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Secrecy Oriented Slicing Resource Allocation in 6G Green Vehicular Networks: An Energy-Efficient Design

Minghui Dai[1], Shan Chang[1,*], Zhou Su[2]
[1]School of Computer Science and Technology, Donghua University, Shanghai 201620, China
[2]School of Cyber Science and Engineering, Xi'an Jiaotong University, Xi'an 710049, China
minghuidai@dhu.edu.cn; changshan@dhu.edu.cn; zhousu@ieee.org

***Abstract*—The 6G empowered Internet of vehicles paves the way to autonomous driving era, where the ultra-low latency communication and ultra-reliable connections promote the quality of service (QoS) for vehicle users. However, the high data traffic load and communication resource constraint pose a heavy burden to autonomous driving. This paper proposes a secrecy oriented slicing resource allocation scheme in 6G green vehicular networks. We consider that cellular vehicular user (CUE) and vehicular user equipment (VUE) and eavesdropper coexist in the networks, where VUE can reuse the resource block non-orthogonally with CUE, and the eavesdropper may overhear the data transmission of CUE and VUE. To meet the QoS and green communication requirements, we formulate a joint optimization for energy-efficient resource allocation subject to the data rate and secrecy capacity. Despite the non-convex of the formulated problem, we propose corresponding algorithms to derive the optimal resource allocation strategies. Simulation performance validate the effectiveness of our proposal in comparison with benchmark algorithms.**

***Index Terms*—6G green vehicular networks, slicing resource allocation, and energy efficiency.**

I. Introduction

The upcoming 6G vehicular communication with ultra-low latency and ultra-reliable connection will greatly promote the intelligent transportation system (ITS), especially for the autonomous driving [1]–[3]. The growing requirement of vehicle users for high-bandwidth is expected to guarantee diverse services and applications of vehicle users. Therefore, in autonomous driving era, the driving experience can be significantly improved by refining vehicle user's driving actions. However, the heavy traffic burden (e.g., high-load sensing, communication) poses challenges to autonomous driving. For instance, the requested multimedia contents by vehicle users need to be delivered promptly, which causes the data congestion. Thus, the resource allocation for improving the quality of service (QoS) of autonomous driving should be investigated in 6G vehicular networks [4]–[6].

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*Corresponding author: Shan Chang.

In 6G green vehicular networks, a large number of on-board devices (e.g., communication and computing units) will lead to high energy consumption. Firstly, considering the high frequency bands in 6G communication, the extensive communication requirements cause a surge energy consumption in autonomous driving [7]. For instance, the drastic growth in traffic data streaming (e.g., traffic flow, vehicle speed) leads to the high energy consumption for wireless communications. Secondly, the intelligent decision algorithms and applications for autonomous driving depend on the big data analysis and artificial intelligence (AI), which also consumes high energy consumption. Therefore, the energy efficiency for constructing the 6G green vehicular networks is a vital issue [8]–[10].

Due to the diverse behaviors of vehicle users (e.g., honest users, speculative users, malicious users), the communications among vehicle users may be overheard by eavesdroppers (i.e., malicious users) [11]. Therefore, it is vital to consider the interference and secrecy communication for 6G green vehicular networks. Recently, the secrecy communication has aroused wide concern from researchers. For instance, the authors in [12] adopt the physical layer security (PLS) technique to enhance the secure communication between vehicles and roadside unit (RSU). The authors in [13] focus on the scenario of vehicle-to-vehicle (V2V) underlay cellular communication and formulate a joint optimization of secrecy capacity maximization for vehicular users. The authors in [14] investigate the secure and reliable communication for connected vehicles, where the secrecy outage probability is derived to achieve perfect secrecy. However, in most aforementioned works, the security performance for both cellular vehicular user (CUE) and vehicular user equipment (VUE) does not take into account, and the above studies are not well targeted for secrecy communication in 6G green vehicular networks to satisfy the security requirements while guaranteeing the energy efficiency.

Therefore, motivated by the above challenges in 6G green vehicular networks, this work proposes a secrecy oriented energy efficient resource allocation scheme to improve the resource utilization. We consider that multiple CUEs, VUEs, and eavesdropper coexist in 6G green vehicular networks. The radio resources are equally partitioned into a number of resource blocks (RBs). VUEs can reuse the RB non-orthogonally with CUEs. The eavesdropper may overhear the information of CUE and VUE. We measure the data rate of VUE pair as the QoS metric, and formulate an optimization problem by jointly optimizing the power control, time allocation and RB allocation. We present efficient algorithms to obtain the resource allocation strategy. Simulation results also provided to validate the effectiveness of our proposal.

