Optimal Resource Allocation for NOMA-Assisted Backscatter Communication in 6G Internet of Vehicles Networks

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***Abstract*—Non-orthogonal multiple access (NOMA) is considered as an emerging technology to improve the spectral efficiency performance for 6G networks. Ambient backscatter communication (BackCom) is another promising solution owing to its advantages in increasing spectral and power efficiency. The investigation of integrating NOMA with BackCom is conducted to enhance the connectivity of the emerging 5G low-powered Internet-of-Vehicles (IoVs) and future 6G transportation systems. This study proposes an optimal resource allocation scheme for the NOMA-assisted BackCom IoV network. Specifically, multiple Road-Side Units (RSUs) are considered sending superimposed signals to the subscribed IoVs in the downlink NOMA. BackCom tags are considered to transmit data symbols to nearby IoVs by reflecting the signals of RSUs. Thus, we aim to maximize the total data rate performance of the NOMA-assisted BackCom IoV network. A joint problem that simultaneously optimizes the IoV clustering, IoV power allocation, and reflection coefficients of BackCom tags is formulated. To solve the problems efficiently, multiple subproblems are decomposed that can be solved using CVX optimization tool. To validate the performance of the proposed method, we compare it with those of state-of-the-art benchmark schemes. Numerical results will be provided to show the superiority of the proposed framework.**

***Index Terms*—Backscatter communication, Internet of Vehicles, non-orthogonal multiple access, resource allocation.**

I. Introduction

RESOURCE allocation is crucial for improving the performance of communication systems that inspires research efforts. According to many researches, the future transportation will be updated to enhance safety and comfort. Lots of applications such as autonomous driving, safety awareness, infotainment, and road traffic management are developed. The upcoming sixth-generation (6G) transportation networks will employ modernest wireless technologies that serve secure data sharing, ubiquitous connectivity, rapid computation, and energy-efficient transmissions. Compared to the fifth-generation (5G) Internet of Vehicles (IoVs), 6G ones will concentrate on ensuring the sharing of more detailed traffic information, autonomous driving reliability, Virtual Reality (VR) and Augmented Reality (AR)-based traffic services, gaming applications, and advanced multimedia. 6G IoVs will have very high data rates. The reliability of the packet delivery has to reach a new high level with super low latency. These challenges motivate researchers to work on advanced technologies such as blockchain technology, terahertz communications, reconfigurable intelligent surfaces, backscatter communications (BackCom), and Non-orthogonal Multiple Access (NOMA)to promote reliable communications of 6G systems.

First, connecting massive IoVs in 6G would be a big challenge owing to limited energy and spectral resources. In this regard, BackCom and NOMA are two emerging candidates. Without changing in the Radio-frequency (RF) signal, BackCom technology enables IoVs and roadside-unites (RSUs) to reduce the consumed power, hence providing a green solution. The key of BackCom technology is to enable a BackCom tag to transmit data by reflecting and modulating incident RF signals. Additionally, NOMA is extensively utilized in the 6G systems to increase the access capacity. NOMA can accommodate multiple IoVs to simultaneously transmit data using the same spectral/time resources. NOMA first superimposed multiple signals at the transmitter side over the same resource block using power domain and then using successive interference cancellation (SIC) technique at the receiver side to decode the superimposed signals. Recently, many researches have proposed NOMA-based frameworks. In particular, several studies have investigated the integration of BackCom with NOMA to improve the energy efficiency and reliability for vehicular networks.

II. System Model

As illustrated in Fig. 1, NOMA Backscatter IoV networks are considered, each of which comprises of multiple roadside-unites (RSUs), backscatter tags, and many internet of vehicles (IoVs) with various mobility. This study focuses on the efficient communication for downlink data transmissions from RSUs to IoVs under NOMA and BackCom. First, NOMA is adopted because of its benefit in improving the wireless capacity and spectral efficiency. Specifically, each RSU superimposes multiple intended signals and subsequently sends the composite signal to the IoVs. Additionally, BackCom tags are adopted to support the low-power communications and improve the energy efficiency. By receiving the incident signals from RSUs, BackCom tags harvest energy for modulating information and reflecting it towards the IoVs. Furthermore, in order to make the network model more realistic, the mobility of IoVs is considered.

