Efficient joint resource allocation for cognitive internet of vehicles networks based on asymmetric relay transmission

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Abstract
In the internet of vehicles (IoV) networks, a direct connection from the source end to the destination end may not be established due to the fast vehicle speed, long distance between vehicles, variable vehicle density, serious channel fading etc. In this paper, a joint resource allocation (RA) in the relay-aided IoV networks is modelled as a mixed binary integer non-linear programming (MBINP), which maximises the throughput of cognitive IoV networks among different subcarriers and relays. To further reduce the computational complexity, a suboptimal scheme is presented. First, the appropriate relay and subcarrier pairs are obtained by averaging the power allocation among the cognitive sources and relays. Second, an alternative optimisation mechanism is proposed to the power allocation. Simulation results show that, different from the symmetric time-slot relay transmission, the asymmetric one can significantly increase the degree of freedom for transmission. Therefore, it is more robust to the impact of the relay node location on the throughput. Moreover, the proposed suboptimal RA algorithm not only can obtain the system capacity close to the optimal one, but also can reduce the computational complexity. At the same time, unacceptable degradation caused by severe channel fading is avoided.

1 | INTRODUCTION

Internet of vehicles (IoV) [1] refers to an enormously interactive vehicular network composed of the current and upcoming traffic information. IoV has been considered to be an important societal application to provide timely and efficient exchange of vehicle speed, location and route information to reduce road accidents, improve the traffic efficiency, save the fuel consumption and offer location-based services.

Nowadays, resource allocation (RA) [2–10], an important aspect for the IoV, which usually involves subcarrier assignment and power allocation, presents unique challenges. One of these challenges is spectrum resource shortage. The US Federal Communication Commission (FCC) has allocated 75 MHz spectrum bandwidth to support IoV communications[11]. However, with the increasing number of infrastructures of IoV and related applications, the traffic volume of communication increases greatly, resulting in the shortage of dedicated short-range communication (DSRC) spectrum resources. Since IoV is the basis of Intelligent Transportation System (ITS), another challenge is imposed by higher transmission rate and reliability requirements, which are rigorous for the safety consideration[12]. Furthermore, as a result of the uncertainty of inter-vehicle distance and the variation of vehicle density, the coverage of the IoV is also a focal point to be considered.

Studies have shown that spectrum resources of wireless networks are often underutilised when the traffic is light in the licensed networks and the scarcity of spectrum resources is partly due to the inefficiency of the regulatory spectrum assignment policy[13]. Cognitive radio (CR)[14] is conceived as a communication paradigm that utilises radio spectrum more effectively through intelligent sensing and dynamic access of the licensed spectrum. Opportunistic spectrum access (OSA) is adopted to reduce the collision and the contention delay caused by dense nodes, which improves the real-time performance of communication. Therefore, the concept of cognitive IoV is emerged when CR is integrated into IoV networks.
Among many candidate technologies, orthogonal frequency division multiplexing (OFDM)[15] is widely considered as a highly popular multiplexing scheme of CR networks because of its ability to allocate the idle spectrum dynamically among unlicensed secondary users (SUs), as well as its flexibility to monitor the spectral occupancy of primary users (PUs) without additional cost. RA for OFDM-based wireless CR networks has been widely considered and is still actively pursued. The optimisation objectives of the RA include maximising the throughput, the energy efficiency, and the number of users with quality of service (QoS) guarantee or minimising the interference etc. In [28], He et al. propose a RA scheme based on semi-Markov decision process to maximise the quality of video streaming while guaranteeing the background users’ call-level performance and QoS provisioning. In [17], to formulate the inter-cell RA, two alternative bargaining solutions are proposed to achieve a good trade-off between weighted fairness and efficiency in cognitive IoV. A robust energy efficiency power allocation algorithm is proposed for channel uncertainty underlay CR systems considering the constraints of interference power threshold and minimum target SINR requirement [18]. In order to efficiently distribute the available subcarriers among SUs and maximise the throughput of CR networks, in [19], a centralised subcarrier pairing scheme with associated power allocation mechanism is proposed for underlay multi-user OFDM taking the threshold of interference and rate loss that PUs can tolerate into consideration. In [20], an algorithm of power allocation for OFDM-based CR networks is proposed, which operates in licensed frequency bands to minimise the total interference introduced to PUs under the minimum capacity and the total transmit power constraints of the SUs. But all the papers above only consider the direct transmission between sources and destinations. To the best of our knowledge, it is difficult to establish and maintain an end-to-end connectivity in cognitive IoV networks due to the fast vehicle speed, the uncertainty of inter-vehicle distance, the variable vehicle density, and the severe channel fading. Relay strategy can provide reliable end-to-end communication and reduce fading effects, which can be used to increase the coverage area of IoV. Typically, there are three kinds of nodes in a relay communication system, i.e. source, relay and destination. Three representative relay transmission protocols, namely, amplify-and-forward (AF), decode-and-forward (DF), and coded-cooperation (CC) have been discussed in detail [21–25]. In [26], a robust power allocation scheme with imperfect channel situation information is investigated to improve worst-case energy efficiency for uplink underlay OFDM CR system using AF relay protocol. In [27], a power allocation strategy with the uncertainty of spectrum sensing is proposed to maximise the total capacity of SUs in a cognitive network with DF relay protocol, in which the relay device is powered with a capacity-limited battery. In [28], an asymmetric cross-layer RA in relay-aided CR networks is studied, which includes AF and DF relays with the queue stability and QoS requirements. Among the three relay transmission protocols mentioned above, the DF has the high transmission rate and low bit error rate, which is the most suitable protocol for cognitive IoV network.