II. System Model

The system model of 6G green vehicular networks is shown in Fig. 1. In the coverage of 6G RSU, CUEs, VUEs and eavesdropper coexist in the networks. The set of CUEs in the networks is denoted as $\mathcal{K} = \{1, \ldots, k, \ldots, K\}$. CUEs can communicate with RSU via vehicle-to-infrastructure (V2I) communication. The radio resources are equally partitioned into a set of RBs denoted by $\mathcal{N} = \{1, \ldots, n, \ldots, N\}$. The N RBs are orthogonally assigned to K CUEs. The number of CUEs K, VUEs I and RBs N satisfies $I \leq K \leq N$. The n-th RB is assigned to k-th CUE. VUEs can reuse RBs with CUEs via V2V communication. The set of VUE pairs in the networks is denoted as $\mathcal{I} = \{1, \ldots, i, \ldots, I\}$. The total data to be transmitted by VUE pair i is denoted by D_i^{tot}. We use $t_{i,n}$ to denote the transmission time for VUE pair i to send its data. The binary variable $a_{i,n} \in \{0, 1\}$ is adopted to indicate that whether n-th RB is reused by i-th VUE. If n-th RB is reused by i-th VUE, $a_{i,n} = 1$. Otherwise, $a_{i,n} = 0$. We consider that malicious node in the networks can overhear the communications among CUEs and VUEs.

The wireless channel gain between k-th CUE and i-th VUE receiver can be modeled as

$$g_{k,i} = G\alpha_{k,i}\lambda_{k,i}d_{k,i}^{-\theta}, \forall k \in \mathcal{K}, \forall i \in \mathcal{I}, \tag{1}$$

where G denotes the path loss constant. θ means the path loss exponent. $\alpha_{k,i}$ indicates the fast fading gain between k-th CUE and i-th VUE receiver, which follows the exponential distribution. $\lambda_{k,i}$ expresses the slow fading gain between k-th CUE and i-th VUE receiver, which obeys the log-normal distribution. $d_{k,i}$ menas the distance between k-th CUE and i-th VUE receiver.

If n-th RB assigned to k-th CUE is reused by i-th VUE, we can express the signal-to-interference-plus-noise (SINR) of i-th VUE as

$$\gamma_{i,n} = \frac{p_{i,n}g_{i,n}}{p_{k,n}g_{k,i} + N_0}, \forall i \in \mathcal{I}, \forall n \in \mathcal{N}, \tag{2}$$

where $p_{k,n}$ and $p_{i,n}$ denote the transmission power of k-th CUE and i-th VUE of reusing n-th RB, respectively. $g_{i,n}$ denotes the channel gain of i-th VUE pair. The value of $g_{i,n}$ can be obtained by the channel gain similar to eq. (1). N_0 denotes the additive white Gaussian noise.

Therefore, the achievable data rate of i-th VUE can be expressed as

$$r_{i,n} = W \log_2 (1 + \gamma_{i,n}), \forall i \in \mathcal{I}, \forall n \in \mathcal{N}, \tag{3}$$

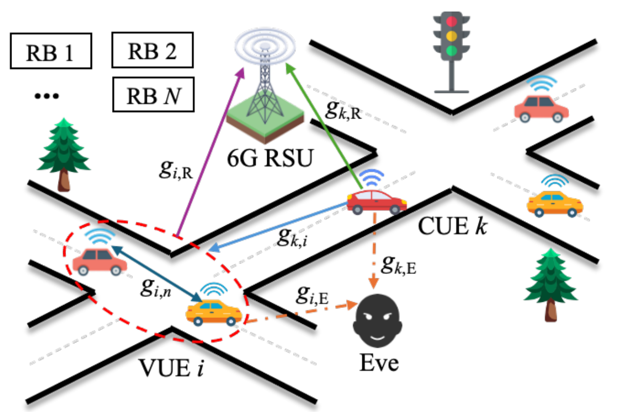

Fig. 1: System model of energy-efficient resource allocation in vehicular networks.

where W is the bandwidth of RB.

Let $r_{i,n}^{\min}$ denote the minimum data rate of i-th VUE pair. The QoS requirement for resource allocation is measured by the minimum data rate of VUE pairs, which can be expressed as

$$r_{i,n} \geq r_{i,n}^{\min}, \forall i \in \mathcal{I}, \forall n \in \mathcal{N}. \tag{4}$$

We consider that the channel state information of the eavesdropper in the networks is imperfectly known. According to [15], we adopt a bounded uncertainty model to denote the eavesdropping channel gain. The eavesdropping channel gain on n-th RB between i-th VUE receiver and the eavesdropper is denoted by $g_{i,\mathrm{E}}$, which is given by $g_{i,\mathrm{E}} \in \mathcal{G}_{i,\mathrm{E}} \triangleq \{|g_{i,\mathrm{E}} - \widetilde{g_{i,\mathrm{E}}}| \leq \sigma\}$. Here, $\widetilde{g_{i,\mathrm{E}}}$ denotes the estimated channel gain, σ means the maximum estimated error.

Considering the worst-case lower bound, the secrecy capacity of i-th VUE at the worst-case lower bound can be expressed as

$$r_{i,n}^{\mathrm{sec}} = \left[r_{i,n} - \underbrace{W \log_2 \left(1 + \frac{p_{i,n} g_{i,\mathrm{E}}^{\max}}{p_{k,n} g_{k,\mathrm{E}}^{\min} + N_{\mathrm{E}}} \right)}_{r_{i,\mathrm{E}}^{\mathrm{ub}}} \right]^+, \quad \forall i \in \mathcal{I}, \forall n \in \mathcal{N}, \tag{5}$$

where $[\times]^+ = \max\{\times, 0\}$. N_{E} denotes the additive white Gaussian noise at the eavesdropper. $r_{i,\mathrm{E}}^{\mathrm{ub}}$ means the upper bound of the achievable data rate at the eavesdropper for eavesdropping i-th VUE, which can be obtained at $g_{i,\mathrm{E}}^{\max} = \widetilde{g_{i,\mathrm{E}}} + \sigma$ and $g_{k,\mathrm{E}}^{\min} = \widetilde{g_{k,\mathrm{E}}} - \sigma$.

