Energy-Efficient NOMA Multicasting System for Beyond 5G Cellular V2X Communications With Imperfect CSI

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***Abstract*— The integration of non-orthogonal multiple access (NOMA) in vehicle-to-everything (V2X) communications has recently shown great potential to improve traffic efficiency, control, and reliability of beyond 5G transportation systems. In V2X communications, it is vital to inspect imperfect channel state information (CSI) because the high mobility of vehicles leads to more channel estimation uncertainties. This paper proposes an energy-efficient power allocation scheme for the road-side unit (RSU) assisted NOMA multicasting in beyond 5G cellular V2X networks. In particular, the energy efficiency maximization problem is investigated under the outage probability of vehicles under imperfect CSI, quality of services (QoS), and power limit constraints. Since the problem is non-convex and difficult to solve directly, we first convert outage probability constraint to non-probabilistic constraint through approximation and adopt a low complexity gradient assisted binary search (GABS) method to obtain the efficient power allocation at RSUs. Then, a successive convex approximation (SCA) technique is exploited to transform the power allocation problem of vehicles associated with each RSU into a tractable concave-convex fractional programming (CCFP) problem. The optimal solution to the CCFP problem is achieved through Dinkelbach and the dual decomposition method. The global optimal power allocation through the GABS-Exhaustive scheme act as a benchmark, which has considerable computational complexity. Simulation results unveil that the proposed suboptimal scheme (GABS-Dinkelbach) can achieve near-optimal performance with very low complexity.**

***Index Terms*— Beyond 5G V2X communications, imperfect channel estimation, power allocation, energy efficiency, multicasting.**

I. Introduction and Motivations

IN THE last decade, there has been a rapid advancement in connected vehicles and their related technologies. Connected vehicles, which are also called V2X communications, emerged as an important integral part of the architecture of the intelligent transport system (ITS) [1], [2]. V2X enables many applications associated with vehicles, drivers, passengers, vehicle traffic, and pedestrians, which makes driving safer and more efficient for everyone. It includes vehicle-to-infrastructure (V2I), vehicle-to-pedestrian (V2P), vehicle-to-vehicle (V2V), and vehicle-to-network (V2N) communications. Through these communications, V2X can enhance traffic efficiency, road safety, and can provide entertainment services [3]. The energy management for building such a network is a challenging task because of many limiting factors such as explosive growth of connected vehicles, high mobility wireless channels, asynchronous transmissions, congested spectrum, and hardware imperfections. In vehicular networks, high mobility results in channel estimation errors, which affect the link reliability and system robustness [4]. Therefore, energy-efficient, high-reliability networking, and communications are essential for building ITS.

International standards are mandatory for the implementation of V2X communication systems. They provide specifications that ensure the interconnection between V2X systems and their components, and provide multi-vendor interoperability. Wireless access in vehicular environments (WAVE) standard is the core part of dedicated short-range communications (DSRC) technology, which has been installed on the roads in many countries since its release [5]. DSRC is a known technology for its robust performance in V2V communication and its ability to utilize the distributed channel access [6]. However, DSRC faces many challenges because of the design of its physical (PHY) and medium access control (MAC) layer. It cannot match the low latency, the high bandwidth, and the network coverage requirement of future V2X applications, especially in dense environments [7]. Limitations of DSRC and current development in cellular technologies like LTE-V in 3GPP Release 14 [8], motivated researchers to investigate cellular V2X (C-V2X) communications. In C-V2X, numerous applications can be provided through two main types of connections, that is infrastructure-based communication (V2I/I2V) through the cellular interface and V2V communication through the PC5 interface. V2V communication is essential for safety applications, while infrastructure-based communication plays a role in coordination. It is vital for the gathering of local or global real-time information such as data collections at remote RSUs for smart navigation and logistics, traffic management,

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and environmental monitoring. Then, provisioning real-time safety-related, location, and condition-based services, such as accident warning, intersection safety, speed limit information, safe distance warning, traffic jam warning, and lane-keeping support besides the entertainment services [9]. These services can be provided to vehicles and other users in ITS through both base stations and RSU, which prevent accidents by delivering timely information. RSUs can be deployed on the roads with heavy data traffic, which can be an effective solution to alleviate the severe congestions in the cellular network [10].

5G mobile network plays a vital role in establishing V2X communications because it ensures the desired reliability, capacity, and low latency in exchanging information among vehicles [11]. NOMA is an effective solution for providing low-latency and ultra-high reliability V2X services. NOMA mitigates resource collisions because of its high overloading transmissions through limited resources [12], thereby enhancing spectral efficiency and reducing latency for V2X services [13]. Many researchers used NOMA in wireless networks to achieve ultra-high reliability and low-latency requirements. Low-latency and high-reliability (LLHR) V2X broadcasting system for a dense network is proposed in [14], [15]. This broadcasting system used a mixed centralized/distributed method based on NOMA. NOMA-spatial modulation (SM) is proposed in [16] to deal with the hostile V2V environment. It is proved that the bandwidth efficiency can be improved by using spatial modulation (SM) against channel correlation in multi-antenna V2V communication along with NOMA. A novel full-duplex (FD) decentralized V2X system based on NOMA is presented in [17], which meets the demands of massively connected vehicles and their various quality of services (QoS). Cooperative communication, in combination with NOMA as a broadcasting/multicasting scheme for 5G C-V2X communications, is used in [18]. The power allocation problem is formulated for half-duplex (HD) relay-aided and full-duplex (FD) relay-aided NOMA system, in which RSUs are considered as a relay for the base station.

Moreover, as the power domain is exploited in NOMA for multiple access, power allocation algorithms will greatly affect the performance of the NOMA systems. Power allocation in NOMA has been extensively studied. Most of the existing NOMA literature focused on fixed power allocation algorithms [19]. The optimal global performance of NOMA can be realized through exhaustive search (ES) power allocation [20]. However, the complexity of the ES method is exponential [21]. The energy-efficient power allocation problem for V2X communications based on cellular D2D is proposed in [22]. In [23], authors presented an energy-efficient power allocation scheme for uplink relay assisted transmissions for V2X applications. The energy efficiency problem is formulated under transmit and circuit power constraints, as well as delay constraints. The power allocation problem for broadcasting/multicasting scheme based on cooperative NOMA for LLHR 5G C-V2X communications is formulated in [18] and [29]. They considered RSUs as relay in half-duplex(HD) mode in [29], while in both HD and FD mode in [18] for base station transmissions, and analyzed the power allocation problem for broadcasting/multicasting scheme with fairness among vehicles.

Besides, cooperative transmission is a promising way for V2X communications to improve the system performance [24]–[26]. Cooperative NOMA communications through DF RSUs for broadcasting/multicasting in 5G C-V2X network is studied in [18]. They analyzed the power allocation problem for broadcasting/multicasting schemes with fairness among vehicles. Authors in [27], optimized the system performance for backscatter enabled cooperative NOMA C-V2X communications. In their analysis, they considered that vehicles are linked to the BS through different DF RSUs and the backscatter tags. The success probability of relay-assisted C-V2X communications is analyzed in [28]. They investigated 3 different cooperative transmission schemes between wireless road nodes (including RSUs and vehicles) with the help of BS, which operates in half-duplex DF relaying mode. There are many studies about cooperative C-V2X communications that have focused on either the optimization of the reliability [18], [27], [28] or latency [23] performance of C-V2X networks. Inspired and motivated by the above research contributions, RSUs assisted energy-efficient and reliable multicasting system for beyond 5G C-V2X communications is proposed through alternating optimization algorithm in this paper. Our major contribution is summarized as follows.

- *Energy-Efficient and Reliable NOMA Multicasting System for C-V2X:* An energy-efficient and reliable NOMA multicasting system for C-V2X communications is proposed in which multiple RSUs are assisting base station, vehicles, roadside sensors, or any other Intelligent Transportation System (ITS) entity and multicast their information to the vehicles in their coverage. BS is installed with multiple antennas, which serve each RSU as a beamforming group. Besides, the BS also serves the vehicles directly in its vicinity. The system achieves energy efficiency and reliability through a proposed alternating optimization algorithm named as GABS-Dinkelbach, which first obtains the optimal transmit power for each RSU through GABS under channel outage probability constraint and RSU transmits power limit constraint. The probabilistic optimization problem under the channel outage probability requirement constraint is transformed into a non-probabilistic optimization problem for the problem's efficient solution through approximation. Then, for optimal RSU transmit power, the energy-efficient power allocation problem for vehicles associated with RSU is formulated under QoS constraint. This non-convex problem is converted into a tractable CCFP problem through SCA, which is solved by Dinkelbach's and dual decomposition method.
- *Channel Reliability:* The proposed multicasting system is developed under the consideration of channel reliability constraint under imperfect CSI. In vehicular systems, the high mobility nature of vehicles results in more uncertainties in channel estimations, which affect link reliability and system robustness. Therefore, it is necessary to inspect imperfect CSI in a vehicular

environment [4]. For successful decoding and successive interference cancellation (SIC) at vehicles, the vehicles' transmission rate should not exceed their corresponding maximum achievable rate [18]. Therefore, the communication will stop if the transmission rate of the vehicles exceeds their corresponding achievable rate. The outage probability measures whether the transmission rate of vehicles exceeds the achievable rate. It is a link/channel reliability constraint under imperfect channel estimation.

- *Low Complexity:* In the proposed multicasting system, RSUs are not utilizing their maximum transmit power all the time. Instead, they obtain their optimal energy efficiency under their transmit power limits. The optimal energy efficiency of RSUs is achieved through a low-complexity gradient assisted binary search (GABS) based iterative algorithm. Then, power allocations factors for vehicles associated with RSU under their QoS constraints are obtained through low complexity iterative algorithm based on Dinkelbach's algorithm [30]. The obtained results for the proposed alternating optimization algorithm are compared with global optimal GABS-Exhaustive (benchmark algorithm having high computational complexity) and is observed that our proposed power allocation scheme through alternating optimization algorithm obtains near-optimal EE with low acceptable computational complexity for practical implementations.
- *Analysis Under Vehicular Framework:* The proposed NOMA multicasting is analyzed under the vehicular framework for urban road scenario as presented in 3GPP TR 36.885 [8] and also in [4]. The main simulation parameters for vehicular setup are presented in detail in the simulation section.

The rest of the paper is organized as follows. Section II describes the system model and problem formulation with its solution for the proposed energy-efficient multicasting scheme for V2X communications. Section III presents the simulation results to verify the efficacy of the proposed alternating optimization algorithm. Section IV provides concluding remarks of the paper and future work.