Without loss of generality, it can be assumed that the RSU and tag deployments are fixed. For simplicity, each RSU is with one tag so that all RSUs and their corresponding tags can be co-specified by $k \in \mathcal{K} = \{1, \dots, K\}$, where K denote the number of RSUs/tags. Let M denote the number of IoVs and the IoVs can be specified by $m \in \mathcal{M} = \{1, \dots, M\}$. While IoVs moving, they change the network topology including the IoV-RSU distances as well as antenna gain, resulting in significant variations of the channel state information (CSI). In this work, all IoVs are assumed to only move inside the network model. The mobility of each IoV m can be characterized by (d_m, v_m), where d_m and v_m describe the moving direction and speed, respectively. Let $\mathcal{D} = \{1, \dots, D\}$ and $\mathcal{V} = \{1, \dots, V\}$ denote the sets of moving directions and speeds, respectively. Here, the moving directions and speeds specified by the values in $\mathcal{D}$ and $\mathcal{V}$, respectively, are corresponding to several predefined directions and speeds, e.g., moving forward, backward, left, and right (directions), and slow, normal, and fast (speeds). Considering that the network operate during T time slots, the IoV mobility can be modeled as a Markov chain model. Specifically, at each time slot, the mobility jumps from an observed state to another state under various transition probabilities. Within the scope of this study, these transition probabilities are assumed to be well-known, which can be easily obtained per specific locations. For instance, in the long way, the IoV mobility mostly remains unchanged while it usually varies at the intersections because of the cross flows and traffic lights.

According to the Third Generation Partnership Project (3GPP)'s NOMA standardization for Long Term Evolution (LTE) [1] and 5G New Radio (NR) [2], two users are allowed to share a NOMA channel. Thus, each RSU will select two among several existing IoVs for performing NOMA. Considering RSU k, let two IoVs, m and n ($m < n$), are selected. Then, the IoV grouping (clustering) of IoVs m and n under RSU k is characterized by $x_{k,m} = 1$ and $x_{k,n} = 1$, respectively, while the other IoVs are non-served, i.e., $x_{k,o} = 0, \forall o \in \mathcal{M} | o \neq m, o \neq n$. The composite signal of RSU k for its selected IoVs, m and n, is expressed as

$$s_k^R = \sqrt{P_k \upsilon_{k,m}}\alpha_m + \sqrt{P_k \upsilon_{k,n}}\alpha_n, \tag{1}$$

where P_k is the transmit power of RSU k, $\upsilon_{k,m}$ and $\upsilon_{k,n}$ are the power allocation of RSU k for IoVs m and n, respectively ($\upsilon_{k,m} + \upsilon_{k,n} = 1$), and α_m and α_n are the information symbols of IoVs m and n, respectively. Each backscatter tag k delivers a reflection coefficient, denoted by ν_k, by adjusting its impedance value. The reflected signal from backscatter tag k is a double-path signal, which is computed as

$$s_k^B = \sqrt{\nu_k g_{k,k}} s_k^R \alpha_k, \tag{2}$$

where $g_{k,k}$ is the channel gain from RSU k to its corresponding backscatter tag k and α_k is the information symbol modulated by backscatter tag k.

The IoVs m and n receive both of the composite signal from RSU k and the reflected signal from backscatter tag k, in addition to the inter-RSU interference and noise. Here, the inter-tag interference is neglected because backscatter tags are composed of passive RF components only. Therefore, the signals received at IoVs m and n can be computed as

$$s_m = \sqrt{g_{k,m}} s_k^R + \sqrt{h_{k,m}} s_k^B + \sum_{k'=1, k' \neq k}^{K} \sqrt{g_{k',m}} s_{k'}^R + N_0, \tag{3}$$

$$s_n = \sqrt{g_{k,n}} s_k^R + \sqrt{h_{k,n}} s_k^B + \sum_{k'=1, k' \neq k}^{K} \sqrt{g_{k',n}} s_{k'}^R + N_0, \tag{4}$$

where $g_{k,m}$ and $h_{k,m}$ are the channel gains of IoV m from RSU k and backscatter tag k, respectively, $g_{k,n}$ and $h_{k,n}$ are the channel gains of IoV n from RSU k and backscatter tag k, respectively, $g_{k',m}$ and $g_{k',n}$ are the inter-RSU interference channel gains from RSU $k^{'}$ affected to IoVs m and n, respectively, $s_{k'}^R$ is the composite signal of RSU $k^{'}$, and N_0 is the white Gaussian noise with variance σ^2.