This paper considers the RA problem for a cognitive IoV network sharing the spectrum resources with a licensed network. The SU’s in the cognitive IoV network adopt the OFDM, while it is not essential for the licensed network to apply OFDM. A point-to-point two-hop relay model with DF protocol is utilised. First, the source transmits the information to the relay in the 1st time-slot, and then the relay transfers the information to the destination in the 2nd time-slot. The lengths of the two time-slots are not necessarily equal. The joint RA based on asymmetric relay transmission is proposed to maximise the throughput. The main contributions of this paper are highlighted as follows:

1. Considering the difference of channel conditions between cognitive source, relay and cognitive destination, the asymmetric slot length is adopted. The joint RA problem is formulated as mixed binary integer non-linear programming (MBINP), and the optimization target is to maximise the overall system throughput.

2. We divide the original joint RA problem into three sub-problems, i.e., subcarrier pairing problem, relay selection problem and power allocation problem. The resolvable power relay protocols can utilize the dual decomposition technique to obtain the optimal solution together, under the constraints of available power, interference threshold, transmission rate and other constraints.

3. We propose a sub-optimal joint RA scheme with low computational complexity to meet the real-time requirements of IoV. By averaging the power of each subcarrier, appropriate subcarrier pairing and relay can be obtained quickly. Then, the alternative optimisation mechanism could be used to allocate power. The simulation result shows that the performance of the sub-optimal algorithm is pretty much close to that of the optimal algorithm, and strike a balance between the throughput and the computational complexity.

2 | SYSTEM MODEL AND PROBLEM FORMULATION

2.1 | System model

In this paper, an OFDM-based relay-aided cognitive IoV network is considered. As illustrated in Figure 1, a cognitive IoV network coexists with a licensed network. Each relay-aided cognitive IoV link contains a cognitive source node, a cognitive destination node and several candidate relay nodes to be selected. Secondary users (SUs) coexist with the licensed primary users (PUs) in the same geographical region. Meanwhile, the SUs can utilise the PUs’ bandwidth under the condition that their transmission interference to the primary system is lower than the interference threshold $I_d$. The cognitive IoV network divides the available bandwidth into several orthogonal subchannels. Each subchannel can, thus, be modelled as an additive white Gaussian noise (AWGN) channel with time-varying gain.

It is assumed that there is no line-of-sight transmission link between the source node and the destination node due to the existence of obstacles or a long distance. The DF protocol is utilised in relay nodes, where the received signal from the source
node is decoded and re-encoded before forwarded to the destination node in the second phase of the transmission time-slot. It is also assumed that the channel state information (CSI) is available at the receiver, and it can be perfectly fed back to the transmitter. The total bandwidth $B$ in the network is divided into $N$ subcarriers with an equal bandwidth of $\Delta f$. The subcarrier set is defined as $\mathcal{N} = \{1, 2, \ldots, N\}$, where $N$ is the total number of subcarriers. There are a cluster of candidate DF relay nodes. One or more candidate relay node(s) with satisfactory second hop CSI are eventually selected as relay nodes and named as the selected relay node(s). Each selected relay node $m (m \in [1, \ldots, M])$ operates in a two time-slot time division duplex (TDD) mode over a subcarrier pairing $(j, k)$. In the 1st time-slot, the cognitive source node transmits information through the $j$th subcarrier to candidate DF relays. In the 2nd time-slot, each selected relay $m$ transmits data through the $k$th subcarrier to the cognitive destination node.

According to the considered model, the interference from the $i$th subcarrier of SU to the licensed network can be formulated as \cite{29}

$$J_i = \int_{-\Delta f/2}^{\Delta f/2} G_i \phi(f) \, df = P_i \rho_i$$

where $G_i$ represents the square of the channel gain between the $i$th subcarrier and the PUs’ band; $P_i$ is the transmission power of the $i$th subcarrier; $\phi(f)$ denotes the baseband power spectral density (PSD) of OFDM signal; $d_i$ represents the spectral distance between the $i$th subcarrier and the PUs’ band; $\rho_i$ represents the interference factor of the $i$th subcarrier to the PUs’ band.