II. System Model and Problem Formulation

A. System Model

The detail of the proposed system model for an energy-efficient and reliable NOMA multicasting system is depicted in Fig. 1, in which the base station (BS) is deployed at the center of the system. BS serves B vehicles (denoted by $\mathcal{B}-VUs$) in the regions where direct links between BS and vehicles are strong and can satisfy the QoS requirements. There are I RSUs in the system, where $\mathcal{R} = \{RSU_i | i = 1, 2, 3, \cdots, I\}$. Each RSU is viewed as a relay with a single antenna, which serves one group of vehicles (denoted by $\mathcal{R}-VUs$) in its coverage in half-duplex decode-and-forward (DF) relaying mode. Each RSU can serve K vehicles at a time. The vehicle k connected with RSU_i is denoted by $\mathcal{V}_{k,i}$. It is assumed that RSUs are deployed in the regions, where a direct link between the BS and vehicles associated with RSU is weak due to large path loss and cannot fulfill the QoS requirement of vehicles. BS is operated with multiple antennas and zero-forcing technique and handles each RSU as a beamforming group. The antenna array size at BS should be much more than the number of RSU and the beamforming group size, which results in the elimination of interference among RSUs. Consequently, the interference between different RSUs can be neglected. In the proposed system, for convenience, it is assumed that the transmission powers of $\mathcal{B}-VUs$ are allocated equally by the BS, and the EE of the system is obtained through multiple RSUs.

In the multicasting scheme, vehicles linked with the same RSU require different information. Therefore NOMA is applied at RSUs to transmit the data in multicasting form [18]. Thus, vehicles connected with the same RSU have interference among them, known as NOMA user interference, and they also have interference from $\mathcal{B}-VUs$, known as $\mathcal{B}-VUs$ interference. In NOMA, interference from the vehicles with worse channel conditions associated with the same RSU can be removed through SIC technology. The interference cancellation from other vehicles is successful, if the signal-to-interference-plus-noise ratio (SINR) of a vehicle with large channel gain is greater than or equal to the SINR of a vehicle with inferior channel gain, for its own signal [33]. Without loss of generality, It is assumed that the SINR of vehicles associated with RSU_i can be ordered as

$$\frac{|H_{k+1,i}|^2}{|G_{k+1,i}|^2 \sum_{b=1}^{B} P_b + \sigma^2} \geq \frac{|H_{k,i}|^2}{|G_{k,i}|^2 \sum_{b=1}^{B} P_b + \sigma^2}, \tag{1}$$

where, $H_{k,i}$ and $G_{k,i}$ are the channel coefficients from RSU_i to $\mathcal{V}_{k,i}$ (information link) and BS to $\mathcal{V}_{k,i}$ (interference link), respectively. P_b is the transmission power of the b^{th} $\mathcal{B}-VU$ from BS. σ^2 is the variance of additive white Gaussian noise (AWGN). In NOMA, receivers are exploiting the SIC technique, therefore the signal received by $\mathcal{V}_{k,i}$ can be expressed as

$$y_{k,i} = \underbrace{H_{k,i}\sqrt{P_i\alpha_{k,i}}s_{k,i}}_{\text{desired signal}} + \underbrace{H_{k,i}\sum_{m=k+1}^{K}\sqrt{P_i\alpha_{m,i}}s_{m,i}}_{\text{NOMA user interference}} + \underbrace{G_{k,i}\sum_{b=1}^{B}\sqrt{P_b}s_b}_{\mathcal{B}-VUs\text{ Interference}} + \underbrace{n_{k,i}}_{\text{noise}}, \tag{2}$$

where P_i is the total transmission power of the RSU_i, $\alpha_{k,i}$ and $s_{k,i}$ represent the power allocation factor and the modulated symbol of $\mathcal{V}_{k,i}$, respectively. s_b is the transmitted modulated symbol of b^{th} B-VU. $n_{k,i}$ denotes AWGN with zero mean and variance (σ^2).

The channel between RSU_i-$\mathcal{V}_{k,i}$ information link and BS-$\mathcal{V}_{k,i}$ interference link consist of the following components, respectively.

$$H_{k,i} = D_{k,i} \times h_{k,i}, \tag{3}$$

and

$$G_{k,i} = D'_{k,i} \times g_{k,i}, \tag{4}$$

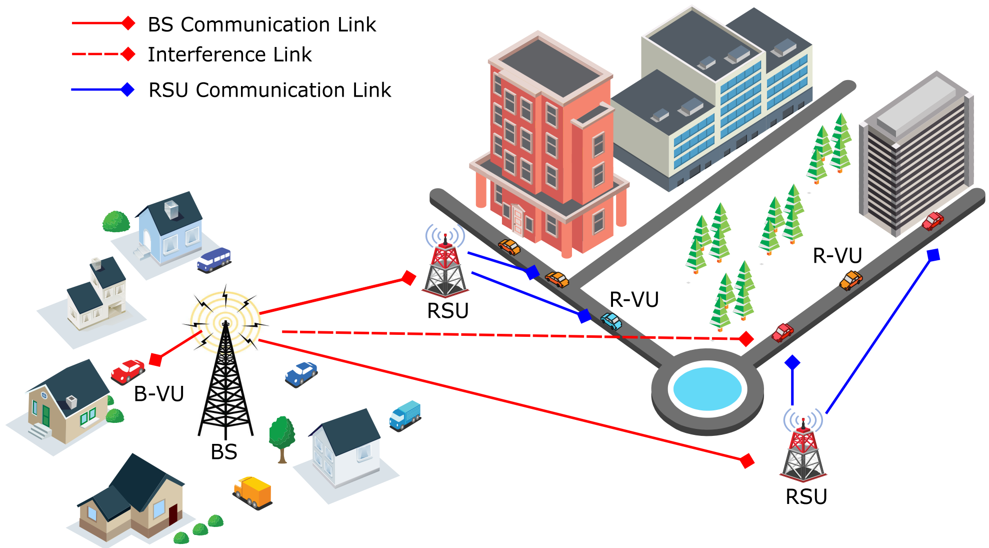

Fig. 1. Illustration of System model.

where $h_{k,i}$ and $g_{k,i}$ are the fast fading component of the RSU_i-$\mathcal{V}_{k,i}$ information link and BS-$\mathcal{V}_{k,i}$ interference link, respectively. $D_{k,i} = \sqrt{{d_{k,i}}^{-\beta}\vartheta_{k,i}}$ and $D\acute{}_{k,i} = \sqrt{{d\acute{}_{k,i}}^{-\beta}\vartheta\acute{}_{k,i}}$, where $d_{k,i}$ and $d\acute{}_{k,i}$ are the distance from the RSU_i to $\mathcal{V}_{k,i}$ and BS to $\mathcal{V}_{k,i}$, respectively. β is the path-loss exponent. $\vartheta_{k,i}$ and $\vartheta\acute{}_{k,i}$ represent log normal shadowing random variable with 8 dB standard deviation for RSU_i-$\mathcal{V}_{k,i}$ information link and BS-$\mathcal{V}_{k,i}$ interference link, respectively.

The high mobility nature of vehicles results in channel estimation errors. The estimation of channel state information (CSI) of links is pilot based. By using the minimum mean square error (MMSE) channel estimation error model [4], [31], the Rayleigh fading coefficients between RSU_i-$\mathcal{V}_{k,i}$ information link and BS-$\mathcal{V}_{k,i}$ interference link, respectively, can be modeled as

$$h_{k,i} = \hat{h}_{k,i} + \epsilon_{k,i}, \tag{5}$$

and

$$g_{k,i} = \hat{g}_{k,i} + \epsilon\acute{}_{k,i}, \tag{6}$$

where $h_{k,i}$ and $g_{k,i}$ are the accurate Rayleigh channel coefficients, $\hat{h}_{k,i} \sim \mathcal{CN}(0, 1 - \sigma_{RSU}^2)$ and $\hat{g}_{k,i} \sim \mathcal{CN}(0, 1 - \sigma_{BS}^2)$ are the estimated channel gains, $\epsilon_{k,i} \sim \mathcal{CN}(0, \sigma_{RSU}^2)$ and $\epsilon\acute{}_{k,i} \sim \mathcal{CN}(0, \sigma_{BS}^2)$ are the estimated channel errors, which are Gaussian distributed with zero mean and variances σ_{RSU}^2 and σ_{BS}^2, respectively. It is assumed that estimated coefficients and their errors are uncorrelated.

From Eq. 1, the received SINR of $\mathcal{V}_{k,i}$ after SIC is as follow,

$$\gamma_{k,i} = \frac{P_i \alpha_{k,i} |H_{k,i}|^2}{\underbrace{|H_{k,i}|^2 \sum_{m=k+1}^{K} P_i \alpha_{m,i}}_{\text{NOMA user interference}} + \underbrace{|G_{k,i}|^2 \sum_{b=1}^{B} P_b}_{\mathcal{B}-VUs\text{ Interference}} + \sigma^2}. \tag{7}$$

Under the conditions of perfect CSI, the maximum achievable transmission/data rates of $\mathcal{V}_{k,i}$ can be written as, respectively.

$$C_{k,i} = BW \log_2(1 + \gamma_{k,i}). \tag{8}$$

Under the conditions of imperfect CSI, the estimated received SINR of $\mathcal{V}_{k,i}$ is given as

$$\hat{\gamma}_{k,i} = \frac{P_i \alpha_{k,i} |\hat{H}_{k,i}|^2}{\underbrace{|\hat{H}_{k,i}|^2 \sum_{m=k+1}^{K} P_i \alpha_{m,i}}_{\text{NOMA user interference}} + \underbrace{|\hat{G}_{k,i}|^2 \sum_{b=1}^{B} P_b}_{\mathcal{B}-VUs\text{ Interference}} + \sigma^2}. \tag{9}$$

where $\hat{H}_{k,i} = D_{k,i} \times \hat{h}_{k,i}$ and $\hat{G}_{k,i} = D\acute{}_{k,i} \times \hat{g}_{k,i}$. The corresponding estimated or scheduled data rate of $\mathcal{V}_{k,i}$ can be written as

$$R_{k,i} = BW \log_2 \left(1 + \hat{\gamma}_{k,i}\right). \tag{10}$$

Under imperfect CSI, the scheduled data transmission rate of vehicles may easily surpass the maximum achievable rate of vehicles, which fails the decoding and successive interference cancellation (SIC) at vehicles. Therefore, outage probability has been adopted that measure whether the scheduled rate of vehicles exceeds the maximum achievable rate of vehicles with imperfect CSI. Then, the average outage sum-rate of the RSU_i can be given as follow,

$$R_i = \sum_{k=1}^{K} R_{k,i}.Pr\left[R_{k,i} \leq C_{k,i} | \hat{h}_{k,i}, \hat{g}_{k,i}\right]. \tag{11}$$