III. Problem Formulation

We define the RB allocation strategy as a matrix $\mathbf{A} = \{a_{i,n}\}_{\forall i \in \mathcal{I}, \forall n \in \mathcal{N}}$. Each element in $\mathbf{A}$ corresponds to an allocation strategy of RB. The power control strategy for each VUE is defined as a matrix $\mathbf{P} = \{p_{i,n}\}_{\forall i \in \mathcal{I}, \forall n \in \mathcal{N}}$. The element in $\mathbf{P}$ denotes the power control allocation for each VUE. The time allocation strategy for each VUE is denoted by a matrix $\mathbf{T} = \{t_{i,n}\}_{\forall i \in \mathcal{I}, \forall n \in \mathcal{N}}$. The element in $\mathbf{T}$ means the time allocation for data transmission of each VUE. Let E_c indicate the circuit energy consumption of all VUEs. Based on the above modeling, to guarantee the QoS requirement and green communications in 6G vehicular networks (i.e., to transmit more bits on unit Joule), the optimization problem can be mathematically expressed as follows

$$\textbf{(P1)}: \ \Theta_{\mathrm{EE}} = \max_{\mathbf{A},\mathbf{P},\mathbf{T}} \frac{\sum\limits_{i=1}^{I}\sum\limits_{n=1}^{N} a_{i,n} r_{i,n}}{\sum\limits_{i=1}^{I}\sum\limits_{n=1}^{N} a_{i,n} p_{i,n} t_{i,n} + E_c}$$

$$\text{subject to}: \ a_{i,n} \in \{0,1\}, \forall i \in \mathcal{I}, \forall n \in \mathcal{N}, \tag{6}$$

$$\sum_{n=1}^{N} a_{i,n} \leq 1, \forall i \in \mathcal{I}, \tag{7}$$

$$\sum_{i=1}^{I} a_{i,n} \leq 1, \forall n \in \mathcal{N}, \tag{8}$$

$$0 \leq t_{i,n} \leq T^{\max}, \forall i \in \mathcal{I}, \forall n \in \mathcal{N}, \tag{9}$$

$$0 \leq p_{i,n} \leq P^{\max}, \forall i \in \mathcal{I}, \forall n \in \mathcal{N}, \tag{10}$$

$$r_{i,n}^{\mathrm{sec-min}} \leq r_{i,n}^{\mathrm{sec}}, \forall i \in \mathcal{I}, \forall n \in \mathcal{N}, \tag{11}$$

$$\text{constraint } (4).$$

Constraint (7) guarantees that each VUE can only reuse one RB. Constraint (8) ensures that each RB can be reused by one VUE. Constraint (9) denotes that the transmission delay should be within the maximum $T^{\max}$. Constraint (10) means that the transmission power of VUE cannot exceed the maximum $P^{\max}$. Constraint (11) ensures that the secrecy capacity of i-th VUE should be higher than the minimum $r_{i,n}^{\mathrm{sec-min}}$.

P1 is a combinatorial programming problem due to the existing of binary variable, which is NP-hard. Based on Dinkelbach method [16], we introduce an additional variable $\Im$, such that the objective function in **P1** can be rewritten as follows

$$f(\mathbf{A},\mathbf{P},\mathbf{T},\Im) = \sum_{i=1}^{I}\sum_{n=1}^{N} a_{i,n} r_{i,n} - \Im\left(\sum_{i=1}^{I}\sum_{n=1}^{N} a_{i,n} p_{i,n} t_{i,n} + E_c\right). \tag{12}$$

It can be identified from (12) that $f(\mathbf{A},\mathbf{P},\mathbf{T},\Im)$ is monotonically decreasing with $\Im$.

Proposition 1. *We use $\mathbf{\Omega}$ to denote the feasible domain of power optimization, time allocation and RB allocation. Let $\Im^*$ denote the maximum value of **P1**.*

$$\Im^* = \max_{\{\mathbf{A},\mathbf{P},\mathbf{T}\} \in \mathbf{\Omega}} \frac{\sum\limits_{i=1}^{I}\sum\limits_{n=1}^{N} a_{i,n} r_{i,n}}{\sum\limits_{i=1}^{I}\sum\limits_{n=1}^{N} a_{i,n} p_{i,n} t_{i,n} + E_c}. \tag{13}$$

The optimal value of $\Im^*$ is derived if and only if $F(\Im^*) = \max_{\{\mathbf{A},\mathbf{P},\mathbf{T}\} \in \mathbf{\Omega}} f(\mathbf{A},\mathbf{P},\mathbf{T},\Im^*) = 0$.

