication takes advantage of the cellular network for establishing long-range links among vehicles. This work mainly focuses on the uplink part of C-V2X communication due to its ability to incorporate a large number of vehicles in the network.

In general, there are two modes of communication in C-V2V, namely the direct communications (DC) and network-based communications (NC) modes. For the DC mode, the vehicles are able to directly communicate with each other, whereas, NC mode exploits the role of the cellular base station (BS) or roadside unit (RSU) in assisting communication among vehicles [3]. However, it has been observed that the current communication architecture is unable to scale up with the increasing number of vehicles on the road. Since orthogonality is one of the necessities of the present networks, it is very likely that the mobile (i.e., vehicles) and static users cannot be served with varying transmit rates and improved quality of service (QoS). Due to the ever-present constraint of spectral resources, non-orthogonal multiple access (NOMA) has attracted the interest of researchers as an alternative to orthogonal multiple access (OMA) [4], [5]. Using the power variations at the transmitter side, NOMA supports multiple users over the same spectrum resource [6]. Then, the successive interference cancellation (SIC) is used at the receiver side to decode different signals [7]. Moreover, since NOMA is inherently immune to the effect of carrier frequency offset (CFO), it is considered as one of the promising solutions for vehicular communications [1]. This article mainly explores the utility of NOMA in vehicular communications and its feasibility for mitigating the spectrum bottleneck of such networks.

A. RECENT WORKS

Recently, there exist several studies in the literature on NOMA-enabled vehicular communication networks. For vehicular-to-everything (V2X) networks [8], Di *et al.* proposed scheduling and resource allocation problems to reduce latency and improve the reliability of the NOMA-enabled system. The authors first provided centralized semi-persistent scheduling for transmitter-receiver selection and sub-channel allocation. And then distributed scheme for power allocation was exploited. The same authors in [9] further extended the work by proposing both resource allocation and power control schemes. By employing matching theory, here, the BS performed semi-persistent scheduling and sub-channel allocation in a centralized way. Then, by using iterative signaling control, the vehicles autonomously calculated the power management in a distributed manner. In [10], Xiao *et al.* proposed a dynamic vehicle clustering and power management scheme for the NOMA-enabled V2X systems. The authors' system model was composed of a single BS and multiple vehicle clusters, and the objective was to enhance the minimum achievable rate of the vehicles. To mitigate interference and increase the sum rate, the authors of [11] investigated a resource allocation problem in device-to-device (D2D)-enhance V2X NOMA networks. Moreover, they proposed a greedy algorithm based on a hyper-graph three-dimension (3D) matching algorithm to solve the interference mitigation resource management problem. The same authors presented three-partite (3P) to model the complex interference environment and then employed an interference hyper-graph 3D matching resource management scheme based on greedy and iterative algorithms.

By considering a road junction scenario where the vehicles at cross-road junction have very similar channel gains and the NOMA technique is difficult to apply, the work of [12] proposed two-channel gain stretching strategies to artificially generate channel gain difference among different vehicles on the same spectrum resource. The authors then derived a closed-form expression for the outage probability, where the NOMA-enabled V2X system outperformed the conventional OMA-enabled system. References [13] and [14] applied a centralized resource allocation scheme to improve the sum rate of D2D-enhanced V2X NOMA networks. The authors first constructed an interference hypergraph to model interference environment and, based on this constructed hypergraph model, a cluster coloring algorithm for interference hyper-graph resource management scheme was investigated. Guo and Zhou [15] studied a power control problem in NOMA-enabled heterogeneous vehicular networks to improve spectral efficiency and reliability. By considering the imperfect channel estimation, the authors formulated a chance-constrained optimization problem to enhance the uplink transmission rate of the vehicular network. Moreover, the chance constraints were first transformed into deterministic constraints and then they derived the corresponding feasible region and optimal solution. The same authors in [16] modified the work of [15] by considering joint spectrum and power allocation in heterogeneous vehicular networks. They first decouple the resource management problem for channel assignment and power control subproblems and then designed a cascaded Hungarian algorithm for efficient channel allocation. Later, for assigned channels, the authors used an approximation to transform the chance constraints into deterministic constraints and accordingly obtain the optimal solution. In [17], the power allocation scheme based on vehicle mobility was proposed in NOMA-enabled uplink vehicular-to-infrastructure (V2I) systems. The goal was to reduce the bit error rate and increase the spectral efficiency under the Rayleigh fading channels.

A joint framework of cell association and power control for the vehicle-to-small-cell (V2S) network was investigated in [18]. The authors' aim was to enhance the system's long-term performance and to reduce the number of handovers. By employing the gradient scheduling method, the optimization problem was first transformed to per time frame weighted sum-rate maximization problem and then a hierarchical power control algorithm was adopted based on Karush-Kuhn-Tucker (KKT) conditions and successive convex approximation to obtain the optimal solutions. Xu and Gu [19] studied the resource management problem in the NOMA-enabled vehicle-to-vehicle (V2V) network.

They solved the NP-hard problem using a centralized resource management algorithm and their objective was to optimize the packet receive ratio. The same authors in [20] extended the work of V2V as discussed in [19] by considering multiple-input multiple-output and special modulation techniques. Here, the target was to optimize spectrum efficiency and the bit error rate of the NOMA-enabled V2V system. The power control problems for achievable rate maximization were proposed in NOMA-enabled V2X broadcasting and multicasting systems [21]. To obtain efficient solutions, they employed bisection methods to handle quasi-concave power optimization problems. A resource allocation problem for the V2X network [22] where cellular users max-min rate fairness and vehicular users minimum signal-to-interference-plus-noise ratios (SINRs) were considered. The authors first decouple the optimization problem into three subproblems, and then the Perron-Frobenius theorem, Kuhn-Munkres algorithm, and matching theory were exploited to obtain efficient solutions. Of late, Zhang *et al.* [23] provided a full-duplex decentralized NOMA-enabled V2X system. The authors considered both urban and suburban scenarios, where the objectives were to enhance the system capacity. To tackle the non-convex problem in both scenarios, the authors derived the closed-form expression for efficient solutions.

B. MOTIVATION AND CONTRIBUTIONS

Although a substantial amount of work has already been done on NOMA-enabled vehicular communications, the tradeoff between rate and transmit power of these networks is not well understood. To date, most of the studies on vehicular communications have focused on single-objective optimization, such as optimizing spectral efficiency and energy efficiency. However, in practice, the system parameters are dependent on each other and optimizing one function may lead to degradation of the other. Thus, it is more desirable to optimize more than one function with different objectives, which raises the requirement of multiobjective optimization [24]. To the best of the authors' knowledge, the multiobjective optimization aspect of NOMA-enabled vehicular networks has not been explored yet due to the associated complexity in analysis. Thus, with the intent to provide novel insights on these matters, this article presents a novel framework for optimizing the tradeoff between the sum-rate and total transmit power of the NOMA-enabled vehicular networks. The main contributions of our work are summarized as follows:

1) We develop an uplink NOMA-enabled V2I communication network and formulate a problem keeping in view the QoS constraints of such networks. These constraints include the achievable rate and battery power of the vehicles.
2) Based on the formulated problem, detailed insights have been provided on the tradeoff between sum-rate and total transmit power of uplink NOMA-enabled V2I networks.
3) To optimize this tradeoff, a multiobjective optimization framework has been proposed. The superiority of the proposed multiobjective solution has been shown via comparison with a benchmark single objective optimization solution.