Similarly, the interference power induced by a PU signal with PSD $\phi_p(f)$ into the $i$th subcarrier can be formulated as \cite{29}

$$I_i = \int_{-\Delta f/2}^{\Delta f/2} G_i \phi_p(f) \, df$$

The channel gain over the $j$th subcarrier from the cognitive source to the $m$th relay is $h_{j,m}$. The allocated power is $P_{j,m}$, and the transmitted symbol is $x_{j,m}$. The signal received at the relay node $m$ is

$$Y_{j,m} = \sqrt{P_{j,m}} l_{j,m} h_{j,m} x_{j,m} + \sigma^2_{j,m}$$

where $l_{j,m}$ is the path loss (PL) factor; $\sigma^2_{j,m}$ is the sum of the variance of AWGN $\sigma^2_{\text{AWGN},j}$ and the $J_i$ is the interference power introduced by the PU signal into the $j$th subcarrier ($\sigma^2_{j,m} = \sigma^2_{\text{AWGN},j} + J_i$). AWGN is modelled as AWGN by applying the law of large number or by assuming the primary network. The independent and random Gaussian code words are used in the cognitive IoV network \cite{30}.

If the relay node $m$ is chosen to DF the signal on the $k$th subcarrier, the symbol received at the cognitive destination node in the 2nd time-slot is

$$Y_{m,k} = \sqrt{P_{m,k} l_{m,k}} h_{m,k} x_{m,k} + \sigma^2_{m,k}$$

where $x_{m,k}$ is the symbol decoded by the relay node, which is similar to the process from the cognitive source node to the relay node; $l_{m,k}$ is the PL factor; $h_{m,k}$ is the channel gain from relay node $m$ to $k$th the subcarrier in the cognitive destination node; $P_{m,k}$ is the allocated power; $\sigma^2_{m,k}$ is the sum of the AWGN power $\sigma^2_{\text{AWGN}}$ and interference power $J_k$ introduced by the $k$th subcarrier to PUs ($\sigma^2_{m,k} = \sigma^2_{\text{AWGN}} + J_k$).

Denote the square of the channel gain of the relay node $m$ over the $j$th subcarrier as $H_{j,m}$, and over the $k$th subcarrier as $H_{m,k}$. Denote the duration in the 1st time-slot as $T_1$, the duration in the 2nd time-slot as $T_2$, and the total duration from the cognitive source to the cognitive destination as $T = T_1 + T_2$.

The achievable transmission rate $R(j, m, k)$ over the subcarrier pairing $(j, k)$ and the relay $m$ can be evaluated by

$$R(j, m, k) = \min \left\{ \frac{R_{j,m}}{T_1} \log_2 \left( 1 + \frac{P_{j,m} H_{j,m} L_{j,m}}{\sigma^2_{j,m}} \right), \frac{R_{m,k}}{T_2} \log_2 \left( 1 + \frac{P_{m,k} H_{m,k} L_{m,k}}{\sigma^2_{m,k}} \right) \right\}$$

It is assumed that the noise variance is a constant for all the subcarriers of SUs. That is $\sigma^2_{j,m} = \sigma^2_{m,k} = \sigma^2$ and $L_{j,m} = L_{m,k} = L$. So $R(j, m, k)$ in (5) can be rewritten as

$$R(j, m, k) = \min \left\{ \frac{R_{j,m}}{T_1} \log_2 \left( 1 + \frac{P_{j,m} H_{j,m} L}{\sigma^2} \right), \frac{R_{m,k}}{T_2} \log_2 \left( 1 + \frac{P_{m,k} H_{m,k} L}{\sigma^2} \right) \right\}$$

FIGURE 1 System model of relay-aided cognitive IoV network
2.2 | Problem formulation

The objective of the proposed algorithm is to maximise the throughput of the cognitive IoV networks by optimizing the subcarrier pairing, relay selection and the power allocation with multiple practical constraints.

The power constraint of the cognitive source nodes and the relay nodes should satisfy

\[
C1 : \sum_{m=1}^{M} \sum_{j=1}^{N} P_{j,m} \leq P_s
\]

\[
C2 : \sum_{k=1}^{N} P_{m,k} \leq P_m, \forall m
\]

where \(P_s\) and \(P_m\) are the maximum transmission power budgets of the cognitive source nodes and the relay nodes.

The interference constraints in the 1st and the 2nd time-slot should satisfy

\[
C3 : \sum_{m=1}^{M} \sum_{j=1}^{N} P_{j,m} \phi_j \leq I_{th}
\]

\[
C4 : \sum_{m=1}^{M} \sum_{k=1}^{N} P_{m,k} \rho_{m,k} \leq I_{th}
\]

where \(I_{th}\) is the prescribed interference threshold of PUs, \(\phi_j\) and \(\rho_{m,k}\) are the interference factor of the \(j\)th subcarrier to the PUs' band from the cognitive source SU, and the interference factor of the \(k\)th subcarrier from the relay node \(m\) respectively.