Based on the above analysis, **P1** can be transformed as

$$\textbf{(P2)}: \ \max_{\mathbf{A},\mathbf{P},\mathbf{T},\Im} f(\mathbf{A},\mathbf{P},\mathbf{T},\Im)$$
$$\text{subject to}: \ \text{constraints } (4), (6)-(11).$$

IV. Proposed Algorithms for Solving the Formulated Problem

By exploiting the feature of **P2**, we propose a vertical decomposition method to solve it effectively. We first optimize the power control $\mathbf{P}$ under the given values of $\mathbf{A}$, $\mathbf{T}$ and $\Im$. Then, based on the obtained value of $\mathbf{P}$ and the given values of $\mathbf{A}$ and $\Im$, we optimize the time allocation $\mathbf{T}$. After obtaining the values of $\mathbf{P}$ and $\mathbf{T}$, we optimize the RB allocation $\mathbf{A}$. Finally, the value of $\Im$ will be converged through iteratively updating based on the monotonic feature of $f(\mathbf{A},\mathbf{P},\mathbf{T},\Im)$.

A. Proposed Algorithm to Determine the Power Control

Given the variables of RB allocation $\mathbf{A}$ and transmission time $\mathbf{T}$, we find that the RB allocation for CUE and VUE is determined. It can be identified that the objective function of **P2** is concave. We can transform constraint (4) into the following convex form

$$(p_{k,n} g_{k,i} + N_0)\left(2^{\frac{r_{i,n}^{\min}}{W}} - 1\right) - p_{i,n} g_{i,n} \leq 0, \quad \forall i \in \mathcal{I}, \forall n \in \mathcal{N}. \tag{14}$$

We adopt the successive convex approximation (SCA) operations to obtain a convex form of constraint (11). Specifically, we first introduce

$$R_{i,\mathrm{E}} = W \log_2\left(1 + \frac{p_{i,n} g_{i,\mathrm{E}}^{\max}}{p_{k,n} g_{k,\mathrm{E}}^{\min} + N_{\mathrm{E}}}\right), \forall i \in \mathcal{I}. \tag{15}$$

We use the first-order Taylor expansion of $\{p_{i,n}\}_{\forall i \in \mathcal{I}, n \in \mathcal{N}}$ for a given feasible transmission power $\{p_{i,n}^{\tau}\}_{\forall i \in \mathcal{I}, n \in \mathcal{N}}$ at the τ-th iteration as its lower bound in (15), denoted as

$$R_{i,\mathrm{E}} \geq R_{i,\mathrm{E}}^{\mathrm{lb}} \triangleq W \log_2\left(1 + \frac{p_{i,n}^{\tau} g_{i,\mathrm{E}}^{\max}}{p_{k,n} g_{k,\mathrm{E}}^{\min} + N_{\mathrm{E}}}\right) + \frac{W g_{i,\mathrm{E}}^{\max}\left(p_{i,n} - p_{i,n}^{\tau}\right)}{\left(p_{k,n} g_{k,\mathrm{E}}^{\min} + p_{i,n}^{\tau} g_{i,\mathrm{E}}^{\max} + N_{\mathrm{E}}\right)\ln 2}, \forall i \in \mathcal{I}. \tag{16}$$

Therefore, the lower bound of $r_{i,n}^{\mathrm{sec}}$ in constraint (11) can be obtained as follows

$$r_{i,n}^{\mathrm{sec-lb}} \triangleq W \log_2\left(1 + \frac{p_{i,n} g_{i,n}}{p_{k,n} g_{k,i} + N_0}\right) - R_{i,\mathrm{E}}^{\mathrm{lb}}, \quad \forall i \in \mathcal{I}, \forall n \in \mathcal{N}. \tag{17}$$

Notice that we do not consider $[\times]^+$ in (17). If the solution in (17) leads to $r_{i,n}^{\mathrm{sec-lb}} < 0$, it means that the communication link for i-th VUE will be failure, i.e., $\{p_{i,n} = 0\}_{\forall i \in \mathcal{I}, n \in \mathcal{N}}$.

Based on the above operations, we can rewrite **P2** for power control (PC) problem as follows

$$
\begin{aligned}
(\textbf{P3-PC}): \max_{\{p_{i,n}\}_{\forall i\in\mathcal{I},n\in\mathcal{N}}} & W\log_2\left(1+\frac{p_{i,n}g_{i,n}}{p_{k,n}g_{k,i}+N_0}\right) \\
& -\Im\left(p_{i,n}t_{i,n}+E_c\right) \\
\text{subject to}: \ & (p_{k,n}g_{k,i}+N_0)\left(2^{\frac{r_{i,n}^{\min}}{W}}-1\right) \\
& -p_{i,n}g_{i,n}\leq 0,\forall i\in\mathcal{I},\forall n\in\mathcal{N}, \\
& 0\leq p_{i,n}\leq P^{\max},\forall i\in\mathcal{I},\forall n\in\mathcal{N}, \\
& r_{i,n}^{\mathrm{sec-min}}\leq W\log_2\left(1+\frac{p_{i,n}g_{i,n}}{p_{k,n}g_{k,i}+N_0}\right) \\
& -R_{i,\mathrm{E}}^{\mathrm{lb}},\forall i\in\mathcal{I},\forall n\in\mathcal{N}.
\end{aligned}
$$

It can be identified that **P3-PC** is a strictly convex optimization problem and is strong duality based on Slater's condition. This feature enables us to obtain the power control allocation by adopting the Karush-Kuhn-Tucker (KKT) conditions. We can obtain the optimal power control for each VUE via solving the dual problem with zero duality gap.