For downlink NOMA, the worse users decode their signals considering other signals as noise while the better users can apply SIC to decode their desired signals after subtracting the worse users' signals [2]. Without loss of generality, it can be assumed that IoV m receive the better channel condition from RSU k compared to IoV n, i.e., $g_{k,m} \geq g_{k,n}$. Then, the signal to interference plus noise ratio (SINR) of IoVs m to decode the signal of user n can be expressed as

$$\Phi_{k,m}^n = \frac{P_k \upsilon_{k,n} \left(g_{k,m}^2 + \nu_k g_{k,k}^2 h_{k,m}^2 \right)}{P_k \upsilon_{k,m} \left(g_{k,m}^2 + \nu_k g_{k,k}^2 h_{k,m}^2 \right) + \sum_{k'=1, k' \neq k}^{K} P_{k'} g_{k',m}^2 + \sigma^2}, \tag{5}$$

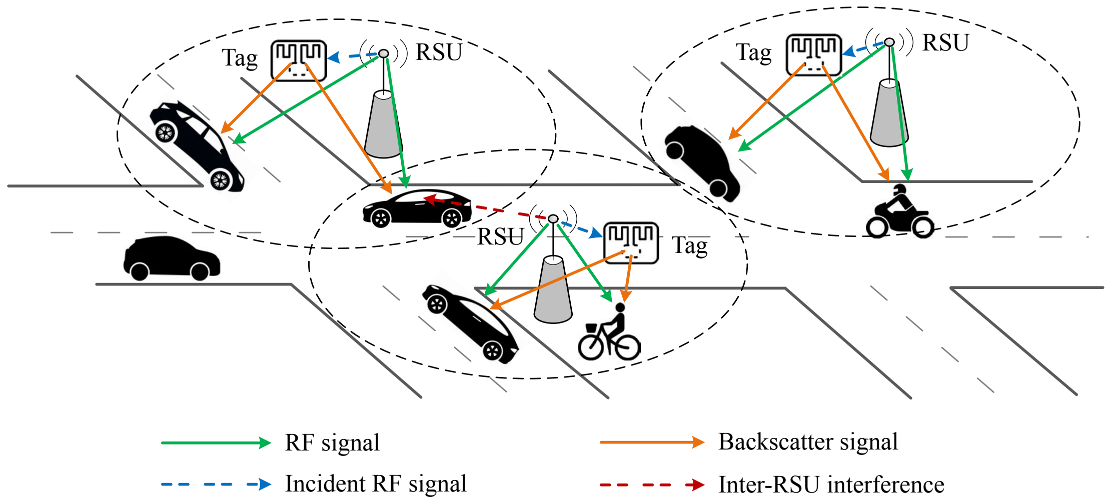

Fig. 1. An illustration of NOMA Backscatter IoV networks.

where $P_{k'}$ is the transmit power of RSU $k^{'}$. The SINRs of IoVs m and n to decode their own signals are computed as

$$\Phi_{k,m}^{m} = \frac{P_k \upsilon_{k,m}\left(g_{k,m}^2 + \nu_k g_{k,k}^2 h_{k,m}^2\right)}{\sum\limits_{k'=1,k'\neq k}^{K} P_{k'} g_{k',m}^2 + \sigma^2}, \tag{6}$$

$$\Phi_{k,n}^{n} = \frac{P_k \upsilon_{k,n}\left(g_{k,n}^2 + \nu_k g_{k,k}^2 h_{k,n}^2\right)}{P_k \upsilon_{k,m}\left(g_{k,n}^2 + \nu_k g_{k,k}^2 h_{k,n}^2\right) + \sum\limits_{k'=1,k'\neq k}^{K} P_{k'} g_{k',n}^2 + \sigma^2}. \tag{7}$$

It is worth noting that RSUs are allowed to simultaneously serve at most two IoVs. Then, there exists one or some RSUs serving one IoV in the proper time. For instance, when there is only one IoV with an RSU, e.g. IoV m with RSU k, the RSU k can serve IoV m only. Then, the SINR to decode IoV m's signal can be computed as $\Phi_{k,m}^{m}$ in formula (6) that considers the inter-RSU interference and white Gaussian noise only. Let $\Lambda_k \in \{0,1,2\}$ denote the number of IoVs served by RSU k, which is counted as $\Lambda_k = \sum_{m=1}^{M} x_{k,m}$. Applying Shannon's formula for the information capacity of a communication channel, the data rate of RSU k can be computed as

$$\Xi_k = \begin{cases} 0 & \text{if } \Lambda_k = 0, \\ \sum\limits_{m=1}^{M} x_{k,m} \log_2(1+\Phi_{k,m}^{m}) & \text{if } \Lambda_k = 1, \\ \sum\limits_{m=1}^{M-1} \sum\limits_{n=m+1}^{M} x_{k,m} x_{k,n} \Upsilon_{k,m,n} & \text{if } \Lambda_k = 2, \end{cases} \tag{8}$$