B. Problem Formulation

Energy-efficient multicasting through multiple RSUs is the primary purpose of the optimization problem. The main objective is to maximize the system sum-rate with the unit power cost. Therefore, the energy efficiency of the system is formulated as the ratio of the sum-rate of the system to the total power consumption of the system. The energy efficiency maximization problem is expressed as

$$
\begin{aligned}
&\max_{P_i,\boldsymbol{\alpha}} \sum_{i=1}^{I} E_i \\
&= \max_{P_i,\boldsymbol{\alpha}} \sum_{i=1}^{I} \frac{R_i}{\sum_{k=1}^{K} P_i\alpha_{k,i} + P_c}, \\
&\quad s.t.\ C1: Pr\Big[R_{k,i} > C_{k,i}|\hat{h}_{k,i},\hat{g}_{k,i}\Big] \le P_{out}, \forall\, k,i, \\
&\qquad C2: P_i\alpha_{k,i}|\hat{H}_{k,i}|^2 \ge \Big(2^{R_{min}}-1\Big)\times\Big(|\hat{H}_{k,i}|^2 \\
&\qquad \sum_{m=k+1}^{K} P_i\alpha_{m,i} + |\hat{G}_{k,i}|^2\sum_{b=1}^{B} P_b + \sigma^2\Big), \quad \forall\, k,i, \\
&\qquad C3: P_{low} \le P_i \le P_{high}, \quad \forall i, \\
&\qquad C4: \sum_{k=1}^{K}\alpha_{k,i} \le 1, \quad \forall\, k,i, \\
&\qquad C5: \alpha_{k,i} \ge 0, \quad \forall\, k,i,
\end{aligned}
\tag{12}
$$

where E_i represents energy efficiency of the RSU_i. $\sum_{k=1}^{K} P_i\alpha_{k,i}$ and P_c are the transmission power and circuit power consumption of the RSU_i, respectively. $\alpha_{k,i}$ is the power allocation factor of the $\mathcal{V}_{k,i}$ associated with RSU_i, while $\boldsymbol{\alpha} = \{\alpha_{1,i},\alpha_{2,i},\ldots,\alpha_{K,i}\}$ is the vector of power allocation factors of vehicles associated with RSU_i. R_i is the scheduled sum rate of vehicles associated with RSU_i. $C1$ constraint ensure the requirement of channel outage probability (P_{out}). $C2$ guarantees QoS (minimum required rate) provisioning for each vehicle. $C3$ enforces the transmission power limit of RSUs. $C4$ constraint describes the condition for power allocation factor of vehicles connected with RSU_i. $C5$ ensures that the power assigned to each vehicle is non-negative.

The optimization problem in Eq. (12) cannot achieve an optimal global solution under probabilistic constraint $C1$, which is transformed into a non-probabilistic problem via approximation or relaxation. For instance, The maximum achievable data rate of $\mathcal{V}_{k,i}$ can be rewritten as

$$C_{k,i} = BW\log_2\Big(1+\gamma_{k,i}\Big) = BW\log_2\Big(1+\frac{x_{k,i}}{y_{k,i}}\Big), \tag{13}$$

where

$$x_{k,i} = P_i\alpha_{k,i}|H_{k,i}|^2, \tag{14}$$

and

$$y_{k,i} = |H_{k,i}|^2\sum_{m=k+1}^{K} P_i\alpha_{m,i} + |G_{k,i}|^2\sum_{b=1}^{B} P_b + \sigma^2. \tag{15}$$

The scheduled data rate or estimated data rate of $\mathcal{V}_{k,i}$ can be expressed as

$$R_{k,i} = BW\log_2\Big(1+\hat{\gamma}_{k,i}\Big) = BW\log_2\Big(1+\frac{\hat{x}_{k,i}}{\hat{y}_{k,i}}\Big), \tag{16}$$

where

$$\hat{x}_{k,i} = P_i\alpha_{k,i}|\hat{H}_{k,i}|^2, \tag{17}$$

and

$$\hat{y}_{k,i} = |\hat{H}_{k,i}|^2\sum_{m=k+1}^{K} P_i\alpha_{m,i} + |\hat{G}_{k,i}|^2\sum_{b=1}^{B} P_b + \sigma^2. \tag{18}$$

The outage probability requirements are always satisfied by the strict constraints [31], [32]. The mathematical proof is demonstrated in Appendix A. These strict constraints are presented as follow,

$$Pr\Big[x_{k,i} \le \hat{x}_{k,i}|\hat{h}_{k,i},\hat{g}_{k,i}\Big] = \frac{P_{out}}{2}, \tag{19}$$

and

$$Pr\Big[y_{k,i} \ge \hat{y}_{k,i}|\hat{h}_{k,i},\hat{g}_{k,i}\Big] \le \frac{P_{out}}{2}. \tag{20}$$

Putting the value of $x_{k,i}$ from Eq. (14) into the strict constraint described in Eq. (19), we can derive $\hat{x}_{k,i}$ as follow.

$$Pr\Big[P_i\alpha_{k,i}|H_{k,i}|^2 \le \hat{x}_{k,i}|\hat{h}_{k,i},\hat{g}_{k,i}\Big] = \frac{P_{out}}{2}, \tag{21}$$

Since $H_{k,i} = D_{k,i}h_{k,i}$, therefore

$$Pr\Big[P_i\alpha_{k,i}D_{k,i}^2|h_{k,i}|^2 \le \hat{x}_{k,i}|\hat{h}_{k,i},\hat{g}_{k,i}\Big] = \frac{P_{out}}{2}, \tag{22}$$

or,

$$Pr\Big[|h_{k,i}|^2 \le \frac{\hat{x}_{k,i}}{P_i\alpha_{k,i}D_{k,i}^2}|\hat{h}_{k,i},\hat{g}_{k,i}\Big] = \frac{P_{out}}{2}, \tag{23}$$

The above equation can be written as

$$F_{|h_{k,i}|^2}\Big(\frac{\hat{x}_{k,i}}{P_i\alpha_{k,i}D_{k,i}^2}\Big) = \frac{P_{out}}{2}, \tag{24}$$

Then we have

$$\hat{x}_{k,i} = F^{-1}_{|h_{k,i}|^2}\Big(\frac{P_{out}}{2}\Big)P_i\alpha_{k,i}D_{k,i}^2, \tag{25}$$

where $|h_{k,i}|^2 \sim \mathcal{CN}(\hat{h}_{k,i},\sigma^2_{RSU})$ is a random variable with non central chi-squared distribution, which has 2 degrees of freedom. $F_{|h_{k,i}|^2}$ is its corresponding cumulative distribution function (CDF) while $F^{-1}_{|h_{k,i}|^2}$ denotes inverse CDF of the non central chi square distribution.

Similarly, we can derive $\hat{y}_{k,i}$ by substituting the value $y_{k,i}$ from Eq. (15) into the strict constraint described in Eq. (20) and then applying Markov inequality [31], as follow

$$
\begin{aligned}
Pr\Big[&|H_{k,i}|^2\sum_{m=k+1}^{K} P_i\alpha_{m,i} + |G_{k,i}|^2\sum_{b=1}^{B} P_b + \sigma^2 \\
&\ge \hat{y}_{k,i}|\hat{h}_{k,i},\hat{g}_{k,i}\Big] \le \frac{P_{out}}{2},
\end{aligned}
\tag{26}
$$

or,

$$
\begin{aligned}
Pr\Big[&D_{k,i}{}^2|h_{k,i}|^2\sum_{m=k+1}^{K} P_i\alpha_{m,i} + \acute{D_{k,i}}{}^2|g_{k,i}|^2\sum_{b=1}^{B} P_b \\
&\ge \hat{y}_{k,i} - \sigma^2|\hat{h}_{k,i},\hat{g}_{k,i}\Big] \le \frac{P_{out}}{2},
\end{aligned}
\tag{27}
$$

According to Markov inequality, the above equation can be written as,

$$\leq \frac{E\Big[D_{k,i}{}^2|h_{k,i}|^2\sum_{m=k+1}^{K}P_i\alpha_{m,i}+\acute{D}_{k,i}{}^2|g_{k,i}|^2\sum_{b=1}^{B}P_b\Big]}{\hat{y}_{k,i}-\sigma^2} \leq \frac{P_{out}}{2}. \tag{28}$$

It implies that,

$$= \frac{D_{k,i}{}^2|h_{k,i}|^2\sum_{m=k+1}^{K}P_i\alpha_{m,i}+\acute{D}_{k,i}{}^2|g_{k,i}|^2\sum_{b=1}^{B}P_b}{\hat{y}_{k,i}-\sigma^2} = \frac{P_{out}}{2}, \tag{29}$$

or,

$$\hat{y}_{k,i} = \frac{2}{P_{out}}\Big(\acute{D}_{k,i}{}^2|g_{k,i}|^2\sum_{b=1}^{B}P_b + D_{k,i}{}^2|h_{k,i}|^2\sum_{m=k+1}^{K}P_i\alpha_{m,i}\Big) + \sigma^2. \tag{30}$$

Now, the scheduled rate of $\mathcal{V}_{k,i}$ with the channel outage probability constraint in the form of non-probabilistic form after relaxation or approximation can be written as

$$R^*_{k,i} = BW\log_2\Big(1+\hat{\gamma}^*_{k,i}\Big), \tag{31}$$

where, $\hat{\gamma}^*_{k,i}$ is the transformed estimated SINR of the $\mathcal{V}_{k,i}$, which can be obtained by inserting the value of $\hat{x}_{k,i}$ and $\hat{y}_{k,i}$ from Eq. (25) and Eq. (30) respectively, as follow

$$\hat{\gamma}^*_{k,i} = \frac{\hat{x}_{k,i}}{\hat{y}_{k,i}} = \frac{X_{k,i}P_i\alpha_{k,i}}{Y_{k,i}+Z_{k,i}\sum_{m=k+1}^{K}P_i\alpha_{m,i}}, \tag{32}$$

where,

$$X_{k,i} = P_{out}F^{-1}_{|h_{k,i}|^2}\Big(\frac{P_{out}}{2}\Big)D^2_{k,i}, \tag{33}$$

$$Y_{k,i} = 2\acute{D}_{k,i}{}^2\Big(|\hat{g}_{k,i}|^2+\sigma^2_{BS}\Big)\sum_{b=1}^{B}P_b + P_{out}\sigma^2, \tag{34}$$

$$Z_{k,i} = 2D_{k,i}{}^2\Big(\big|\hat{h}_{k,i}\big|^2+\sigma^2_{RSU}\Big). \tag{35}$$

In Eq. (35), $(|\hat{h}_{k,i}|^2+\sigma^2_{RSU}) = |h_{k,i}|^2$ and $(|\hat{g}_{k,i}|^2+\sigma^2_{BS}) = |g_{k,i}|^2$ in Eq. (34). Now, the average sumrate of RSU_i can be written as

$$R^*_i = \Big(1-P_{out}\Big)\sum_{k=1}^{K}R^*_{k,i}. \tag{36}$$

Based on the above approximation, the optimization problem in Eq. (12) can be rewritten as a transformed non-probabilistic optimization problem as follow

$$\begin{aligned}
&\max_{P_i,\boldsymbol{\alpha}}\sum_{i=1}^{I}E^*_i = \max_{P_i,\boldsymbol{\alpha}}\sum_{i=1}^{I}\frac{R^*_i}{\sum_{k=1}^{K}P_i\alpha_{k,i}+P_c},\\
&s.t.\ C1: X_{k,i}P_i\alpha_{k,i} \geq \Big(2^{R_{min}}-1\Big),\\
&\quad\times\Big(Y_{k,i}+Z_{k,i}\sum_{m=k+1}^{K}P_i\alpha_{m,i}\Big), \forall\, k,i,\\
&\quad C2: P_{low} \leq P_i \leq P_{high}, \quad \forall i,\\
&\quad C3: \sum_{k=1}^{K}\alpha_{k,i} \leq 1, \quad \forall\, k,i,\\
&\quad C4: \alpha_{k,i} \geq 0, \quad \forall\, k,i.
\end{aligned} \tag{37}$$

The above non-probabilistic optimization problem with respect to $\alpha_{k,i}$ is still non-convex. Therefore, it is challenging to get a global optimal solution in practice. A low complexity energy-efficient optimal power allocation algorithm is required and essential, which will be designed and addressed in the rest of the paper.