B. Proposed Algorithm to Obtain the Transmission Time

After solving **P3-PC**, we continue to optimize the transmission time. However, the objective function for transmission time cannot be mathematically expressed. Exploiting **P2**, we find that the value of $t_{i,n}$ is within the interval $[0, T^{\max}]$. Therefore, we can obtain the optimal transmission time $t_{i,n}^*$ via a linear-searching method.

C. Proposed Algorithm to Determine the RB Allocation

The RB allocation strategy is a binary assignment problem. We introduce a two-sided matching $\{\sqsupset(i)\in\mathcal{N}\}_{\forall i\in\mathcal{I}}$ to denote the pairings between RBs and VUEs. Here, $\{\sqsupset(i)=n\}_{\forall i\in\mathcal{I},\forall n\in\mathcal{N}}$ denotes that VUE $i\in\mathcal{I}$ selects RB $n\in\mathcal{N}$ to form a pair. Our objective is to determine the best pairing between VUEs and RBs, such that no participants have incentive to break the stable pairing. The preference list for VUEs and RBs is introduced to facilitate the stable pairing. We first define the *net-rewards* for VUEs and RBs to obtain the preference list. The *net-reward* for VUE pair i is associated with the utility in sending its data and the energy consumption, which can be defined as

$$\daleth_i(n)=\mathcal{U}_i\left(D_i^{\mathrm{tot}}\right)-\varkappa p_{i,n}t_{i,n},\forall i\in\mathcal{I},\forall n\in\mathcal{N}, \tag{18}$$

where parameter $\varkappa$ denotes the marginal cost of energy consumption. $\mathcal{U}_i\left(D_i^{\mathrm{tot}}\right)$ denotes the utility of VUE pair i for sending its data. The utility can be defined as $\mathcal{U}_i\left(D_i^{\mathrm{tot}}\right)=\varsigma\log\left(1+D_i^{\mathrm{tot}}\right)$ and parameter ς means the marginal reward for sending data. We can rewrite the *net-reward* for VUE pair i as follows

$$\daleth_i(n)=\varsigma\log\left(1+D_i^{\mathrm{tot}}\right)-\varkappa p_{i,n}t_{i,n},\forall i\in\mathcal{I},\forall n\in\mathcal{N}. \tag{19}$$

Therefore, we can denote the preference of VUE pair i with respect to two different RBs n and n' as follows

$$n'\prec_{\mathrm{VUE}} n\Leftrightarrow\daleth_i(n')<\daleth_i(n),\forall i\in\mathcal{I},\forall n\in\mathcal{N}. \tag{20}$$

Algorithm 1: Proposed Algorithm to Determine the RB Allocation

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Input: The set of VUEs $\mathcal{I}$ and the set of RBs $\mathcal{N}$.
Initialization: Initialize the current paired as $\{\sqsupset(i)=\emptyset\}_{\forall i\in\mathcal{I}}$. Set $\Omega=\mathcal{I}$.
while $\Omega\neq\emptyset$ **do**
  for each VUE $i\in\Omega$ **do**
    VUE i selects the most preferred RB $\hat{n}$ (which did not reject VUE i before) from the preference list $\mathcal{P}_i^{\mathrm{list}}$.
    A proposal is sent to the current selected RB $\hat{n}$ by VUE i.
  end for
  for each RB $n\in\mathcal{N}$ **do**
    Set $\mho_n$ as the set of VUEs which have offered proposals to RB n in the current iteration.
    Set $i^{\mathrm{best}}=\arg\min_{\forall i\in\mho_n}\{\daleth_n(i)\}$ as the best VUE in $\mho_n$ from the perspective of RB n.
    if $\daleth_n\left(i^{\mathrm{best}}\right)<\daleth_{\sqsupset(i)}(i)$ **then**
      RB n rejects its currently paired VUE i.
      Update $\Omega\longleftarrow\{\Omega\backslash i\}\cup\left\{i^{\mathrm{best}}\right\}$.
      RB n updates its pairing as $\sqsupset\left(i^{\mathrm{best}}\right)=n$.
    else
      RB n maintains its currently paired VUE i.
    end if
  end for
end while
Output: Each VUE i yields its currently paired RB $\{\sqsupset(i)=n\}_{\forall i\in\mathcal{I}}$ as the stable pairing.

Let $\mathcal{P}_i^{\mathrm{list}}$ denote the preference list of VUE pair i for all RBs. $\mathcal{P}_i^{\mathrm{list}}$ can be established by the descending order based on the value of $\{\daleth_i(n)\}_{\forall n\in\mathcal{N}}$. The top RB in the preference list $\mathcal{P}_i^{\mathrm{list}}$ of VUE pair i can be determined by $\arg\max_{\forall n\in\mathcal{N}}\{\daleth_i(n)\}$.