where $\Upsilon_{k,m,n} = \log_2(1+\Phi_{k,m}^{m}) + \log_2(1+\Phi_{k,n}^{n})$. The data rate of RSU k can also be written as

$$\Xi_k = \mathbf{1}_{\{\Lambda_k=1\}} \sum_{m=1}^{M} x_{k,m} \log_2(1+\Phi_{k,m}^{m}) + \mathbf{1}_{\{\Lambda_k=2\}} \sum_{m=1}^{M-1} \sum_{n=m+1}^{M} x_{k,m} x_{k,n} \Upsilon_{k,m,n}, \tag{9}$$

where $\mathbf{1}_{\{*\}}$ is a binary indicator, i.e., $\mathbf{1}_{\{*\}} = 1$ if $(*)$ is true and otherwise $\mathbf{1}_{\{*\}} = 0$. In formula (9), the first term is the achievable rate for a potential solely served IoV while the second term is that for paired IoVs.

III. Problem Formulation

On the one hand, we aim to maximize the achievable data rate for all RSUs, which can be strictly affected by many variables, such as the IoV clustering, power allocations for IoVs, and reflection coefficients of backscatter tags. It is impossible to achieve the optimal data rate by separately optimizing these variables. On the other hand, because of the dynamic nature of IoV systems, it is reasonable to perform the long-term optimization. As a result, this study investigates a joint optimization problem of the IoV clustering, power allocations for IoVs, and reflection coefficients of backscatter tags to maximize the overall long-term data rate of all RSUs. Then, the corresponding problem is mathematically formulated as follows:

$$\max_{\mathbf{x}(t),\mathbf{u}(t),\mathbf{v}(t)} \sum_{t=0}^{T-1} \sum_{k=1}^{K} \gamma^t \Xi_k(t), \tag{10}$$

$$\text{s.t.} \quad x_{k,m}(t) \in \{0,1\}, \forall k \in \mathcal{K}, m \in \mathcal{M}, \tag{10a}$$

$$\sum_{m=1}^{M} x_{k,m}(t) \leq 2, \forall k \in \mathcal{K}, \tag{10b}$$

$$0 \leq \upsilon_{k,m}(t) \leq 1, \forall k \in \mathcal{K}, m \in \mathcal{M}, \tag{10c}$$

$$0 \leq \nu_k(t) \leq 1, \forall k \in \mathcal{K}, \tag{10d}$$

$$\Phi_{k,m}^{n}(t) \geq \Phi_{\min}, \forall k \in \mathcal{K}, m,n \in \mathcal{M} | m<n, \; x_{k,m}(t) = x_{k,n}(t) = 1, \tag{10e}$$

where $\mathbf{x}(t) = \{x_{k,m}(t)|k \in \mathcal{K}, m \in \mathcal{M}\}$ is the IoV clustering vector, $\mathbf{u}(t) = \{\upsilon_{k,m}(t)|k \in \mathcal{K}, m \in \mathcal{M}\}$ is the power allocation vector, $\mathbf{v}(t) = \{\nu_k(t)|k \in \mathcal{K}\}$ is the reflection coefficient vector, $\gamma \in (0,1)$ is a discounting factor, and $\Phi_{\min}$ is a threshold SINR that is predetermined to guarantee the succeed of SIC decoding. Constraints (10a) and (10b) ensure that at most two IoVs are allowed to be active with each RSU. Constraint (10c) sets the range of power allocations which should not exceed the transmit power of the RSUs. Similarly, constraint (10d) describes the range of reflection coefficients that take values from 0 to 1. Finally, constraint (10e) enables the lower bound of SINR for efficient SIC decoding to enhance the quality of service (QoS).

IV. Algorithm Design

It can be observed that the formulated problem is a mixed-integer nonlinear programming problem, which cannot be solved straightforwardly because of the mixed binary and numerical variables in addition to a nonlinear objective function. Therefore, we decompose the joint problem into subproblems of IoV clustering, power allocation, and reflection coefficient. In the following subsections, a novel algorithm is presented that iteratively obtains the optimal IoV clustering, power allocations, and reflection coefficients. In particular, the optimal IoV clustering is trained using deep neural networks while the optimal power allocations and reflection coefficients are obtained using convex optimization tool.