TABLE 1. The list of different symbols and their definitions.

No.	Symbol	Definition
1.	V	Set of mobile vehicles in the network
2.	V_j	Indicate mobile vehicle j
3.	y_j	Received signal at V_j
4.	g_j	Channel gain of V_j
5.	p_j	Transmit power of V_j
6.	z_j	signal of V_j
7.	N_j	Additive white Gaussian noise of V_j
8.	σ^2	Variance of additive white Gaussian noise
9.	R_j	Data rate of V_j
10.	γ_j	SINR of V_j
11.	β	Gap among vehicles power for efficient SIC
12.	R_{min}	Minimum threshold of QoS requirements
13.	itr	Indicate iteration number
14.	λ_j	Lagrangian multiplier/dual variable
15.	μ_j	Lagrangian multiplier/dual variable
16.	η_j	Lagrangian multiplier/dual variable
17.	L	Lagrangian function
18.	D	Dual problem
19.	ω	Step size
20.	ρ_j	Binary variable for vehicle selection

C. ORGANIZATION

The rest of the article is organized as follows. Section II depicts the system model and provides problem formulation steps. Section III presents the proposed multiobjective based solution. In Section IV, the numerical results and discussion are provided. Finally, Section V provides concluding remarks and future research directions. A list of definitions of commonly used symbols is provided in Table 1.

II. SYSTEM MODEL AND PROBLEM FORMULATION

This section provides the details of the considered system model and, subsequently, discusses the problem formulation procedure.

A. SYSTEM MODEL

We consider an uplink transmission of the NOMA-enabled vehicular communication network as depicted in Fig. 1. Our considered scenario consists of a single RSU and J mobile vehicles, where $\mathcal{V} = \{V_j | j = 1, 2, 3, \ldots J\}$. All vehicles are multiplexed on the same spectrum resource at the same time by using power multiplexing NOMA. The RSU and mobile vehicles are assumed to equip with a single antenna. Since the mobile vehicles are associated with the RSU, we consider that RSU has the knowledge of channel state information (CSI) of all the mobile vehicles.[1] Moreover, we assume that the

[1] Following the approach of [25], [26], we have not considered the mobility of the vehicles on the road. By considering the mobility of the vehicles, the channel characteristics and the CSI estimation of vehicles are expected to vary leading to different admission control policies and vehicle associations. Since our main objective is to optimize the energy and spectral efficiencies, the issues pertaining to imperfect CSI and fast fading would be considered in future studies.

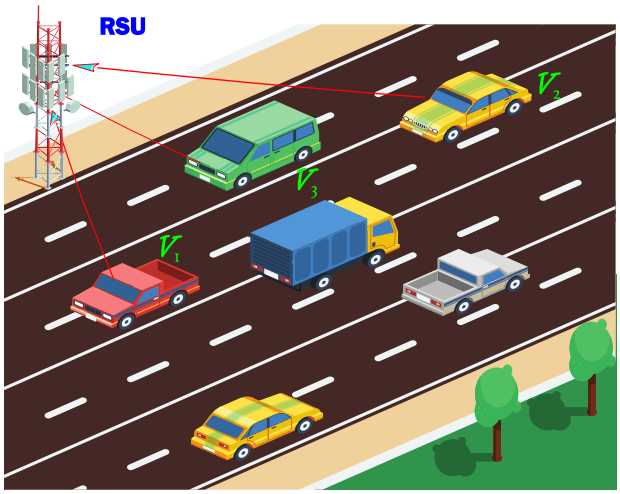

FIGURE 1. An illustration of system model.

wireless channels between RSU and its associated mobile vehicles follow Nakagami-m fading [27]. Without loss of generality, we sort the channel gains of mobile vehicles as[2] $|g_1| \leq |g_2| \leq \cdots \leq |g_j| \leq \cdots \leq |g_J|$. Different from the downlink NOMA where the nearest mobile vehicle (the one with strongest channel quality) can detect and subtract the signal of far mobile vehicle (the one with weak channel quality), in uplink NOMA, the RSU will not apply SIC for near mobile vehicle and decodes it with the interference of far mobile vehicle while the RSU apply SIC for far mobile vehicle, subtract all other vehicles' signals and then decode it [30]. Following these trends, the signal of V_1 is first decoded followed by V_2 and so on. Thus, V_1 cannot apply SIC and decodes its signal by treating the signals of all other mobile vehicles as noise, while V_J decodes its signal after eliminating interference from all other vehicles by applying SIC technique. After the SIC process, the received signal of V_j at RSU can be expressed as:

$$y_j = g_j\sqrt{p_j}z_j + g_j\sum_{i=1}^{j-1}\sqrt{p_i}z_i + N_j, \tag{1}$$

where g_j is the channel gain between V_j and RSU in the uplink transmission, p_j represents the transmit power of V_j, and z_j is the data symbol of V_j, respectively. The second term in (1) denotes the interference of other vehicles sharing the same spectrum resource in which p_i is the transmit power and z_i is the data symbol of V_i at RSU, respectively. The noise term $N_j \sim \mathcal{CN}(0, \sigma^2)$ is the additive white Gaussian noise with zero mean and variance σ^2. Based on the received signal expressed in (1), the achievable rate of V_j at RSU can be expressed as:

$$R_j = \rho_j \log_2(1 + \gamma_j), \tag{2}$$

[2]As per [28], [29], we sort the channel gains of different vehicles in ascending order for efficient SIC decoding at receivers.

where

$$\gamma_j = \frac{p_j|g_j|^2}{|g_j|^2\sum_{i=1}^{j-1}\rho_i p_i + \sigma^2}, \tag{3}$$

is the SINR of V_j, and ρ_j in (2) denotes the binary variable for vehicle selection such as $\rho_j = 1$, if V_j is selected for communication and $\rho_j = 0$, otherwise.

To make the SIC process successful at RSU, the transmit power of all mobile vehicles must satisfy the minimum required gap as [31]:

$$\rho_j p_j|g_j|^2 - \sum_{i=j+1}^{J}\rho_i p_i|g_i|^2 \geq \beta, \tag{4}$$

where β is the minimum power gap between vehicles' signals to apply SIC process successfully at the RSU. Following the condition in (4), the J vehicles transmit powers must satisfy as $p_1 > p_2 > \cdots > p_j > \cdots > p_J$. It is important to note that the SIC constraints for an uplink network where J mobile vehicles are sharing the same spectrum resource will always be $(J-1)$ [32]. This is because when J mobile vehicles are communicated on the same spectrum resource using ascending or descending order of channel gains, a mobile vehicle having a weak channel gain can apply a SIC technique at RSU and decodes all other mobile vehicle signals first before decoding its own signal. The mobile vehicle with strong channel gain, however, can not use the SIC technique at RSU and decodes its signal by treating the other mobile vehicle's interference as noise. Thus, the SIC constraints of J mobile vehicles on the same spectrum resource are always $J-1$ in power-domain NOMA. Next, we discuss the joint formulation of energy and spectrum efficiency optimizations.