The *net-reward* for RB n is related to the increment of transmission rate, which can be expressed as

$$
\begin{aligned}
\daleth_n(i)=\ & W\log_2\left(1+\frac{p_{i,n}g_{i,n}}{N_0}\right) \\
& -W\log_2\left(1+\frac{p_{i,n}g_{i,n}}{p_{k,n}g_{k,i}+N_0}\right),\forall i\in\mathcal{I},\forall n\in\mathcal{N}.
\end{aligned} \tag{21}
$$

We can express the preference of RB n with respect to two different VUE pairs i and i' as follows

$$i'\prec_{\mathrm{RB}} i\Leftrightarrow\daleth_n(i')>\daleth_n(i),\forall i\in\mathcal{I},\forall n\in\mathcal{N}. \tag{22}$$

We use $\mathcal{P}_n^{\mathrm{list}}$ to denote the preference list of RB n for all VUE pairs, which can be obtained by the increment order based on the values of $\{\daleth_n(i)\}_{\forall i\in\mathcal{I}}$. The top VUE pair in the preference list $\mathcal{P}_n^{\mathrm{list}}$ of RB n can be determined by $\arg\min_{\forall i\in\mathcal{I}}\{\daleth_n(i)\}$.

Based on the preference list of VUEs and RBs, we aim to determine the stable pairing $\{\sqsupset^*(i)=n\}_{\forall i\in\mathcal{I},\forall n\in\mathcal{N}}$, such that VUE pair i is the best choice from the perspective of RB n, and RB n is the best choice from the perspective of VUE pair i in the stable pairing. We propose a stable pairing for VUEs and RBs in Algorithm 1. The main idea and process of the proposal are explained as follows.

1) Each VUE i first chooses its most preferred RB $\hat{n}$ (which did not reject VUE i before) based on the preference list $\mathcal{P}_i^{\mathrm{list}}$. Then, VUE i proposes a matching to the current selected RB $\hat{n}$.
2) After receiving the proposals from all VUEs, each RB n will update its currently paired VUE i^{cur}. If the currently

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Algorithm 2: Proposed Algorithm to Solve P2

Input: The convergence threshold Θ, the maximum number of iterations $\Lambda^{\max}$.
Initialization: Initialize the loop index as $m = 0$, and set the current value as $\Im_m = 0$.
while $\Theta \le |F(\Im_m)|$ or $m \le \Lambda^{\max}$ **do**
    Obtain the current optimal solutions of $\widehat{p_{i,n}}$, $\widehat{t_{i,n}}$, and $\widehat{a_{i,n}}$.
    Update $\Im_{m+1} \longleftarrow \frac{\sum_{i=1}^{I}\sum_{n=1}^{N}\widehat{a_{i,n}}r_{i,n}}{\sum_{i=1}^{I}\sum_{n=1}^{N}\widehat{a_{i,n}}\widehat{p_{i,n}}\widehat{t_{i,n}}+E_c}$.
    Update $m \longleftarrow m+1$.
end while
Output: The optimal values of $\Im^*$, $p_{i,n}^*$, $t_{i,n}^*$, $a_{i,n}^*$.

---

paired VUE i^{cur} can guarantee $\daleth_n(i^{\text{cur}}) > \daleth_n(i)$, RB n will update its paired VUE $\daleth_n(i^{\text{cur}}) = n$.

The process of the proposed pairing will be ended until there is no blocking pair. Finally, it will yield the stable pairing $\{\beth^*(i) = n\}_{\forall i\in\mathcal{I},\forall n\in\mathcal{N}}$ for VUEs and RBs.

D. Proposed Algorithm to Solve **P2**

We exploit an iterative approach to solve **P2**. Specifically, the Dinkelbach method first chooses an initial value $\Im_0$ and then performs a number of iterations until it satisfies the convergence threshold Θ. In the m-th iteration, we set $\Im = \Im_m$ to address the following problem

$$\begin{aligned}(\mathbf{P2}-\Im_m):\ &\max_{\Im_m} f(\mathbf{A},\mathbf{P},\mathbf{T},\Im_m)\\ \text{subject to}:\ &F(\Im_m) \le \Theta.\end{aligned}$$

Algorithm 2 shows the details for solving the **P2**. Specifically, we first obtain the optimal power control $p_{i,n}^*$ via Lagrange dual function approach. The optimal transmission time $t_{i,n}^*$ is obtained via linear-searching. We next determine the optimal RB allocation strategy $a_{i,n}^*$ based on the stable paring. Finally, we obtain the resource allocation through iterative algorithm until it reaches the convergence threshold.

V. Performance Evaluation

A. Simulation Setup

In the simulations, we consider a crossroad map with 300m $\times$ 300m in vehicular networks. The RSU is located at the center of the crossroad to provide communications for CUEs. There are five CUEs driving on the road. Five VUE pairs can reuse the RB of CUEs for information transmission. One eavesdropper may overhear the information of CUEs and VUEs. The transmitted data is within $[5, 10]\,\text{Mbits}$. The allocated bandwidth of RB is $[4, 5]\,\text{MHz}$. The maximum number of iterations is set as 50. The convergence threshold is set as 0.001. The maximum transmission delay is 1sec. The maximum transmission power is 5mW. Our proposal is compared with the following baseline algorithms.