C. Energy Efficient Multicasting Scheme Design

The energy efficiency maximization problem defined in Eq. (37) is coupled on optimization variables P_i and $\alpha_{k,i}$, which make the problem highly intractable. Therefore, this problem can be solved through an alternating optimization algorithm (GABS-Dinkelbach) that decouples the problem into subproblems for each optimization variable. In the proposed alternating optimization, for the given power allocation coefficients of vehicles, firstly, a low complexity GABS algorithm is used for the optimal power (P^*_i) allocation of the RSU_i.Then, for the optimal transmit power of i^{th} RSU, the problem of the power allocation coefficient of vehicles connected with RSU_i is solved through the Dinkelbach algorithm.

1) Power Allocation Scheme for RSUs: Maximum energy efficiency for all RSUs can be achieved if each RSU attains its optimal energy efficiency. Therefore, a low complexity GABS algorithm is used, which searches for an optimal P^* for maximizing $E(P^*)$. The global optimality of GABS is ensured by the quasi-concavity of $E(P^*)$ [34]. In [34], the GABS algorithm is used for channel selection in OFDMA networks, while in this paper, it is used for optimal transmit power of RSUs in NOMA networks under considered system model. As the GABS algorithm works on the principles of quasi concavity, therefore we demonstrate that our proposed problem is quasi concave as follow, The optimization problem for optimal power allocation for RSUs can be formulated as follow,

$$\begin{aligned}
&\max_{P_i}\sum_{i=1}^{I}E^*_i = \max_{P_i}\sum_{i=1}^{I}\frac{\Big(1-P_{out}\Big)\sum_{k=1}^{K}R^*_{k,i}}{\sum_{k=1}^{K}P_i\alpha_{k,i}+P_c},\\
&s.t.\ C1: P_{low} \leq P_i \leq P_{high}, \forall i.
\end{aligned} \tag{38}$$

For simplicity, the objective function in the above optimization problem for the RSU_i can be rewritten as

$$E_i^* = \frac{\left(1 - P_{out}\right)\sum_{k=1}^{K} R_{k,i}^*}{\sum_{k=1}^{K} P_i\alpha_{k,i} + P_c} = \frac{\left(1 - P_{out}\right)BW}{\sum_{k=1}^{K} P_i\alpha_{k,i} + P_c} \times \sum_{k=1}^{K}\left[\log_2\left(1 + \frac{X_{k,i}P_i\alpha_{k,i}}{Y_{k,i} + Z_{k,i}\sum_{m=k+1}^{K} P_i\alpha_{m,i}}\right)\right]. \quad (39)$$

E_i^* is strictly quasi-concave with respect to P_i, which proof is presented in Appendix B. The unique optimal P_i^* obtained through GABS algorithm should result in $\frac{\partial E_i^*(P_i)}{\partial P_i}|P_i = P_i^* = 0$. The detailed GABS algorithm for our problem is presented in Algorithm 1.

As $E_i^*(P_i)$ is strictly quasi-concave, therefore according to GABS, there is unique P_i^* such that for any

$$\begin{cases} P_i < P_i^*, & \dfrac{\partial E_i^*(P_i)}{\partial P_i} > 0; \\ P_i > P_i^*, & \dfrac{\partial E_i^*(P_i)}{\partial P_i} < 0. \end{cases} \quad (40)$$

Hence, we have the following lemma to seek P_i^* between two points P_{low} and P_{high}, such that $P_{low} \le P_i^* \le P_{high}$.

Lemma 1: Initialize, $P_i^{[a]} > P_{low}$ and set the step size $c > 1$, then for any $a \ge 0$

$$P_i^{[a+1]} = \begin{cases} P_i^{[a]}c, & \dfrac{\partial E_i^*(P_i^{[a]})}{\partial P_i^{[a]}} > 0; \\ \dfrac{P_i^{[a]}}{c}, & \dfrac{\partial E_i^*(P_i^{[a]})}{\partial P_i^{[a]}} < 0. \end{cases} \quad (41)$$

Repeat Eq. (41) until $P_i^{[A]}$, such that $\frac{\partial E_i^*(P_i^{[A]})}{\partial P_i^{[A]}}$ has a dissimilar sign from $\frac{\partial E_i^*(P_i^{[0]})}{\partial P_i^{[0]}}$. Then, P_i^* must be between $P_i^{[A]}$ and $P_i^{[A-1]}$ ($P_i^{[A-1]} \le P_i^* \le P_i^{[A]}$). To seek P_i^* between $P_i^{[A]}$ and $P_i^{[A-1]}$, let $\hat{P} = \frac{P_i^{[A]} + P_i^{[A-1]}}{2}$. If $\frac{\partial E_i^*(\hat{P})}{\partial \hat{P}} = 0$, P_i^* is found. If $\frac{\partial E_i^*(\hat{P})}{\partial \hat{P}} < 0$, then replace $P_i^{[A]}$ with $\hat{P}$ ($P_i^{[A-1]} \le P_i^* \le \hat{P}$). Otherwise, replace $P_i^{[A-1]}$ with $\hat{P}$ ($\hat{P} \le P_i^* \le P_i^{[A]}$) for $\frac{\partial E_i^*(\hat{P})}{\partial \hat{P}} > 0$. This leads to maximum $E_i^*(P_i^*)$. GABS algorithm is summarized in detail in Algorithm 1. GABS converges to the global optimal power P_i^* in at most N_g iterations, where $N_g \ge \log_2(\frac{(c-1)P_i^*}{\Delta} - 1)$ [34]. c is the step size, and Δ is the maximum tolerance used in Algorithm 1.

2) Power Allocation Scheme for Vehicles With QoS Provisioning: Through GABS optimal power for RSU is obtained. Now the optimization problem for allocating powers to vehicles under QoS constraint can be rewritten as,

$$\max_{\boldsymbol{\alpha}} \sum_{i=1}^{I} E_i^* = \max_{\boldsymbol{\alpha}} \sum_{i=1}^{I} \frac{R_i^*}{\sum_{k=1}^{K} P_i\alpha_{k,i} + P_c},$$
$$s.t.\ C1: X_{k,i}P_i\alpha_{k,i} \ge \left(2^{R_{min}} - 1\right) \times \left(Y_{k,i} + Z_{k,i}\sum_{m=k+1}^{K} P_i\alpha_{m,i}\right), \forall\, k, i,$$
$$C2: \sum_{k=1}^{K} \alpha_{k,i} \le 1, \quad \forall\, k, i,$$
$$C3: \alpha_{k,i} \ge 0, \quad \forall\, k, i. \quad (42)$$

Algorithm 1 GABS for Optimal Power Allocation of RSUs

Initialization: RSU allocates transmit power to each vehicle through NOMA principles without QoS constraint and $P_i = \frac{P_{low} + P_{high}}{2}$.
Compute $G_1 = \frac{\partial E_i^*(P_i)}{\partial P_i}$ and $c > 1(step\ size)$.
if $G_1 > 0$ **then**
  while $G_1 > 0$ **do**
    $P_i^{(1)} = P_i$ and $P_i = P_i \times c$
    Compute $G = \frac{\partial E_i^*(P_i)}{\partial P_i}$
  end while
else
  $P_i^{(1)} = \frac{P_i}{c}$ and compute $G_2 = \frac{\partial E_i^*(P_i^{(1)})}{\partial P_i^{(1)}}$
  while $G_2 < 0$ **do**
    $P_i = P_i^{(1)}$ and $P_i^{(1)} = \frac{P_i^{(1)}}{c}$.
    Compute $G_2 = \frac{\partial E_i^*(P_i^{(1)})}{\partial P_i^{(1)}}$
  end while
end if
while $|P_i - P_i^{(1)}| > \Delta$ **do**
  $P_i^* = \frac{P_i + P_i^{(1)}}{2}$ and $\acute{G} = \frac{\partial E_i^*(P_i^*)}{\partial P_i^*}$
  if $\acute{G} < 0$ **then**
    $P_i = P_i^*$
  else
    $P_i^{(1)} = P_i^*$
  end if
end while
Output P_i^*

The above optimization problem is non-convex respect to $\alpha_{k,i}$. Its objective function has a non-linear fractional form, which is very challenging to solve. Successive convex approximation (SCA) is adopted, reducing complexity and transforming the optimization problem into tractable concave-convex fractional programming (CCFP) problem. SCA in each iteration approximate the non-convex objective function by logarithmic approximation [35] as follows

$$\Pi \log_2\left(SINR\right) + \Phi \le \log_2\left(1 + SINR\right), \quad (43)$$

where $\Pi = \frac{SINR_0}{1+SINR_0}$ and $\Phi = \log_2(1 + SINR_0) - \frac{SINR_0}{1+SINR_0}\log_2(SINR_0)$. When $SINR = SINR_0$, the bound becomes tight. By using the lower bound of inequality in Eq. (43),the data rate of vehicle k associated with RSU_i can be given as

$$\overline{R}_{k,i}^* = BW\left(\Pi_{k,i}\log_2\left(\hat{\gamma}_{k,i}^*\right) + \Phi_{k,i}\right), \quad (44)$$

where

$$\Pi_{k,i} = \frac{\hat{\gamma}^*_{k,i}}{1+\hat{\gamma}^*_{k,i}}, \tag{45}$$

and

$$\Phi_{k,i} = \log_2\left(1+\hat{\gamma}^*_{k,i}\right) - \frac{\hat{\gamma}^*_{k,i}}{1+\hat{\gamma}^*_{k,i}}\log_2\left(\hat{\gamma}^*_{k,i}\right). \tag{46}$$