B. MULTIOBJECTIVE PROBLEM FORMULATION

Our objective is to jointly maximize the sum-rate and minimize the total transmit power of uplink NOMA vehicular network while satisfying the constraints of QoS, maximum transmit power and successful SIC process. These joint objectives can be achieved by solving a multiobjective optimization problem which can be formulated as (P1):

$$\begin{aligned}
\text{(P1)}\quad & \underset{\rho_j p_j}{\text{Max}}\sum_{j=1}^{J}\rho_j R_j \ \text{ and } \ \underset{\rho_j p_j}{\text{Min}}\sum_{j=1}^{J}\rho_j p_j,\\
\text{s.t. C1:}\ & \rho_j R_j \geq R_{min}, \quad \forall j,\\
\text{C2:}\ & \rho_j p_j \leq P_{max}, \quad \forall j,\\
\text{C3:}\ & \rho_j p_j|g_j|^2 - \sum_{i=j+1}^{J}\rho_i p_i|g_i|^2 \geq \beta, \quad \forall j, i,\\
\text{C4:}\ & \rho_j p_j \geq 0, \quad \forall j,\\
\text{C5:}\ & \rho_j \in \{0, 1\}, \quad \forall j.
\end{aligned} \tag{5}$$

where the two objectives are for total transmit power minimization and sum-rate maximization, respectively. Constraint C1 guarantees the QoS requirement of each vehicle where R_{min} denotes the minimum achievable rate to obtain per vehicle QoS requirements. Constraint C2 limits the mobile

vehicles maximum transmit power where P_{max} represents the battery power budget of V_j. Constraint C3 ensures the successful completion of SIC process at RSU for V_j. Besides, the constraint in C4 demonstrate the non-negative transmit power of V_j. Finally, constraint C5 shows the binary variable for optimal vehicle selection such that $\rho_j = 1$, if V_j is selected for communication, and $\rho_j = 0$, otherwise.

In this optimization framework, the optimal vehicle selection before NOMA transmission should satisfy the following criterion

$$\rho_j^* = \begin{cases} 1 & \text{if } j = \underset{j \in J}{\text{argmax}}\, R_j \\ 0 & \text{otherwise.} \end{cases} \tag{6}$$

where all the selected vehicles transmit over single-carrier according to the power-domain NOMA principle. By considering the decoding complexity of SIC at the receivers, we define a set of active vehicles at any given time as $\mathcal{A}$, where $\mathcal{A}$ is a subset of set $\mathcal{V}$ such as $|\mathcal{A}| \ll \mathcal{V}$. Moreover, $\mathcal{A}$ can keep at most $\mathcal{A}_{max}$ active vehicles at one time. In each interval, we first search an optimal V_j^* according to (6) which provides a high data rate among all vehicles. Then we record this V_j^* on $\mathcal{A}$ and exclude it from set $\mathcal{V}$. Similarly, we find another vehicle that provides a high data rate after V_j^* and repeats the same process. Finally, we check the number of optimal vehicles in $\mathcal{A}$. If the number of vehicles is less than $\mathcal{A}_{max}$, continue the aforementioned procedure to select more optimal vehicles. However, the process is terminated when the number of vehicles in $\mathcal{A}$ is equal to $\mathcal{A}_{max}$.

The complexity of proposed vehicle selection algorithm in terms of iterations depends on the number of vehicles in the system. If the number of vehicles in the system is J, then the complexity of the proposed vehicle selection algorithm in each iterations can be computed as $\mathcal{O}(J^2)$. Now let us assume that the total iterations needed for algorithm is T, then the total complexity of the proposed vehicle selection algorithm has became $\mathcal{O}(TJ^2)$.

III. PROPOSED SOLUTIONS

After selecting the optimal mobile vehicles, now $\mathcal{A}$ represents all active vehicles where $\rho_j = 1$. Next we discuss the performance of uplink NOMA transmission in the joint metrics of sum-rate maximization and total transmit power minimization. These can be achieved by joint optimization of optimal power allocation to the mobile vehicles in the uplink transmission. Further, a low complexity benchmark single-objective optimization scheme of sum-rate maximization is also provided.

A. PROPOSED MULTIOBJECTIVE SOLUTION

In multiobjective optimization, more than one objectives need to be maximized or minimized simultaneously [33]. Here, we use multiobjective optimization in which optimal decisions need to be taken as a tradeoff between two different objectives [34]. Generally, it is very hard to find a single solution for optimizing multiple objectives simultaneously. More specifically, there is no solution exist that optimizes one objective without degrading other objectives, this state is known as Pareto optimality [35]. Pareto optimal is a set of non-dominated and weak solutions where users are able to choose its preferred optimal solution. To compute the joint optimization of power control, we apply the weighted-sum method to handle the multiobjective optimization problem [36]. This has been regarded as one of the most popular methods for solving the multiobjective optimization problem [35], [37]. By this method, the multiple objective functions can be linearly combined into a single objective function. This can be achieved through weighting coefficients which reflect the required preferences [38]. More specifically, the weighting coefficients show the tradeoff among multiple conflicting objectives. To efficiently apply this method, we reformulate the optimization problem (P1) as:

$$\begin{aligned} \text{(P2)}\quad & \underset{p_j}{\text{Min}}\ \alpha \sum_{j\in\mathcal{A}} p_j - (1-\alpha)\sum_{j\in\mathcal{A}} R_j, \\ & \text{s.t. C1: } R_j \geq R_{min}, \quad \forall j \in \mathcal{A}, \\ & \quad \text{C2: } p_j \leq P_{max}, \quad \forall j \in \mathcal{A}, \\ & \quad \text{C3: } p_j|g_j|^2 - \sum_{\substack{i=j+1 \\ i\in\mathcal{A}}} p_i|g_i|^2 \geq \beta, \quad \forall j, i \in \mathcal{A}, \\ & \quad \text{C4: } p_j \geq 0, \quad \forall j \in \mathcal{A}. \end{aligned} \tag{7}$$

where α in (7) represents the weighting coefficient which lies between 0 and 1 such that $0 \leq \alpha \leq 1$, and shows the trade-off between two conflicting objective functions. Here, the higher values of α enhance the sum-rate of mobile vehicles and lower values reduce the total transmit power of mobile vehicles, respectively. Moreover, the proper selection of α depends on the model of vehicle transmission, i.e., if the rate of mobile vehicles is crucial, the higher values of α are chosen. On the other side, if the power of mobile vehicles is critical, the lower values of α are selected.