- *Fixed Matching Algorithm:* In this algorithm, VUEs match with the fixed RBs according to the predefined sorting.

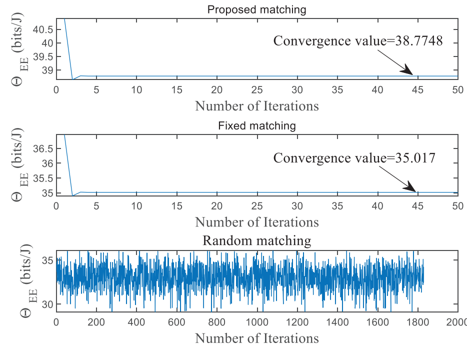

Fig. 2: The comparison of the objective function under different matching scheme.

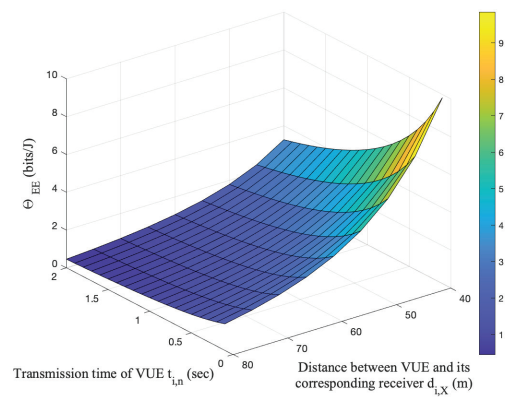

Fig. 3: The changes of the objective function with the values of $t_{i,n}$ and $d_{i,\text{X}}$.

- *Random Matching Algorithm:* In this algorithm, VUEs and RBs are randomly matched with each other.
- *Uniform Power Allocation U($p_{i,n}$) Algorithm:* In this algorithm, the total powers are uniformly allocated to each VUE.
- *Random Power Allocation U($p_{i,n}$) Algorithm:* In this algorithm, the total powers are randomly allocated to each VUE.

B. Numerical Analysis

Fig. 2 depicts the comparison of the objective function under different matching schemes. It can be seen from Fig. 2 that the objective function is convergent in the proposed matching scheme and the fixed matching scheme. This is because the optimal transmission power and time can be obtained by the proposed matching scheme and the fixed matching scheme, which results in the convergence of Θ_{EE}. While in the random matching scheme, VUEs and RBs are randomly matched with each other, which makes the objective function value change randomly.

Fig. 3 demonstrates the changes of the objective function of **P2**. From Fig. 3, we can see that the value Θ_{EE} is decreasing with both the values of $t_{i,n}$ and $d_{i,\text{X}}$. The reasons are as

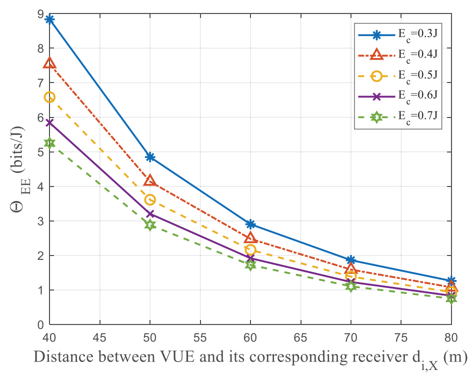

Fig. 4: The changes of the objective function with different values of $d_{i,\mathrm{X}}$.

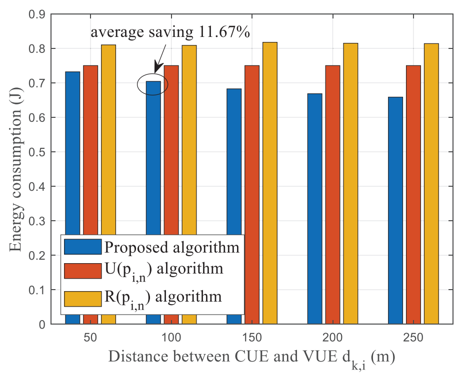

Fig. 5: Performance comparison of the proposal with baseline algorithms under different values of $d_{k,i}$.

follows. First, the large value of $t_{i,n}$ will lead to the high value on the product of the transmission power and time duration. This decreases the value of Θ_{EE}. Second, when increasing the distance between VUE and its corresponding receiver, the channel gain $g_{i,n}$ will reduce. This decreases the data rate and results in the downtrend of Θ_{EE}.

Fig. 4 illustrates the objective function with different values of $d_{i,\mathrm{X}}$. It can be derived from Fig. 4 that the objective function decreases as the value of $d_{i,\mathrm{X}}$ increases. The reason can be explained as follows. The channel gain $g_{i,n}$ is reducing when increasing the distance between VUE and its corresponding receiver $d_{i,\mathrm{X}}$, which results in the low data rate for VUEs.