Now the average sumrate of RSU_i can be rewritten as

$$\overline{R}^*_i = \left(1-P_{out}\right)\sum_{k=1}^{K}\overline{R}^*_{k,i}. \tag{47}$$

Hence the updated optimization problem can be formulated as

$$\begin{aligned} &\max_{\boldsymbol{\alpha}}\sum_{i=1}^{I}\overline{E}^*_i = \max_{\boldsymbol{\alpha}}\sum_{i=1}^{I}\frac{\overline{R}^*_i}{\sum_{k=1}^{K}P_i\alpha_{k,i}+P_c},\\ &s.t.\ C1: X_{k,i}P_i\alpha_{k,i} \geq \left(2^{\frac{R_{min}-\Phi_{k,i}}{\Pi_{k,i}}}\right),\\ &\qquad \times\left(Y_{k,i}+Z_{k,i}\sum_{m=k+1}^{K}P_i\alpha_{m,i}\right), \quad \forall\, k,i\\ &\qquad C2: \sum_{k=1}^{K}\alpha_{k,i} \leq 1, \quad \forall\, k,i,\\ &\qquad C3: \alpha_{k,i} \geq 0, \quad \forall\, k,i. \end{aligned} \tag{48}$$

The objective function in Eq. (48) is still non-convex and is in the form of CCFP. So solving it directly is challenging. This problem can be solved in an affordable complexity through Dinkelbach's algorithm [36]. Let $q = \frac{\overline{R}^*_i}{\sum_{k=1}^{K}P_i\alpha_{k,i}+P_c}$, then the fractional objective function in Eq. (48) can be presented in parametric form as $F(q) = \overline{R}^*_i - q(\sum_{k=1}^{K}P_i\alpha_{k,i}+P_c)$, where q is a real parameter. Finding the roots of the $F(q)$ is equivalent to solving the fractional objective function in Eq. (48) [37]. Now the objective function in Eq. (48) can be written as

$$\begin{aligned} \max_{\boldsymbol{\alpha}}\sum_{i=1}^{I}\overline{E}^*_i &= \max_{\boldsymbol{\alpha}}\sum_{i=1}^{I}F(q)\\ &= \max_{\boldsymbol{\alpha}}\sum_{i=1}^{I}\overline{R}^*_i - q\left(\sum_{k=1}^{K}P_i\alpha_{k,i}+P_c\right). \end{aligned} \tag{49}$$

Form Eq. (49), F(q) is negative when q approaches infinity, while $F(q)$ is positive when q approaches minus infinity. $F(q)$ is convex about q. The convex problem in Eq. (49) is solved by adopting the Lagrangian dual decomposition method. The Lagrangian function can be written as

$$\begin{aligned} &L(\boldsymbol{\alpha},\boldsymbol{\mu},\lambda)\\ &= (1-P_{out})BW\\ &\times\left(\sum_{k=1}^{K}\Pi_{k,i}\times\log_2\left(\frac{X_{k,i}P_i\alpha_{k,i}}{Y_{k,i}+Z_{k,i}\sum\limits_{m=k+1}^{K}P_i\alpha_{m,i}}\right)+\Phi_{k,i}\right)\\ &-q\left(\sum_{k=1}^{K}P_i\alpha_{k,i}+P_c\right)+\sum_{k=1}^{K}\mu_k\left(X_{k,i}P_i\alpha_{k,i}-2^{\frac{R_{min}-\Phi_{k,i}}{\Pi_{k,i}}}\right.\\ &\left.\times\left(Y_{k,i}+Z_{k,i}\sum_{m=k+1}^{K}P_i\alpha_{m,i}\right)\right)+\lambda\left(1-\sum_{k=1}^{K}\alpha_{k,i}\right), \end{aligned} \tag{50}$$

where $\boldsymbol{\mu} = \{\mu_1,\cdots,\mu_K\}$ and λ are the dual variables or Lagrange multipliers. $\boldsymbol{\mu}$ is related to the constraint $C1$ while λ is corresponding to the constraint $C2$ in Eq. (48). For optimizing the power allocation for the vehicles, constraints are the KKT conditions [38]. The Lagrangian dual function is given by

$$g(\boldsymbol{\mu},\lambda) = \max_{\boldsymbol{\alpha}>0,\boldsymbol{\mu},\lambda\geq 0} L(\boldsymbol{\alpha},\boldsymbol{\mu},\lambda) \tag{51}$$

Then, the dual Lagrangian problem is formulated by

$$\min_{\boldsymbol{\mu},\lambda\geq 0} g(\boldsymbol{\mu},\lambda), \tag{52}$$

For the given energy efficiency q and fixed Lagrangian multipliers, its standard optimization problem is based on KKT conditions. The closed-form expression of optimal power allocation factor of k^{th} vehicle associated with RSU_i can be derived in Appendix C as

$$\alpha_{k,i} = \frac{(1-P_{out})BW\Pi_{k,i}}{\ln 2(qP_i+\lambda-\mu_{k,i}(X_{k,i}P_i))+\sum_{l=1}^{k-1}\Theta(\alpha_{l,i})}, \tag{53}$$

where

$$\begin{aligned} \Theta(\alpha_{l,i}) = (1-P_{out})BW\Pi_{l,i}\hat{\gamma}^*_{l,i}\times\frac{Z_{l,i}}{X_{l,i}\alpha_{l,i}}\\ +\ln 2\mu_{l,i}(Z_{l,i}P_i 2^{\frac{R_{min}-\Phi_{l,i}}{\Pi_{l,i}}}). \end{aligned} \tag{54}$$

To utilize the all optimal transmit power of RSU (P^*_i) among its connected vehicles, the vehicle with lowest SINR can get its power allocation factor by $\alpha_{1,i} = 1-\sum_{k=2}^{K}\alpha_{k,i}$. Given the optimal power allocation policy in Eq. (53), the primal problem's dual variables can be computed and updated iteratively by the sub-gradient method [39].

$$\begin{aligned} &\lambda(iter+1)\\ &= \left[\lambda(iter)-\omega_1(iter)\left(1-\sum_{k=1}^{K}\alpha_{k,i}\right)\right]^+ \end{aligned} \tag{55}$$

$$\begin{aligned} &\mu_{k,i}(iter+1)\\ &= \left[\mu_{k,i}(iter)-\omega_2(iter)\left(X_{k,i}P_i\alpha_{k,i}\right.\right.\\ &\left.\left.-(2^{\frac{R_{min}-\Phi_{k,i}}{\Pi_{k,i}}})\times(Y_{k,i}+Z_{k,i}\sum_{m=k+1}^{K}P_i\alpha_{m,i})\right)\right]^+ \quad \forall\, k,i \end{aligned} \tag{56}$$

where $iter$ denotes the iteration index. ω_1 and ω_2 are positive step sizes. The appropriate step size is necessary for the convergence of the iteration process to an optimal solution. The iterative power allocation algorithm for vehicles based on Dinkelbach's algorithm is presented in Algorithm 2.

3) Complexity Analysis: In this subsection, the computational complexity of the proposed alternating optimization algorithm (GABS-Dinkelbach) and benchmark algorithm (GABS-Exhaustive) is analyzed and is presented in table I. The EE maximization problem expressed in Eq. (37) is highly intractable because of the coupled optimization variables (P_i and $\alpha_{k,i}$). The problem is decoupled into sub problems for

TABLE I
COMPLEXITY ANALYSIS OF ALGORITHMS

Algorithm	Complexity	Optimality
GABS-Exhaustive	$O(IN_g) + O(\frac{P_{max}}{\tau})^{IK}$ (High complexity - Impractical)	Global optimal (Benchmark)
GABS-Dinkelbach	$O(IN_g) + O(N(KI)^2)$ (Low complexity - Practical)	Suboptimal (Proposed)

Algorithm 2 Iterative Method Based on Dinkelbach's Algorithm for Optimal Power Allocation to Vehicles Under QoS Provisioning

Initialization: Assign the energy efficiency obtain through GABS (Algorithm 1), maximum iterations N_{max}, and maximum tolerance δ_{max}. Initialize the dual variables($\boldsymbol{\mu}$ and λ) and iteration index n = 1.
while $n \leq N_{max}$ **or** $|\overline{R}_i^*(n) - q(n)(\sum_{k=1}^{K} P_i \alpha_{k,i}(n) + P_c)| \geq \delta_{max}$ **do**
    Compute $\overline{R}_i^*(n)$ by using Eq. (47)
    Compute $q(n) = \frac{\overline{R}_i^*(n)}{\sum_{k=1}^{K} P_i \alpha_{k,i}(n) + P_c}$
    Update dual variables $\lambda(n)$ and $\boldsymbol{\mu}(n)$ by using Eq. (55) and (56), respectively.
    Update the power allocation factor vector $\boldsymbol{\alpha}(n+1)$ of vehicles by using equation (53)
    $n = n + 1$.
end while
Output: Optimal $\boldsymbol{\alpha}^* = \{\alpha_{1,i}^*, \alpha_{2,i}^*, \cdots, \alpha_{K,i}^*\}$

each optimization variable and is solved through proposed alternating optimization algorithm. 1st sub problem Eq. (38) is solved for P_i while 2nd sub problem Eq. (42) is solved for $\alpha_{k,i}$. 1st sub problem is solved through GABS algorithm. GABS algorithm costs at most N_g iterations to search the optimum power allocation for each RSU, where N_g is the minimum integer such that $N_g \geq \log_2(\frac{(c-1)P_i^*}{\Delta} - 1)$. Where c is the step size, P_i^* is the global optimal transmission power of i^{th} RSU and Δ is the maximum tolerance used in Algorithm 1. For c = 1.1, $P_i^* = 0.1726$ (22.4 dbm), and $\Delta = 0.001$, GABS searches optimal transmit power of RSU in at most 5 iterations, which is very low and acceptable complexity for practical implementation.