The multiobjective optimization problem (P2) is a convex problem (see Appendix A and proof therein). Therefore, we employ dual-decomposition methods to obtain the optimal solution [39]. The Lagrangian function of problem (P2) can be expressed as:

$$\begin{aligned} L(p_j, \lambda_j, \mu_j, \eta_j) = {} & \alpha \sum_{j\in\mathcal{A}} p_j - (1-\alpha)\sum_{j=1}^{J} R_j \\ & + \sum_{j\in\mathcal{A}} \lambda_j (R_j - R_{min}) + \sum_{j\in\mathcal{A}} \mu_j (P_{max} - p_j) \\ & + \sum_{j\in\mathcal{A}} \eta_j \left(p_j|g_j|^2 - \sum_{\substack{i=j+1 \\ i\in\mathcal{A}}} p_i|g_i|^2 - \beta \right), \end{aligned} \tag{8}$$

where λ_j, μ_j and η_j are the Lagrangian multipliers also called dual variables. Using this expression, the dual problem of optimization problem (P2) can be derived as:

$$\begin{aligned} & \underset{\lambda_j, \mu_j, \eta_j}{\text{Max}}\ D(\lambda_j, \mu_j, \eta_j), \\ & \text{subject to:} \quad \lambda_j, \mu_j, \eta_j. \end{aligned} \tag{9}$$

where

$$D(\lambda_j, \mu_j, \eta_j) = \underset{p_j}{\text{Min}}\, L(p_j, \lambda_j, \mu_j, \eta_j). \tag{10}$$

Now by applying KKT conditions as in Appendix B, the closed-form expression of p_j for V_j can be derived as:

$$p_j^* = \left[\frac{(\alpha+\lambda_j)|g_j|^2 - \Pi_j|g_j|^2 p_i - \sigma^2(\Pi_j)}{|g_j|^2(\Pi_j)}\right]^+, \tag{11}$$

where $(\theta)^+ = \max(0, \theta)$, and

$$\begin{aligned}\Pi_j &= \mu_i - \sum_{\substack{i=j+1\\ i\in\mathcal{A}}} \eta_i|g_i|^2 - \alpha + \sum_{\substack{l=i+1\\ l\in\mathcal{A}}} \\ &\times \frac{(\alpha+\lambda_i)|g_l|^2}{\left(\sum\limits_{\substack{f=l+1\\ f\in\mathcal{A}}} p_f|g_l|^2 + \sigma^2\right)^2 + \left(\sum\limits_{\substack{f=l+1\\ f\in\mathcal{A}}} p_f|g_l|^2 + \sigma^2\right)p_l|g_l|^2}.\end{aligned} \tag{12}$$

With the optimal value of p_j^*, the dual problem becomes

$$\begin{aligned}\underset{\lambda_j,\mu_j,\eta_j}{\text{Max}}\ & \alpha\sum_{j\in\mathcal{A}} p_j^* - (1-\alpha)\left(\sum_{j\in\mathcal{A}} R_j^*\right) \\ &+ \sum_{j\in\mathcal{A}} \lambda_j\left(R_j^* - R_{min}\right) + \sum_{j\in\mathcal{A}} \mu_j\left(P_{max} - p_j^*\right) \\ &+ \sum_{j\in\mathcal{A}} \eta_j\left(p_j^*|g_j|^2 - \sum_{\substack{i=j+1\\ i\in\mathcal{A}}} p_i|g_i|^2 - \beta\right), \\ \text{s.t. } & \lambda_j, \mu_j, \eta_j.\end{aligned} \tag{13}$$

Now the dual variables in (13) can be obtained and iteratively update using sub-gradient method as [40]:

$$\begin{aligned}&\lambda_j(itr+1) \\ &= [\lambda_j(itr) + \omega(itr) \times (R_{min} - R_j)]^+, \quad \forall j \in \mathcal{A}, \end{aligned} \tag{14}$$

$$\begin{aligned}&\mu_j(itr+1) \\ &= [\mu_j(itr) + \omega(itr) \times (p_j - P_{max})]^+, \quad \forall j \in \mathcal{A}, \end{aligned} \tag{15}$$

$$\begin{aligned}&\eta_j(itr+1) \\ &= \Big[\eta_j(itr) + \omega(itr) \\ &\quad \times \left(\beta - \left(p_j|g_j|^2 - \sum_{\substack{i=j+1\\ i\in\mathcal{A}}} p_i|g_i|^2\right)\right)\Big]^+, \quad \forall j, i \in \mathcal{A}. \end{aligned} \tag{16}$$

where itr is the iteration index, and ω is the step size. In each iteration, λ_j, μ_j and η_j are updated using p_j^* obtained from (11). In the subsequent iterations, the optimal values of λ_j, μ_j and η_j are used to calculate the optimal p_j^*. The iterative process continues until convergence.

The complexity of proposed power allocation technique in terms of iterations depends on the number of selected vehicles in the system. If the number of selected vehicles in the system is $\mathcal{A}$, then the complexity of the proposed vehicle selection algorithm in each iterations can be computed as $\mathcal{O}(\mathcal{A}^2)$. It is important to note that the complexity of the proposed power allocation technique increases when the number selected vehicles increases. Let us consider that the maximum number of selected vehicles for NOMA transmission is $\mathcal{A}_{max}$ and the total number of iterations needed for algorithm is T, then the total complexity of the proposed power allocation algorithm has became $\mathcal{O}(T\mathcal{A}_{max}^2)$.

TABLE 2. Simulation parameters.

Parameter	Definition
Number of total vehicles in the network	$J = 18$
Active mobile vehicles in $\mathcal{A}$ at one time	$\mathcal{A} = 3$
Vehicle battery power	$P_{max} = 4$ W
Channels consideration	Nakagami-m fading
Weighting coefficient	$\alpha = 0.6$ to 1
Per vehicle QoS requirement	$R_{min} = 1$ bits/sec/Hz
Noise power	$\sigma^2 = 0.1$
Power gap among vehicles	$\theta = 0.5$ W
Average channel realization	10^4 realizations

B. BENCHMARK SINGLE-OBJECTIVE SOLUTION

The proposed solution in Section III-A provides a multiobjective optimization for sum rate maximization and total transmit power minimization in uplink NOMA vehicular transmission. In this subsection, to reduce the computational complexity, we present a benchmark single-objective optimization scheme where only power allocation is optimized for sum-rate maximization. Without energy efficiency, the power optimization problem can be formulated as (P3):

$$\begin{aligned}\text{(P3)}\ \underset{p_j}{\text{Max}}\ & \sum_{j\in\mathcal{A}} R_j, \\ \text{s.t. C1: } & R_j \geq R_{min}, \quad \forall j \in \mathcal{A}, \\ \text{C2:} & p_j \leq P_{max}, \quad \forall j \in \mathcal{A}, \\ \text{C3:} & p_j|g_j|^2 - \sum_{\substack{i=j+1\\ i\in\mathcal{A}}} p_i|g_i|^2 \geq \beta, \ \forall j, i \in \mathcal{A}, \\ \text{C4:} & p_j \geq 0, \quad \forall j \in \mathcal{A}. \end{aligned} \tag{17}$$

The problem (P3) is convex and can also be solved by dual-decomposition method with similar steps as discussed in multiobjective optimization solution. However, the detailed steps are omitted here for the sake of brevity. Moreover, the complexity of the single-objective optimization scheme based on KKT conditions can be found in [4].

IV. PERFORMANCE EVALUATION

In this section, we provide some detailed insights on the vehicular network architecture and evaluate the performance of the proposed multiobjective optimization framework. The results were obtained by performing Monte-Carlo simulations in MATLAB by taking 10^4 channel realizations. Throughout the results, the term "Benchmark NOMA Scheme" refers to the single objective scheme as detailed in Section III-B. Whereas, the term "Conventional OMA Scheme" denotes the proposed multiobjective framework applied to OMA. The details of the simulation parameters and their corresponding values are provided in Table 2.