Fig. 5 demonstrates the energy comparison of our proposal with the baseline algorithms under different values of $d_{k,i}$. From Fig. 5, we can see that our proposal can achieve the lower energy consumption than other baseline algorithms. This is because our proposal considers the optimal transmission power for resource allocation, which can reduce the energy consumption.

VI. Conclusion

This paper has proposed a secrecy oriented slicing resource allocation scheme in 6G green vehicular networks, with the objective of maximizing the energy efficiency. To guarantee the QoS requirement and green communication, we have presented a joint problem for energy-efficient slicing resource allocation to optimize the power control, time allocation and RB allocation. We have proposed a layered structure to solve the joint optimization. Finally, we have conducted simulations to validate the performance of our proposal. In the future work, we will study the secure data transmission among vehicle users and RSUs to guarantee the driving safety.

References

[1] J. Wang, J. Liu, and N. Kato, "Networking and communications in autonomous driving: A survey," *IEEE Communications Surveys Tutorials*, vol. 21, no. 2, pp. 1243–1274, 2019.

[2] H. Cao, S. Garg, G. Kaddoum, S. Singh, and M. S. Hossain, "Softwarized resource management and allocation with autonomous awareness for 6G-enabled cooperative intelligent transportation systems," *IEEE Transactions on Intelligent Transportation Systems*, vol. 23, no. 12, pp. 24 662–24 671, 2022.

[3] Z. Su, M. Dai, Q. Xu, R. Li, and H. Zhang, "Uav enabled content distribution for internet of connected vehicles in 5g heterogeneous networks," *IEEE Transactions on Intelligent Transportation Systems*, vol. 22, no. 8, pp. 5091–5102, 2021.

[4] D. A. Chekired, M. A. Togou, L. Khoukhi, and A. Ksentini, "5G-slicing-enabled scalable SDN core network: Toward an ultra-low latency of autonomous driving service," *IEEE Journal on Selected Areas in Communications*, vol. 37, no. 8, pp. 1769–1782, 2019.

[5] B. P. Nayak, L. Hota, A. Kumar, A. K. Turuk, and P. H. J. Chong, "Autonomous vehicles: Resource allocation, security, and data privacy," *IEEE Transactions on Green Communications and Networking*, vol. 6, no. 1, pp. 117–131, 2022.

[6] M. Dai, Z. Su, Q. Xu, and N. Zhang, "Vehicle assisted computing offloading for unmanned aerial vehicles in smart city," *IEEE Transactions on Intelligent Transportation Systems*, vol. 22, no. 3, pp. 1932–1944, 2021.

[7] J. Wang, K. Zhu, and E. Hossain, "Green internet of vehicles (iov) in the 6g era: Toward sustainable vehicular communications and networking," *IEEE Transactions on Green Communications and Networking*, vol. 6, no. 1, pp. 391–423, 2022.

[8] T. Wang, Y. Li, and Y. Wu, "Energy-efficient uav assisted secure relay transmission via cooperative computation offloading," *IEEE Transactions on Green Communications and Networking*, vol. 5, no. 4, pp. 1669–1683, 2021.

[9] D. Saluja, R. Singh, N. Saluja, and S. Kumar, "Energy-efficient strategy for improving coverage and rate using hybrid vehicular networks," *IEEE Transactions on Intelligent Transportation Systems*, vol. 23, no. 1, pp. 430–443, 2022.

[10] Z. Su, Y. Wang, Q. Xu, and N. Zhang, "Lvbs: Lightweight vehicular blockchain for secure data sharing in disaster rescue," *IEEE Transactions on dependable and secure computing*, vol. 19, no. 1, pp. 19–32, 2020.

[11] Y. Wang, Z. Su, and N. Zhang, "Bsis: Blockchain-based secure incentive scheme for energy delivery in vehicular energy network," *IEEE transactions on industrial informatics*, vol. 15, no. 6, pp. 3620–3631, 2019.

[12] H. Song, H. Wen, J. Tang, Y. Chen, F. Xie, R.-F. Liao, and S. Chen, "PLS-based secrecy transmission for VANETs," *IEEE Transactions on Vehicular Technology*, vol. 69, no. 7, pp. 7596–7608, 2020.

[13] X. Luo, H.-H. Chen, and W. Meng, "How much can radio resource allocation help to improve secrecy capacity of V2V underlay cellular networks?" *IEEE Transactions on Vehicular Technology*, vol. 69, no. 12, pp. 14 932–14 944, 2020.

[14] S. Kavaiya, D. K. Patel, Z. Ding, Y. L. Guan, and S. Sun, "Physical layer security in cognitive vehicular networks," *IEEE Transactions on Communications*, vol. 69, no. 4, pp. 2557–2569, 2021.

[15] Y. Zhou, P. L. Yeoh, C. Pan, K. Wang, M. Elkashlan, Z. Wang, B. Vucetic, and Y. Li, "Offloading optimization for low-latency secure mobile edge computing systems," *IEEE Wireless Communications Letters*, vol. 9, no. 4, pp. 480–484, 2020.

[16] W. Dinkelbach, "On nonlinear fractional programming," *Management science*, vol. 13, no. 7, pp. 492–498, 1967.