2nd subproblem is for optimal transmit power to the vehicles through NOMA. In literature, the exhaustive search algorithm is used for NOMA optimal power allocation [40] as well as it is used as a benchmark scheme [20], [21], [41], because it has the best performance from all other algorithms but at the cost of high computational complexity. For the considered system model, GABS-Exhaustive is the global optimal from the perspective of energy efficiency, but it has very high computational complexity because of exhaustive search in 2nd subproblem. If α_{max} is the maximum power allocation coefficient of each vehicle from RSU and τ is the step size for power allocation coefficient of k^{th} vehicle linked with i^{th} RSU. Then, there are $(\frac{\alpha_{max}}{\tau})^K$ choices for the values of power allocation coefficients of K vehicles linked with RSU. For I number of RSUs in the network, there are $(\frac{\alpha_{max}}{\tau})^{KI}$ choices for the values of power allocation coefficients of K vehicles linked with their corresponding RSU. Therefore, the complexity for GABS-Exhaustive algorithm is $\mathcal{O}(IN_g) + \mathcal{O}(\frac{P_{max}}{\tau})^{IK}$. It can be observed that it has very high computational complexity, which makes it impractical. Because of its global optimal performance, GABS-Exhaustive is considered a benchmark scheme. For practical implementation, the 2nd subproblem is solved through dinkelbach algorithm. It requires the complexity order of $\mathcal{O}(N(KI)^2)$ for solving the 2nd subproblem. Dinkelbach algorithm, during each iteration, requires KI operations to calculate EE. Where I is the total number of RSUs in the network and K is the total number of vehicles linked with each RSU. Furthermore, KI operations are required to update dual variables. If N is the number of iterations that dinkelbach algorithm needs to converge, then the total complexity of dinkelbach algorithm (2nd Algorithm) is $\mathcal{O}(N(KI)^2)$. So the complexity of the proposed GABS-Dinkelbach is always less than GABS-Exhaustive (Benchmark scheme). When the number of I RSUs and the number of K vehicles linked with each RSU increases, the complexity of GABS-Exhaustive search increases exponentially while the GABS-Dinkelbach still provides an optimal solution in polynomial time.

III. SIMULATION RESULTS

Simulation results are demonstrated in this section to evaluate the efficacy of the proposed energy-efficient multicasting scheme for NOMA based V2X communications. Two-way urban road scenario is configured with its vehicle drop and mobility model as described in 3GPP TR 36.885 [8]. Vehicles connected with each RSU are generated by a spatial Poisson process, with a density decided by the vehicle speed. In our simulations, each RSU is serving three vehicles through NOMA, which are selected randomly from the generated vehicles. The minimum distance between BS and vehicles associated with RSU is assumed to be 250. The non-line-of-sight (NLOS) path loss model is considered for both communication and interference links. The main simulation parameters for vehicular setup are described in table II and are also listed in [4] and [8]. The global optimal power allocation for multicasting can be acquired through an exhaustive search [20], which is served as a benchmark. The computational complexity of an exhaustive search algorithm is exponential because it is determined by the search space of all possible combinations of power allocation factor of users and the complexity at each search [21]. Therefore, it is not practical for a network with a large number of users. Instead, our proposed algorithm (GABS-Dinkelbach) achieves very close EE to exhaustive search with very low computational complexity, which can be observed from its convergence in Fig. 3.

Fig. 2 presents the EE of RSU versus the transmit power of RSU in dBm, in which $\sigma_{RSU}^2 = 0.01$, $\sigma_{BS}^2 = 0.1$ and

TABLE II
SIMULATION PARAMETERS [4], [8]

Parameter	Value
Carrier frequency	2 GHz
Bandwidth	10 MHz
BS Radius	500 m
RSU Radius	30 m
Noise power (σ^2)	-114 dBm
Transmit power of BS (P_b)	40 dBm
Transmit power of RSU (P_i)	15 dBm - 30 dBm
Circuit power consumption (P_c)	30 dBm
Vehicles minimum data rate R_{min}	1.5 bps/Hz
Vehicle drop model	spatial Poisson process
Vehicle speed (v)	60 km/h
Vehicle density	2.5v, v in m/s
Pathloss model	$128.1 + 37.6\log_{10}(d)$ d in km
Shadowing distribution	Log-normal
Shadowing standard deviation	8 dB
Fast fading	Rayleigh fading

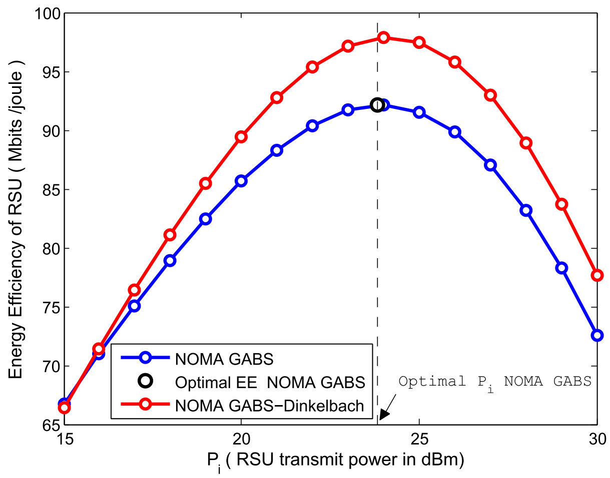

Fig. 2. Energy efficiency of GABS and GABS-Dinkelbach versus RSU transmit powers in dBm.

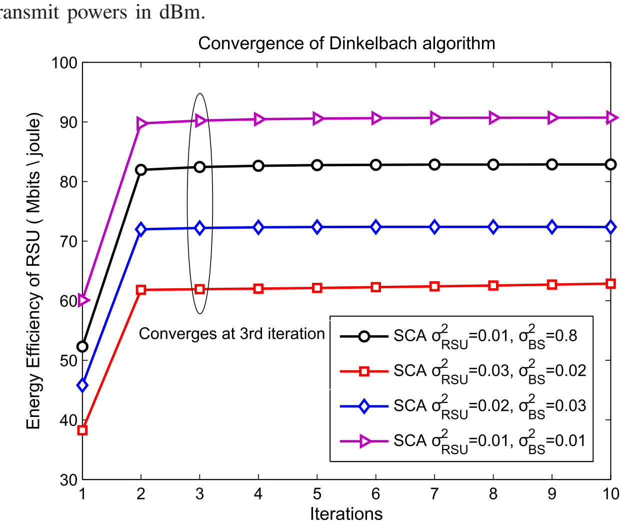

Fig. 3. Energy efficiency Convergence of Algorithm 2 versus number of iterations with different σ^2_{RSU} and σ^2_{BS}.

$P_{out} = 0.05$. From the figure, it can be observed that EE as a function of P_i first increases and then decreases and is quasi concave with regards to P_i. Therefore, optimal P_i

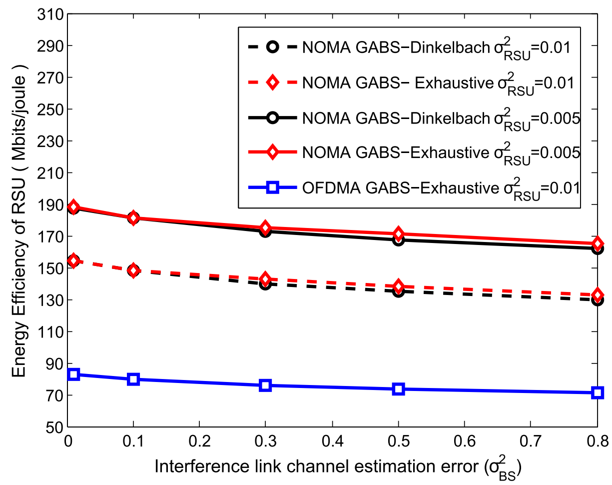

Fig. 4. Energy efficiency of RSU with different transmission link channel error variances (σ^2_{RSU}) versus interference link channel error variances (σ^2_{BS}).

can be obtained through the GABS algorithm, which achieves optimal EE and is presented by the black circle. During the GABS algorithm, the power allocation factor of vehicles connected with RSU is chosen randomly using the NOMA principle without vehicles' QoS constraints. To satisfy the QoS constraints of the vehicle, the RSU with optimal P_i^* is used to provide the energy-efficient power allocation factor to vehicles under their QoS constraint through Dinkelbach's algorithm, which is named as GABS-Dinkelbach Algorithm. GABS-Dinkelbach has optimal EE under optimal P_i^*.

In Fig. 3, EE convergence of Algorithm 2 versus iterations is displayed with different σ^2_{RSU} and σ^2_{BS}, where $P_{out} = 0.05$. The obtained result shows that Algorithm 2 usually converges in three iterations regardless of channel estimation error variances. It is noted that σ^2_{RSU} and σ^2_{BS} influence EE, but their effect on the convergence of Algorithm 2 is almost negligible. Fig. 4 compares the EE of the proposed NOMA GABS-Dinkelbach algorithm with global optimal GABS-Exhaustive algorithm and OFDMA. The comparison is done with different σ^2_{RSU} and σ^2_{BS}, where $P_{out} = 0.05$. The proposed algorithm achieves very close EE performance to the global optimal NOMA GABS-Exhaustive algorithm with very low computational complexity. Moreover, it can be noticed that higher channel error variances reduce the EE. From the results, it can be analyzed that σ^2_{RSU} has a greater influence on EE as compare to σ^2_{BS}.

Fig. 5 demonstrates the total EE of the proposed GABS-Dinkelbach algorithm versus channel outage probability requirement with different σ^2_{RSU} and σ^2_{BS}. The proposed method shows very close performance with the global optimal GABS-Exhaustive algorithm. Moreover, a higher channel outage probability requirement of the system results in higher EE performance. It can be inspected from the figure that σ^2_{RSU} has a more significant influence on EE compared to σ^2_{BS}.

Fig. 6 depicts EE of proposed algorithm 2 (based on Dinkelbach algorithm) versus the transmit power of RSU in dBm with different σ^2_{RSU} and σ^2_{BS}, where $P_{out} = 0.05$. EE first increases and then decreases with increasing P_i. The

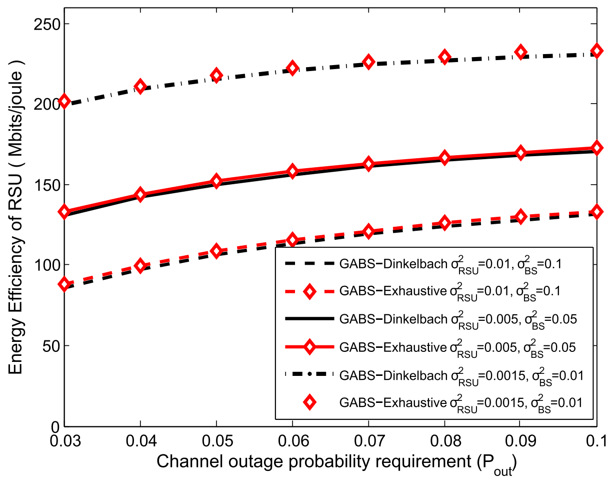

Fig. 5. Energy efficiency of RSU versus P_{out} with different σ^2_{RSU} and (σ^2_{BS}).