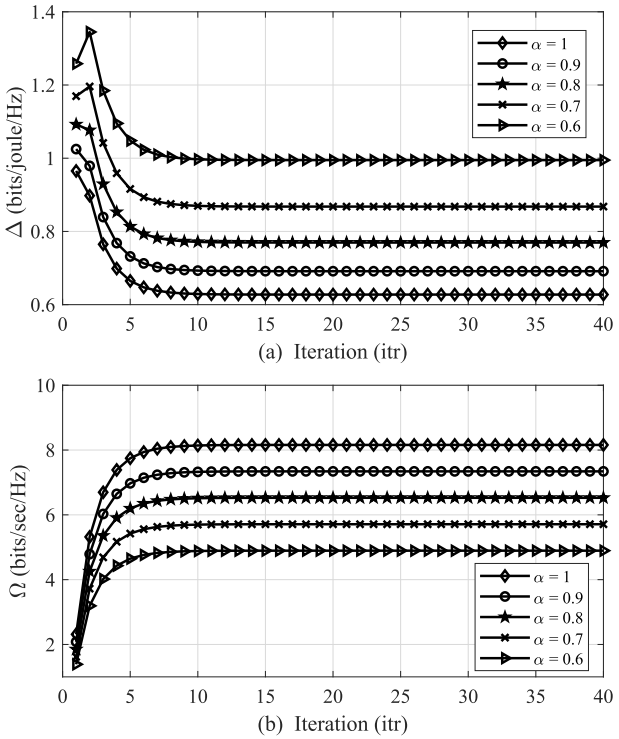

FIGURE 2. Performance of the proposed multiobjective solution with different values of α; (a) Total energy efficiency Δ, (b) Sum-rate Ω.

In this paper, we define the energy efficiency (bits/joule/Hz) of the proposed V2I network as the ratio of mobile vehicles sum-rate to the total transmit power consumption of mobile vehicles plus circuit power consumption. Mathematically, we denote it as Δ in this section, and it can be formulated as:

$$\Delta = \frac{\left(\sum_{j\in\mathcal{A}} \rho_j \log_2(1+\gamma_j)\right)\text{bits/sec/Hz}}{\left(\sum_{j\in\mathcal{A}} p_j + p_c\right)\text{W}}, \tag{18}$$

where p_c represents the circuit power consumption of mobile vehicles. Accordingly, the sum-rate (represented as Ω) of V2I network can be defined as:

$$\Omega = \left(\sum_{j\in\mathcal{A}} \rho_j \log_2(1+\gamma_j)\right)\text{bits/sec/Hz}. \tag{19}$$

Fig. 2 (a) shows the convergence of the energy efficiency (Δ) against the number of iterations (itr). Note that for an increase in the values of α, the Δ declines. Whereas for smaller values of α the Δ improves. In particular, when $\alpha = 1$, the Δ is 0.65 bits/joule/Hz which increases to 1 bits/joule/Hz when $\alpha = 0.6$. By contrast, Fig. 2 (b) indicates that a decrease in the value α reduces the overall sum-rate (Ω). More specifically, as α varies from 1 to 0.6, the corresponding values of the Ω reduce from 8.2 bits/sec/Hz to just 4.5 bits/sec/Hz. However, regardless of the value of α, one can note that the proposed multiobjective optimization framework converges within a reasonable number of itr.

In Fig. 3, we have demonstrated the Δ as a function of increasing transmit power. We have compared the proposed

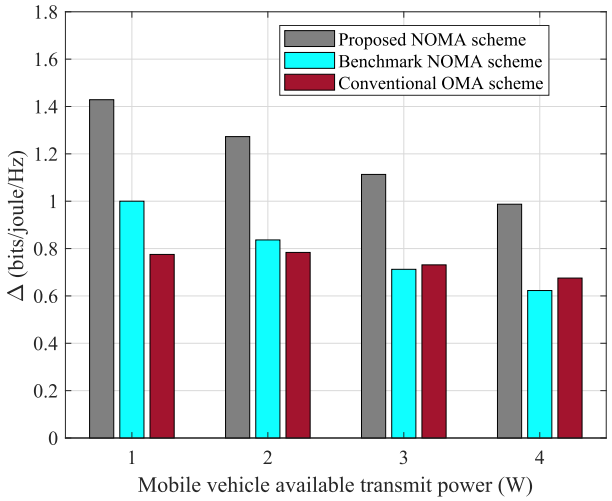

FIGURE 3. Available transmit power of mobile vehicle versus Δ for $\alpha = 0.6$, $R_{min} = 1$ bits/sec/Hz.

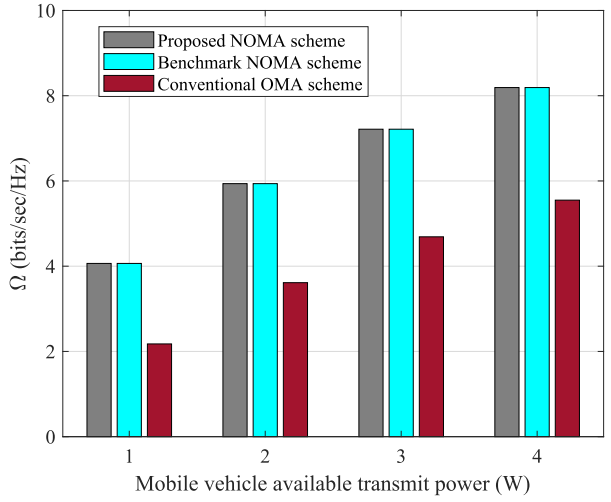

FIGURE 4. Sum rate Ω versus mobile vehicle available battery power (W) for $\alpha = 1$, $R_{min} = 1$ bits/sec/Hz.

optimization scheme with the single objective benchmark NOMA scheme and the conventional OMA scheme. In general, we can observe that the Δ decreases with an increase in the transmit power of the vehicle. However, the proposed NOMA scheme continues to outperform both benchmark NOMA and conventional OMA schemes. Also, it can be observed that at higher values of transmit power (i.e., 4 W), the conventional OMA scheme outperforms the benchmark NOMA scheme. This shows the applicability of our proposed multiobjective framework for not only NOMA but OMA as well. In a similar manner, Fig. 4 shows the Ω for the three schemes. Again, for a particular value of α, the proposed approach seems to perform close to the benchmark NOMA scheme. Whereas, it clearly outperforms the conventional OMA scheme, especially at the larger values of the transmit power.