A. Finding The Optimal Power Allocations

Considering that the IoV clustering and reflection coefficients are given, we aim at finding the optimal power allocations. First, the formulated optimization problem is transformed to the power allocation problem at each time slot. We consider the power allocation problem in the following cases.

1) If $\Lambda_k = 1$ with $x_{k,m}(t) = 1$: $\Xi_k(t)$ becomes a logarithmic function as

$$\Xi_k(t) = \log_2\left(1 + \frac{\mathbf{A}_{k,m}(t)\upsilon_{k,m}(t)}{\mathbf{B}_{k,m}(t)}\right). \quad (11)$$

It is monotonically increasing with respect to $\upsilon_{k,m}(t)$. Therefore, the optimal value for $\upsilon_{k,m}(t)$ is expressed as

$$\upsilon^*_{k,m}(t) = 1. \quad (12)$$

2) If $\Lambda_k = 2$ with $x_{k,m}(t) = x_{k,n}(t) = 1$: The data rate of RSU k is computed as

$$\begin{aligned}\Xi_k(t) = &\log_2\left(1 + \frac{\mathbf{A}_{k,m}(t)\upsilon_{k,m}(t)}{\mathbf{B}_{k,m}(t)}\right)\\ &+ \log_2\left(1 + \frac{\mathbf{A}_{k,n}(t)\upsilon_{k,n}(t)}{\mathbf{A}_{k,n}(t)\upsilon_{k,m}(t) + \mathbf{B}_{k,n}(t)}\right).\end{aligned} \quad (13)$$

The power allocation problem is convex so that it can be solved using CVX optimization tool [3].

B. Finding The Optimal Reflection Coefficients

Considering that the IoV clustering and power allocations are given, we aim at finding the optimal reflection coefficients of backscatter tags. At first, we transform the formulated problem to the reflection coefficient problem at each time step. We consider the reflection coefficient problem in the following cases.

1) If $\Lambda_k = 1$ with $x_{k,m}(t) = 1$: $\Xi_k(t)$ becomes a logarithmic function as

$$\Xi_k(t) = \log_2\left(1 + \frac{\mathbf{D}_{k,m}(t)\nu_k(t) + \mathbf{E}_{k,m}(t)}{\mathbf{B}_{k,m}(t)}\right). \quad (14)$$

It is monotonically increasing with respect to $\nu_k(t)$. Therefore, the optimal value for $\nu_k(t)$ is expressed as

$$\nu^*_k(t) = 1. \quad (15)$$

2) If $\Lambda_k = 2$ with $x_{k,m}(t) = x_{k,n}(t) = 1$: The data rate of RSU k is computed as

$$\begin{aligned}\Xi_k(t) = &\log_2\left(1 + \frac{\mathbf{D}_{k,m}(t)\nu_k(t) + \mathbf{E}_{k,m}(t)}{\mathbf{B}_{k,m}(t)}\right)\\ &+ \log_2\left(1 + \frac{\mathbf{D}_{k,n}(t)\nu_k(t) + \mathbf{E}_{k,n}(t)}{\mathbf{F}_{k,n}(t)\nu_k(t) + \mathbf{G}_{k,n}(t) + \mathbf{B}_{k,n}(t)}\right).\end{aligned} \quad (16)$$

The reflection coefficient problem is also convex so that it can be solved using CVX optimization tool [3].

C. Training The IoV Clustering Using Deep Neural Networks

Even when the optimal power allocations and reflection coefficients are given, the formulated problem remains hard to solve because searching for the optimal IoV clustering often requires exponential time. Therefore, we approach to approximate the optimal IoV clustering using deep neural networks. The weight matrix of neural networks is reinforced in a training process, where an agent is recruited to control the IoV clustering. As the mobility is considered, the decision epoch of the agent is per time slot. The agent can observe sum rate every time it decides an IoV clustering action. At first, the agent needs to collect data sufficient for training via the interaction with network environment. Channel coefficients are collected as the input. A fully connected neural network is designed that employs two hidden layers with ReLU activation function that will make final output decision.

V. Conclusions

In this study, we propose an optimal resource allocation scheme for NOMA-assisted BackCom IoV networks. The objective is to maximize the achievable long-term data rate by jointly optimizing the IoV clustering, IoV power allocation, and reflection coefficients of BackCom tags. The formulated problem is hard to be solved straightforwardly. We decompose the original problem into subproblems, which is convex that can be solved using CVX optimization tool. For IoV clustering, we approach with a deep neural network to train an optimal clustering policy. Simulation results will be provided to demonstrate the reliablility and effectiveness of the proposed framework compared to the benchmark schemes.

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