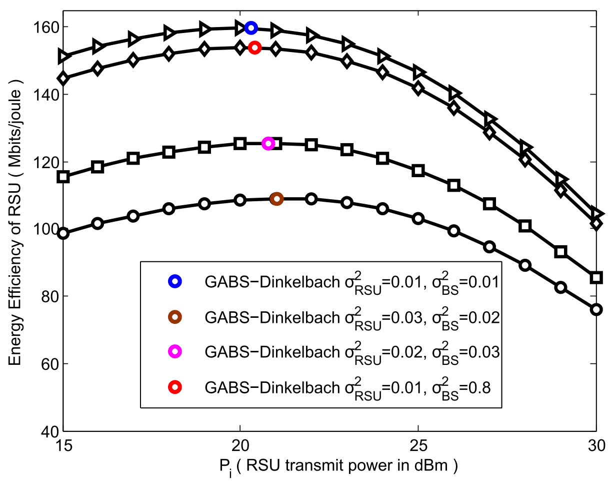

Fig. 6. Energy efficiency of RSU for GABS-Dinkelbach algorithm with different (σ^2_{RSU}) and (σ^2_{BS}) versus P_i in dBm.

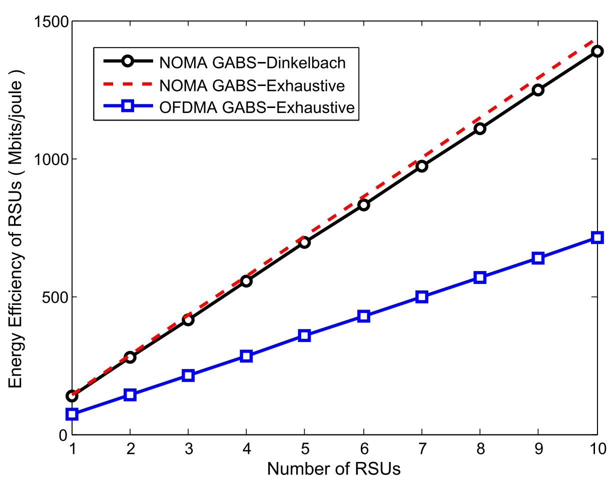

Fig. 7. Energy efficiency of RSUs versus Number of RSUs.

reason is that when P_i is increased beyond the optimal P_i^*, the RSU sum-rate rises very slowly as compared to the power consumption. It can be examined from the obtained results that

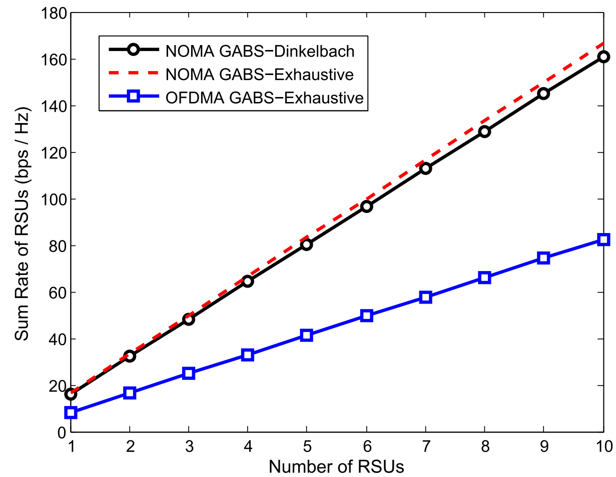

Fig. 8. Sum Rate of RSUs versus Number of RSUs.

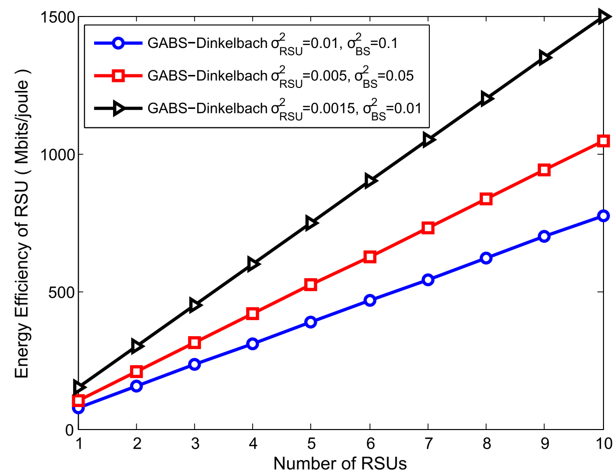

Fig. 9. Energy efficiency of RSUs with different (σ^2_{RSU}) and (σ^2_{BS}) versus Number of RSUs.

the proposed GABS-Dinkelbach (Algorithm 1 + Algorithm 2) gets maximum EE (presented by colored circles) because each RSU transmits with optimal power through algorithm one. Then, algorithm 2 provides the optimal power allocation to the vehicles connected with RSU under their QoS constraints. Furthermore, The EE performance of GABS-Dinkelbach with $\sigma^2_{RSU} = 0.02$, $\sigma^2_{BS} = 0.03$ is higher than its performance with $\sigma^2_{RSU} = 0.03$, $\sigma^2_{BS} = 0.02$, which indicates that σ^2_{RSU} has a greater influence on the EE of GABS-Dinklbach algorithm than σ^2_{BS}. Besides it, it can also be seen from the figure that higher channel error variances have higher degradation in the EE of the proposed algorithm.

Fig. 7 shows the energy efficiency of RSUs versus number of RSUs, in which $\sigma^2_{RSU} = 0.01$, $\sigma^2_{BS} = 0.1$ and $P_{out} = 0.05$. The number of RSUs increases from 1 to 10. It can be examined that NOMA GABS-Dinkelbach attains very close performance to the optimal NOMA GABS-Exhaustive algorithm. It can also be noticed that EE is increasing monotonously with the increase in the number of RSUs. It is due to the fact that there is no interference among RSUs and higher EE can be obtained with a larger number of RSUs.

Fig. 8 presents the sum- rate of RSUs against number of RSUs, in which $\sigma^2_{RSU} = 0.01$, $\sigma^2_{BS} = 0.1$ and $P_{out} = 0.05$. The improvement in the sum-rate of the RSUs through the proposed NOMA GABS-Dinkelbach algorithm is very close to the optimal NOMA GABS-Exhaustive algorithm. It can be noticed that the performance gap between the proposed NOMA GABS-Dinkelbach and OFDMA GABS-Exhaustive widens, as the number of RSU grows up.

In Fig. 9, the EE of proposed NOMA GABS-Dinkelbach versus the number of RSUs is presented with different σ^2_{RSU} and σ^2_{BS}, where $P_{out} = 0.05$. This figure expresses that the proposed algorithm has higher EE with smaller channel error variances.

IV. Conclusion

In this paper, a novel low-complexity, energy-efficient, and reliable NOMA multicasting scheme through alternating optimization algorithm is developed for the beyond 5G C-V2X system. In which each RSU in the network achieves optimal transmit power through the GABS algorithm under its transmit power limits and channel outage probability requirement of vehicles under imperfect CSI. The probabilistic optimization problem under the channel outage probability constraint is converted into a non-probabilistic problem through relaxation. Then, the non-convex power allocation optimization problem of vehicles connected with their corresponding RSU under their QoS constraint is transformed into a tractable CCFP problem through the SCA technique. The exact expressions of power allocation of vehicles are derived where the maximum number of vehicles can be higher than two on a subchannel. The CCFP problem is solved efficiently through Dinkelbach and the dual decomposition method. The efficacy of the proposed algorithm is verified through simulations, which shows that the proposed algorithm (GABS-Dinkelbach) can achieve an optimal solution with very low complexity as compared to the global optimal GABS-Exhaustive search algorithm, which obtains optimality with exponential computational complexity. In the future, it would be interesting to expand our work for full-duplex (FD) RSUs, amplify-and-forward (AF) RSUs, and multi-antenna RSUs.

Appendix A
Proof of Channel Outage Probability Requirements in Term of Strict Constraints

Here, we will prove that the channel outage probability constraint C1 in Eq. (12) can be derived from strict constraints described in Eq. (19) and (20).

The constraint C1 for vehicle k from Eq. (12) is given as follow

$$Pr[R_{k,i} > C_{k,i}|\hat{h}_{k,i}, \hat{g}_{k,i}] \le P_{out},$$

which can be bounded as follow

$$Pr[\hat{\gamma}_{k,i} > \gamma_{k,i}|\hat{h}_{k,i}, \hat{g}_{k,i}] \le P_{out}. \tag{57}$$

From Eq. (13) and (16), it can be written as

$$Pr[\frac{\hat{x}_{k,i}}{\hat{y}_{k,i}} > \frac{x_{k,i}}{y_{k,i}}|\hat{h}_{k,i}, \hat{g}_{k,i}] \le P_{out}. \tag{58}$$

From Eq. (16), it can be derived as

$$\hat{\gamma}_{k,i} = \frac{\hat{x}_{k,i}}{\hat{y}_{k,i}} = 2^{\frac{R_{k,i}}{BW}} - 1. \tag{59}$$

From Eq. (58) and (59),

$$Pr[2^{\frac{R_{k,i}}{BW}} - 1 > \frac{x_{k,i}}{y_{k,i}}|\hat{h}_{k,i}, \hat{g}_{k,i}] \le P_{out}. \tag{60}$$

The above outage probability based on total probability theorem can be presented as follow

$$\begin{aligned} &Pr[x_{k,i} \le \hat{x}_{k,i}|\hat{h}_{k,i}, \hat{g}_{k,i}] \\ &\quad \times Pr[2^{\frac{R_{k,i}}{BW}} - 1 > \frac{x_{k,i}}{y_{k,i}}|x_{k,i} \le \hat{x}_{k,i}, \hat{h}_{k,i}, \hat{g}_{k,i}] \\ &\quad + Pr[x_{k,i} > \hat{x}_{k,i}|\hat{h}_{k,i}, \hat{g}_{k,i}] \\ &\quad \times Pr[2^{\frac{R_{k,i}}{BW}} - 1 > \frac{x_{k,i}}{y_{k,i}}|x_{k,i} > \hat{x}_{k,i}, \hat{h}_{k,i}, \hat{g}_{k,i}] \\ &\le P_{out} \end{aligned} \tag{61}$$

From Eq. (59), $\hat{y}_{k,i} = \frac{\hat{x}_{k,i}}{2^{\frac{R_{k,i}}{BW}} - 1}$. Inserting it into Eq. (20) results in

$$\begin{aligned} &Pr[y_{k,i} \ge \hat{y}_{k,i}|\hat{h}_{k,i}, \hat{g}_{k,i}] \\ &= Pr[y_{k,i} \ge \frac{\hat{x}_{k,i}}{2^{\frac{R_{k,i}}{BW}} - 1}|\hat{h}_{k,i}, \hat{g}_{k,i}] \\ &= Pr[2^{\frac{R_{k,i}}{BW}} - 1 \ge \frac{\hat{x}_{k,i}}{y_{k,i}}|\hat{h}_{k,i}, \hat{g}_{k,i}] \le \frac{P_{out}}{2}. \end{aligned} \tag{62}$$