To further elaborate on the significance of α, Fig. 5 goes on to illustrate the impact of different values of α on Δ and Ω. It can be seen from Fig. 5 (a) that an increase in the value

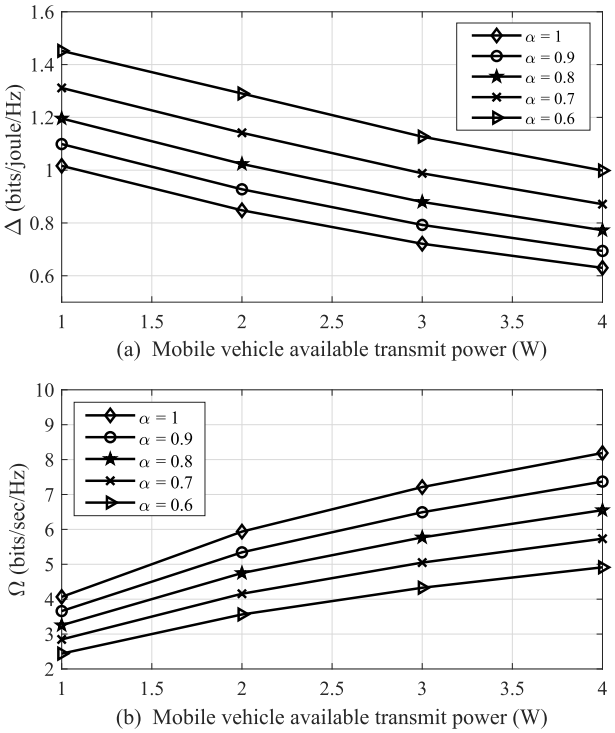

FIGURE 5. Performance of the proposed multiobjective solution with different values of α; (a) Total energy efficiency Δ, (b) Sum-rate Ω.

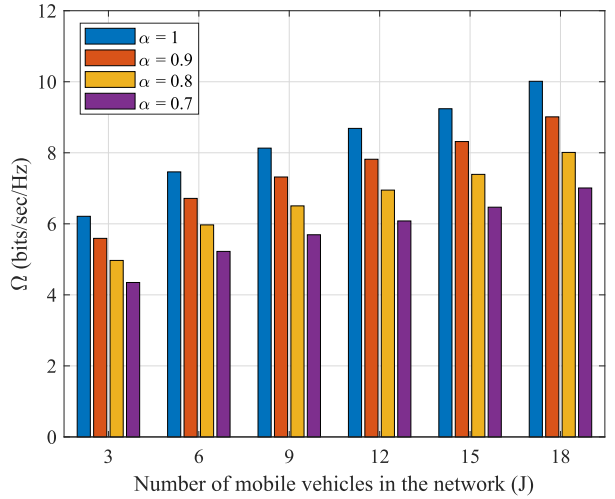

FIGURE 6. The number of vehicles J in the network versus the Ω of the proposed NOMA scheme for different values of α when $P_{max} = 4$ W, $R_{min} = 1$ bits/sec/Hz.

of α causes a reduction in Δ. Moreover, as the values of α decrease, the gap between different curves grow to show the impact of α at larger values of transmit power. On the other hand, Fig. 5 (b) shows the impact of α against increasing values of transmit power. In contrast, we can observe that the Ω improves with larger values of transmit power from the vehicle. Furthermore, it can also be observed that the increasing values of α favor the Ω, resulting in significant improvement when $\alpha = 1$.

The impact of the increasing number of vehicles on the performance of the network is demonstrated in Fig. 6. In general,

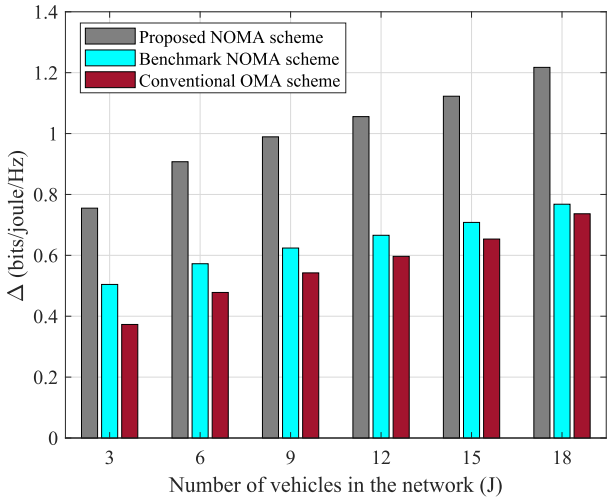

FIGURE 7. The number of mobile vehicles J in the network versus Δ when $\alpha = 0.6$, $P_{max} = 4$ W, $R_{min} = 1$ bits/sec/Hz.

we note an increase in the Ω when the number of vehicles in the network grows. This improvement can be attributed to the improvement in diversity gains ensure by (6). As a result of a decrease in value of α does not influence the performance of the vehicular network much when the number of vehicles is large. Similar trends can be observed in Fig. 7, where the Δ is plotted by keeping the value of α fixed at 0.6. As one can note, the proposed optimization scheme continues to outperform the benchmark NOMA scheme and conventional OMA scheme. Again, this improvement is because of improved diversity gains due to the larger number of vehicles in the network.

Fig. 8 shows the impact of the Nakagami-m factor for both Δ and Ω. We can observe from Fig. 8 (a) that an increase in the value of the Nakagami-m factor results in improving the Δ of the network. In this regard, it is worth highlighting that when $m = 1$, the channel characteristics become similar to a Rayleigh fading channel. Similar trends can be observed in Fig. 8 (b), where an improvement in channel conditions result in considerable performance gains in terms of Ω.

V. CONCLUSION AND FUTURE WORK

V2I communication is an integral part of the vehicular networks. By integrating efficient NOMA techniques in V2I communication, the performance of such a network can be significantly improved. In this backdrop, this work has provided a multiobjective optimization framework to improve the sum-rate and energy efficiency of the NOMA-enabled V2I communications. The proposed framework is not only more energy efficient but also has the capability to improve the overall sum-rate of the network. As illustrated by extensive simulations, the proposed framework can outperform the conventional single-objective NOMA and traditional OMA approaches by a great margin. Moreover, it was shown that an increase in the uplink transmitting vehicles can indeed improve the performance of the network, when operating under the proposed optimization framework, due to the

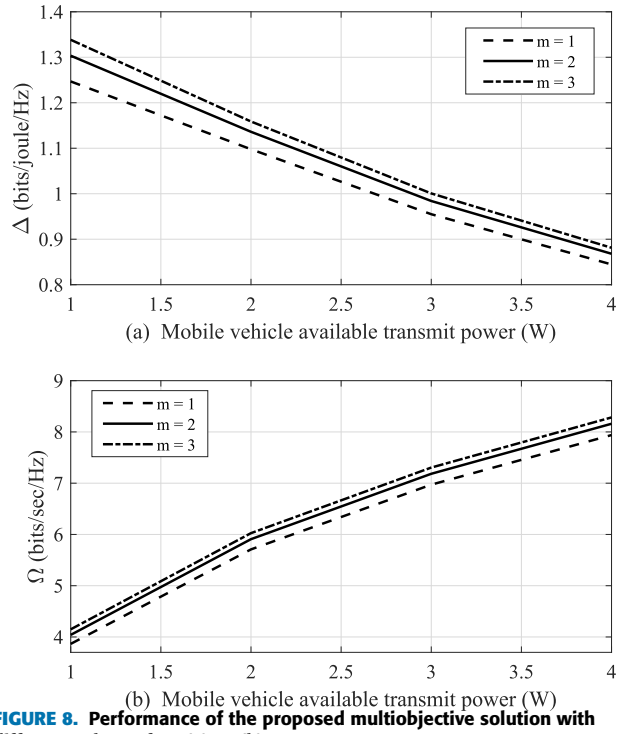

FIGURE 8. Performance of the proposed multiobjective solution with different values of m; (a) Δ, (b) Ω.

increased diversity gains. Finally, the performance of the network under different channel conditions was also illustrated. The results provided in this work are expected to lay the foundations for an extensive number of future studies in this domain.