Based on Eq. (62), when $x_{k,i} > \hat{x}_{k,i}$, we can always have

$$\begin{aligned} &Pr[2^{\frac{R_{k,i}}{BW}} - 1 > \frac{x_{k,i}}{y_{k,i}}|x_{k,i} > \hat{x}_{k,i}, \hat{h}_{k,i}, \hat{g}_{k,i}] \\ &\le Pr[2^{\frac{R_{k,i}}{BW}} - 1 > \frac{\hat{x}_{k,i}}{y_{k,i}}|x_{k,i} > \hat{x}_{k,i}, \hat{h}_{k,i}, \hat{g}_{k,i}] \le \frac{P_{out}}{2}. \end{aligned} \tag{63}$$

From Eq. (19), we can write

$$Pr[x_{k,i} > \hat{x}_{k,i}|\hat{h}_{k,i}, \hat{g}_{k,i}] = 1 - \frac{P_{out}}{2}. \tag{64}$$

Note that

$$Pr[2^{\frac{R_{k,i}}{BW}} - 1 > \frac{x_{k,i}}{y_{k,i}}|x_{k,i} \le \hat{x}_{k,i}, \hat{h}_{k,i}, \hat{g}_{k,i}] \le 1. \tag{65}$$

As Eq. (61) is an equivalent form of constraint C1. Therefore, by putting values from Eq. (19),(65), (64) and (63) in Eq. (61), we have

$$\begin{aligned} \text{The left side of (61)} &\le 1(\frac{P_{out}}{2}) + (1 - \frac{P_{out}}{2})(\frac{P_{out}}{2}) \\ &= -\frac{P_{out}}{4} + P_{out} \approx P_{out}, \end{aligned} \tag{66}$$

for $P_{out} \ll 1$.

Appendix B
Proof of E_i^* Being Strictly Quasi-Concave With Respect to P_i

The objective is to demonstrate that E_i^* is strictly quasi-concave for P_i. For strictly quasi concave functions, if the local maximum exists, it is also globally optimal. According to definition, a function is quasi concave if its super level set for any arbitrary real τ is strictly convex [42]. For E_i^*, the super level set is

$$S_\tau = \{P_i \geq 0 | E_i^*(P_i) \geq \tau\}. \quad (67)$$

When $\tau < 0$, there is no value that can meet $E_i^*(P_i) = \tau$. When $\tau = 0$, $P_i = 0$ can satisfy $E_i^*(P_i) = \tau$. It can be seen for $\tau < 0$, S_τ is convex because by definition if $f(x) \leq 0$, the super level set is convex. For $\tau > 0$, the super level set is given as

$$S_\tau = \{P_i \geq 0 \mid \tau(P_c + P_i) - R_i^* \leq 0\}. \quad (68)$$

Since R_i^* is strictly concave with respect to P_i because its second derivative is always negative (the first and second derivative of R_i^* with respect to P_i are given in Eq. (69) and (70), respectively). Therefore -R_i^* is strictly convex in terms of P_i. Therefore S_τ is strictly convex, and $E_i^*(P_i)$ is strictly quasi concave.

$$\begin{aligned}
&\frac{\partial R_i^*}{\partial P_i} \\
&= \Bigg[\sum_{k=1}^{K-1} \frac{X_{k,i}\alpha_{k,i}Y_{k,i}}{\ln 2\Big(Z_{k,i}(\sum_{m=k+1}^{K} \alpha_{m,i}P_i) + X_{k,i}\alpha_{k,i}P_i + Y_{k,i}\Big)} \\
&\quad \times \frac{1}{\Big(Z_{k,i}(\sum_{m=k+1}^{K} \alpha_{m,i}P_i) + Y_{k,i}\Big)}\Bigg] \\
&\quad + \frac{X_{K,i}\alpha_{K,i}}{\ln 2\Big(X_{K,i}\alpha_{K,i}P_i + Y_{K,i}\Big)},
\end{aligned} \quad (69)$$

and

$$\frac{\partial^2 R_i^*}{\partial^2 P_i =} = \sum_{k=1}^{K-1} \Psi_{k,i} + \Bigg[\frac{-\Big(X_{K,i}\alpha_{K,i}\Big)^2}{\ln 2\Big(X_{K,i}\alpha_{K,i}P_i + Y_{K,i}\Big)^2}\Bigg], \quad (70)$$

where

$$\Psi_{k,i} = \frac{-A_{k,i}}{B_{k,i}}, \quad (71)$$

$$\begin{aligned}
A_{k,i} = X_{k,i}\alpha_{k,i}Y_{k,i}\Big[&2\Big(Z_{k,i}\sum_{m=k+1}^{K}\alpha_{m,i}\Big)^2 P_i + 2Z_{k,i} \\
&\times\Big(\sum_{m=k+1}^{K}\alpha_{m,i}\Big)\Big(X_{k,i}\alpha_{k,i}P_i + Y_{k,i}\Big) + X_{k,i}\alpha_{k,i}Y_{k,i}\Big],
\end{aligned} \quad (72)$$

$$\begin{aligned}
B_{k,i} = \ln 2\Big[&Z_{k,i}\Big(\sum_{m=k+1}^{K}\alpha_{m,i}\Big)P_i + Y_{k,i}\Big]^2 \\
&\times\Big[Z_{k,i}\Big(\sum_{m=k+1}^{K}\alpha_{m,i}\Big)P_i + X_{k,i}\alpha_{k,i}P_i + Y_{k,i}\Big]^2,
\end{aligned} \quad (73)$$

subsequently, The derivative of E_i^* with regards to P_i is given as follow

$$\frac{\partial E_i^*}{\partial P_i} = \frac{\frac{\partial R_i^*}{\partial P_i}(P_i + P_c) - R_i^*}{(P_i + P_c)^2}. \quad (74)$$

Appendix C
Derivation of Closed-Form Expression of Optimal Power Allocation Factor of Vehicles Connected With RSU_i

For successful SIC process at receivers, the SINR of vehicles associated with the RSU_i are ordered as shown in Eq. (1).

When $k = 1$, The closed-form equation of $\alpha_{1,i}$ can be computed as

$$\begin{aligned}
\frac{\partial L(\boldsymbol{\alpha}, \boldsymbol{\mu}, \lambda)}{\partial \alpha_{1,i}} = \ &(1 - P_{out})BW\Pi_{1,i}\Big(\frac{1}{\ln 2 \times \alpha_{1,i}}\Big) - qP_i \\
&+ \mu_{1,i}(X_{1,i}P_i) - \lambda,
\end{aligned} \quad (75)$$

and

$$\alpha_{1,i} = \frac{(1 - P_{out})BW\Pi_{1,i}}{\ln 2\Big(qP_i + \lambda - \mu_{1,i}(X_{1,i}P_i)\Big)}. \quad (76)$$

When $k = 2$, the closed-form solution of $\alpha_{2,i}$ can be calculated as

$$\begin{aligned}
&\frac{\partial L(\boldsymbol{\alpha}, \boldsymbol{\mu}, \lambda)}{\partial \alpha_{2,i}} \\
&= (1 - P_{out})BW\Pi_{2,i}\Big(\frac{1}{\ln 2 \times \alpha_{2,i}}\Big) \\
&\quad - \frac{Z_{1,i}P_i}{\ln 2\Big(Y_{1,i} + Z_{1,i}P_i(\alpha_{3,i} + \alpha_{2,i})\Big)}(1 - P_{out})BW\Pi_{1,i} \\
&\quad - qP_i - \mu_{1,i}\Big(Y_{1,i}P_i 2^{\frac{R_{min} - \Phi_{1,i}}{\Pi_{1,i}}}\Big) + \mu_{2,i}(X_{2,i}P_i) - \lambda = 0.
\end{aligned} \quad (77)$$

Then we have

$$\alpha_{2,i} = \frac{(1 - P_{out})BW\Pi_{2,i}}{\ln 2\Big(qP_i + \lambda - \mu_{2,i}(X_{2,i}P_i)\Big) + \Theta(\alpha_{1,i})}, \quad (78)$$

where

$$\begin{aligned}
\Theta(\alpha_{1,i}) = (1 - P_{out})BW\Pi_{1,i}\hat{\gamma}_{1,i}^*\Big(\frac{Z_{1,i}}{X_{1,i}\alpha_{1,i}}\Big) + \ln 2\mu_{1,i} \\
\times\Big(Z_{1,i}P_i 2^{\frac{R_{min} - \Phi_{1,i}}{\Pi_{1,i}}}\Big).
\end{aligned} \quad (79)$$

When $k = 3$, the closed-form expression of $\alpha_{3,i}$ can be evaluated as

$$\begin{aligned}
&\frac{\partial L(\boldsymbol{\alpha}, \boldsymbol{\mu}, \lambda)}{\partial \alpha_{3,i}} \\
&= (1 - P_{out})BW\Pi_{3,i}\Big(\frac{1}{\ln 2 \times \alpha_{3,i}}\Big) \\
&\quad - \frac{Z_{1,i}P_i}{\ln 2\Big(Y_{1,i} + Z_{1,i}P_i(\alpha_{3,i} + \alpha_{2,i})\Big)}(1 - P_{out})BW\Pi_{1,i} \\
&\quad - \frac{Z_{2,i}P_i}{\ln 2\Big(Y_{2,i} + Z_{2,i}P_i(\alpha_{3,i})\Big)}(1 - P_{out})BW\Pi_{2,i} - qP_i \\
&\quad - \mu_{1,i}\Big(Y_{1,i}P_i 2^{\frac{R_{min} - \Phi_{1,i}}{\Pi_{1,i}}}\Big) - \mu_{2,i}\Big(Y_{2,i}P_i 2^{\frac{R_{min} - \Phi_{2,i}}{\Pi_{2,i}}}\Big) \\
&\quad + \mu_{3,i}(X_{3,i}P_i) - \lambda = 0.
\end{aligned} \quad (80)$$

Then we have

$$\alpha_{3,i} = \frac{(1-P_{out})BW\Pi_{3,i}}{\ln 2\Big(qP_i+\lambda-\mu_{3,i}(X_{3,i}P_i)\Big)+\Theta(\alpha_{1,i})+\Theta(\alpha_{2,i})}. \tag{81}$$

Therefore, by deduction, the closed-form expression for the k-th vehicle on subchannel can be derived as expressed in Eq. (53).

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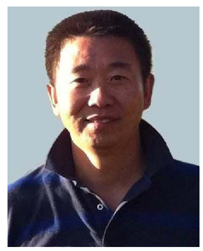

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