The results provided in our work are self-sufficient, however, they are by no means conclusive and can be extended in a number of ways. For instance, future studies can consider a more dynamic network setup by introducing the concept of vehicle association. In this way, the performance of our proposed scheme can be evaluated and a more extended version can be proposed that takes into account the vehicle association aspects. Another promising direction can be to evaluate the proposed multiobjective optimization framework for cooperative vehicular networks. The cooperation among vehicles is expected to improve the performance of these networks. Moreover, the proposed optimization framework could be extended to different types of cooperation schemes. These exciting extensions of the proposed optimization framework would be performed in future work.

APPENDIXES
APPENDIX A
CONCAVITY/CONVEXITY PROOF OF (P2)

Here we show the convexity/concavity proof of the proposed optimization problem (P2). A function can be concave/convex if its Hessian matrix is negative definite. It is worth noting that a Hessian matrix will be negative definite if its leading principal minors are alternate in sign, i.e., negative for odd and positive for even numbers. Next, we derive the Hessian matrix and then prove it as a negative definite.

Firstly, we derive the objective function of proposed joint optimization problem (P2) as:

$$\underset{p_j}{\text{Min}}\ \beta \sum_{j\in\mathcal{A}} p_m - (1-\alpha)\sum_{j\in\mathcal{A}} R_m, \tag{20}$$

where in (20), one can be observed that the first segment is a linear function of power. The rate function in second segment is strictly concave-convex function.

Let us assume the active mobile vehicles per time slot are three, i.e., $\mathcal{A} = 3$. Accordingly, the channel powers of these mobile vehicles are sorted as $|g_1|^2 \le |g_2|^2 \le |g_3|^2$. Then, the sum rate can be derived as:

$$R_{\text{sum}} = \log_2(1+\gamma_1) + \log_2(1+\gamma_2) + \log_2(1+\gamma_3), \tag{21}$$

By expending the rate terms of vehicles, we have

$$R_{sum} = \log_2\left(1+\frac{p_3|h_3|^2}{\sigma^2}\right) + \log_2\left(1+\frac{p_2|h_2|^2}{p_3|h_2|^2+\sigma^2}\right) + \log_2\left(1+\frac{p_1|h_1|^2}{(p_2+p_3)|h_1|^2+\sigma^2}\right), \tag{22}$$

Next we define the Hessian matrix of (22) as:

$$H = \begin{bmatrix} \left(\frac{\partial R_{sum}}{\partial^2 p_1}\right) & \left(\frac{\partial R_{sum}}{\partial p_1 \partial p_2}\right) & \left(\frac{\partial R_{sum}}{\partial p_1 \partial p_3}\right) \\ \left(\frac{\partial R_{sum}}{\partial p_2 \partial p_1}\right) & \left(\frac{\partial R_{sum}}{\partial p_2 \partial p_2}\right) & \left(\frac{\partial R_{sum}}{\partial p_2 \partial p_3}\right) \\ \left(\frac{\partial R_{sum}}{\partial p_3 \partial p_1}\right) & \left(\frac{\partial R_{sum}}{\partial p_3 \partial p_2}\right) & \left(\frac{\partial R_{sum}}{\partial p_3 \partial p_3}\right) \end{bmatrix} \tag{23}$$

By calculating the partial derivations, we get

$$H = \begin{bmatrix} -\xi & -\xi & -\xi \\ -\xi & -\xi+\xi'-\varrho & -\xi+\xi'-\varrho \\ -\xi & -\xi+\xi'-\varrho & -\xi+\xi'-\varrho+\varrho'-\vartheta \end{bmatrix} \tag{24}$$

where

$$\xi = \left(\frac{|g_3|^2}{(p_1+p_2+p_3)|g_3|^2+\sigma^2}\right)^2, \tag{25}$$

$$\xi' = \left(\frac{|g_3|^2}{(p_2+p_3)|g_3|^2+\sigma^2}\right)^2, \tag{26}$$

$$\varrho = \left(\frac{|g_2|^2}{(p_2+p_3)|g_2|^2+\sigma^2}\right)^2, \tag{27}$$

$$\varrho' = \left(\frac{|g_2|^2}{p_3|g_2|^2+\sigma^2}\right)^2, \tag{28}$$

$$\vartheta = \left(\frac{|g_1|^2}{p_3|g_2|^2+\sigma^2}\right)^2. \tag{29}$$

Now the first order principle in (24) can be formulated as

$$\det|H_1| = -\xi. \tag{30}$$

Accordingly, the second order principle minor can be stated as:

$$\det|H_2| = \xi(\varrho-\xi') = \xi\left(\left(\frac{|g_2|^2}{p_2|g_2|^2+\sigma^2}\right)^2 - \left(\frac{|g_3|^2}{p_2|g_3|^2+\sigma^2}\right)^2\right) \tag{31}$$

where after taking least common multiple (LCM), we can obtained as:

$$= \xi\left(\frac{(2p_2|g_3|^2|g_2|^2+|g_3|^2+|g_2|^2)(|g_2|^2-|g_3|^2)}{(p_2|g_3|^2+\sigma^2)^2(p_2|g_2|^2+\sigma^2)^2}\right). \tag{32}$$

Finally, the third principle minor can be expressed as:

$$\begin{aligned}\det|H_3| &= -\xi(\varrho-\xi')(\vartheta-\varrho') \\ &= -\xi\left(\left(\frac{|g_2|^2}{p_2|g_2|^2+\sigma^2}\right)^2-\left(\frac{|g_3|^2}{p_2|g_3|^2+\sigma^2}\right)^2\right) \\ &\quad\times\left(\left(\frac{|g_1|^2}{p_3|g_2|^2+\sigma^2}\right)^2-\left(\frac{|g_2|^2}{p_3|g_2|^2+\sigma^2}\right)^2\right), \quad (33)\end{aligned}$$

Again, by taking LCM of (33), it can be written as:

$$\begin{aligned}&= -\xi \\ &\times\left(\frac{(2(p_2+p_3)|g_3|^2|g_2|^2+|g_3|^2+|g_2|^2)(|g_2|^2-|g_3|^2)}{((p_2+p_3)|g_3|^2+\sigma^2)^2((p_2+p_3)|g_2|^2+\sigma^2)^2}\right) \\ &\times\left(\frac{(2p_3|g_2|^2|g_1|^2+|g_2|^2+|g_1|^2)(|g_1|^2-|g_2|^2)}{(p_3|g_2|^2+\sigma^2)^2(p_3|g_1|^2+\sigma^2)^2}\right). \quad (34)\end{aligned}$$

where ξ, ξ', ϱ, ϱ' and ϑ in (34) are all positive. Therefore, the first and second order principle minors are negative and the third one is positive. Thus, the proposed optimization problem (P2) is concave-convex function.

APPENDIX B
CLOSED-FORM EXPRESSION DERIVATIONS

To perform the SIC process successfully at receivers, we have sorted the channel gain of three vehicles as $|g_1|^2 \le |g_2|^2 \le |g_3|^2$. Accordingly, when $j = 3$, it shows the vehicle with strongest channel gain (i.e., V_3), and can not apply SIC. Thus, it decodes the signal with the interference from all other vehicles with lower channel gains. Note that these interference of other vehicles are acted as a noise for V_3. Therefore, the closed-form expression of V_3 can be calculated as:

$$\begin{aligned}L(p_3,\lambda_3,\mu_3) &= \alpha p_3-(1-\alpha)R_3+\lambda_3(R_3-R_{min}) \\ &\quad+\mu_3(P_{max}-p_3), \quad (35)\end{aligned}$$

By taking $\frac{\partial L(p_3,\lambda_3,\mu_3)}{\partial p_3}$, it can be written as:

$$\frac{\partial L(p_3,\lambda_3,\mu_3)}{\partial p_3} = \alpha p_3+((\alpha-1)+\lambda_3)R_3-\mu_3 p_3, \quad (36)$$

Expanding the rate term of V_3, we have

$$\begin{aligned}&\frac{\partial L(p_3,\lambda_3,\mu_3)}{\partial p_3} \\ &= \alpha p_3+((\alpha-1)+\lambda_3) \\ &\quad\times\log_2\left(1+\frac{p_3|g_3|^2}{\sum_{i=1}^{2}p_i|g_3|^2+\sigma^2}\right)-\mu_3 p_3, \quad (37)\end{aligned}$$

After straightforward derivations, it can be given as:

$$\begin{aligned}\frac{\partial L(p_3,\lambda_3,\mu_3)}{\partial p_3} &= \alpha+((\alpha-1)+\lambda_3) \\ &\quad\times\left(\frac{|g_3|^2}{\sum_{i=1}^{2}p_i|g_3|^2+p_3|g_3|^2+\sigma^2}\right)-\mu_3, \quad (38)\end{aligned}$$

Solving for p_3^*, we set $\frac{\partial L(p_3,\lambda_3,\mu_3)}{\partial p_3}=0$ as:

$$\begin{aligned}&\alpha+((\alpha-1)+\lambda_3) \\ &\quad\times\left(\frac{|g_3|^2}{\sum_{i=1}^{2}p_i|g_3|^2+p_3|g_3|^2+\sigma^2}\right)-\mu_3=0, \quad (39)\end{aligned}$$

By simplification, it can be formulated as:

$$\begin{aligned}&\frac{\alpha+((\alpha-1)+\lambda_3)|g_3|^2}{\mu_3-\alpha}-(p_1+p_2)|g_3|^2-\sigma^2 \\ &\qquad = p_3|g_3|^2, \quad (40)\end{aligned}$$

Thus, the optimal power of V_3 can be derived as:

$$p_3^* = \left[\frac{((\alpha-1)+\lambda_3)|g_3|^2-\zeta_3((p_1+p_2)|g_3|^2-\sigma^2)}{\zeta_3|g_3|^2}\right]^+. \quad (41)$$

where $\zeta_3 = \mu_3-\alpha$.

For second vehicle when $j = 2$, V_2 can apply SIC, first decodes and subtract the signal V_3, and then decode its own signal. Note that V_2 can not decode V_1 signal. Thus, the closed-form expression of V_2 can be stated as:

$$\begin{aligned}L(p_2,\lambda_2,\mu_2) &= \alpha p_2-(1-\alpha)R_2+\lambda_2(R_2-R_{min}) \\ &\quad+\mu_2(P_{max}-p_2)+\eta_2(p_2|g_2|^2-p_3|g_3|^2-\beta), \quad (42)\end{aligned}$$

By taking $\frac{\partial L(p_1,\lambda_1,\mu_1)}{\partial p_1}$ and cancel the constant terms, we obtain as:

$$\begin{aligned}\frac{\partial L(p_2,\lambda_2,\mu_2)}{\partial p_2} &= \alpha p_2+((\alpha-1)+\lambda_2)R_2 \\ &\quad-\mu_2 p_2+\eta_2(p_2|g_2|^2), \quad (43)\end{aligned}$$

Expanding the rate term R_2 of V_2, we have

$$\begin{aligned}&\frac{\partial L(p_2,\lambda_2,\mu_2)}{\partial p_2} \\ &= \alpha p_2+((\alpha-1)+\lambda_2) \\ &\quad\times\log_2\left(1+\frac{p_2|g_2|^2}{p_3|g_2|^2+\sigma^2}\right)+((\alpha-1)+\lambda_1) \\ &\quad\times\log_2\left(1+\frac{p_1|g_1|^2}{\sum_{i=2}^{3}p_i|g_1|^2+\sigma^2}\right)-\mu_2 p_2+\eta_2(p_2|g_2|^2), \quad (44)\end{aligned}$$

After derivations, it can be computed as:

$$\begin{aligned}&\frac{\partial L(p_2,\lambda_2,\mu_2)}{\partial p_2} \\ &= \alpha+\eta_2|g_2|^2+((\alpha-1)+\lambda_2) \\ &\quad\times\left(\frac{|g_2|^2}{p_3|g_2|^2+p_2|g_2|^2+\sigma^2}\right)-\mu_2+((\alpha-1)+\lambda_1) \\ &\quad\times\left(\frac{-|g_1|^2}{\left(\sum_{i=2}^{3}p_i|g_1|^2+\sigma^2\right)^2+(\sum_{i=2}^{3}p_i|g_1|^2+\sigma^2)p_1|g_1|^2}\right), \quad (45)\end{aligned}$$

Solving for p_2^*, we set $\frac{\partial L(p_2,\lambda_2,\mu_2)}{\partial p_2}=0$ as:

$$\begin{aligned}0 &= \alpha+\eta_2|g_2|^2+((\alpha-1)+\lambda_2) \\ &\quad\times\left(\frac{|g_2|^2}{p_3|g_2|^2+p_2|g_2|^2+\sigma^2}\right)-\mu_2+((\alpha-1)+\lambda_1) \\ &\quad\times\left(\frac{-|g_1|^2}{\left(\sum_{i=2}^{3}p_i|g_1|^2+\sigma^2\right)^2+\sum_{i=2}^{3}p_i|g_1|^2+\sigma^2)p_1|g_1|^2}\right), \quad (46)\end{aligned}$$

By simplification, it can be given as:

$$((\alpha-1)+\lambda_2)|g_2|^2=(p_3|g_2|^2+p_2|g_2|^2+\sigma^2)\times\zeta_2, \quad (47)$$

where

$$\zeta_2=\frac{((\alpha-1)+\lambda_1)|g_1|^2}{\left(\sum_{i=2}^{3}p_i|g_1|^2+\sigma^2\right)^2+(\sum_{i=2}^{3}p_i|g_1|^2+\sigma^2)p_1|g_1|^2} +\mu_2-\eta_2|g_2|^2-\alpha, \quad (48)$$

Then, the optimal power of V_2 can be obtained as:

$$p_2^*=\left[\frac{((\alpha-1)+\lambda_2)|g_2|^2-\zeta_2(\sigma^2+p_3|g_2|^2)}{\zeta_2|g_2|^2}\right]^+, \quad (49)$$

Thus, in general, the optimal power of V_j can be derived as (11).

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