The minimum transmission rate of the communication links should satisfy

\[
C5 : R(j, m, k) \geq R_{th}, \forall j, m, k
\]

where \(R_{th}\) is the rate-guarantee threshold.

The subcarrier pairing and relay selection should satisfy

\[
C6 : \sum_{j=1}^{N} \psi(j, m) \leq 1, \forall m, \sum_{k=1}^{N} \omega(m, k) \leq 1, \forall m
\]

\[
C7 : \psi(j, m) \in \{0, 1\}, \omega(m, k) \in \{0, 1\}
\]

where, if the \(j\)th subcarrier of the source node is paired with the relay node \(m\), then \(\psi(j, m) = 1\); otherwise, \(\psi(j, m) = 0\). If the relay node \(m\) receives the signal on the \(j\)th sub-carrier of the cognitive source SU, and then decodes and forwards it on the \(k\)th subcarrier to the cognitive destination SU, then \(\omega(m, k) = 1\); otherwise, \(\omega(m, k) = 0\), which makes sure that each subcarrier in the source node is paired with only one subcarrier in the destination node.

The total time length constraint from the cognitive source node to the cognitive destination node should satisfy

\[
C8 : T = T_1 + T_2
\]

It can be inferred that the maximum of \(R(j, m, k)\) implies \(R_{j,m} = R_{m,k}[31]\). Thus, the optimisation problem can be expressed as

\[
\max_{\psi(j, m) \omega(m, k)} \frac{1}{2} \sum_{m=1}^{M} \sum_{j=1}^{N} \sum_{k=1}^{N} \psi(j, m) \omega(m, k) [R(j, m) + R(m, k)]
\]

s.t. \(C1 - C8\)

\[
C9 : R_{j,m} = R_{m,k}
\]

It is obvious that (15) defines a MBINP, which involves both binary integer variables and real variables. It is difficult to solve (15) directly since the integer constrains generally generate an exponential computational complexity. So the original RA optimisation problem is decomposed into subcarrier pairing, relay selection and power allocation sub-problems, and dual decomposition technique is utilised.

3 | PROPOSED RESOURCE ALLOCATION ALGORITHMS

3.1 | Optimal resource allocation algorithm

The objective function (15) discussed in Section 2 is a MBINP problem and it is hard to be solved directly. It has been shown in [32] that regardless of the convexity, the duality gap of the optimisation problem is zero under the time-sharing condition. For general OFDM systems, when the number of subcarriers is large enough, the time-sharing condition is always satisfied. Therefore, the problem can be successfully solved in the dual domain. According to the dual decomposition method proved in [32], an optimal RA algorithm is derived for the considered cognitive IoV system model in Section 2. The optimal solution is derived as a function of the dual variables, and then, the optimal dual variables can be estimated in each time-slot. Let \(\{\tau, \bar{\tau}, \nu, \bar{\nu}, \varepsilon\}\) denote the Lagrange multipliers of the constraints C1, C2, C3, C4 and C5 respectively. Define \(\mathcal{O} = \{\tau, \bar{\tau}\}\) and \(\mathcal{E} = \{\nu, \bar{\nu}\}\). Therefore, the Lagrangian function for the problem (15) is:

\[
L(\tau, \bar{\tau}, \nu, \bar{\nu}, \varepsilon) = \sum_{m=1}^{M} \sum_{j=1}^{N} \sum_{k=1}^{N} \psi(j, m) \omega(m, k) \frac{1}{2} [R(j, m) + R(m, k)]
\]

\[
+ R(m, k) - \varepsilon [R_{th} - R(j, m, k)]
\]

\[
- \tau \left( \sum_{m=1}^{M} \sum_{j=1}^{N} P_{j,m} - P_S \right) - \bar{\tau} \left( \sum_{m=1}^{M} \sum_{j=1}^{N} P_{j,m} \phi_j - I_{th} \right)
\]

\[
- \nu \left( \sum_{k=1}^{N} P_{m,k} - P_m \right) - \bar{\nu} \left( \sum_{k=1}^{N} P_{m,k} \rho_{m,k} - I_{th} \right)
\]
The Lagrange dual function can be written as

$$g(\tau, u, \varepsilon) = \max_{\psi(j,m) \geq 0, \omega(m,k) \geq 0, P_{j,m} \geq 0, P_{m,k} \geq 0} L(\tau, u, \varepsilon)$$

(19)

Additionally, the dual problem converted from the primal problem (18) can be written as

$$\min_{\tau \geq 0, u \geq 0, \varepsilon \geq 0} g(\tau, u, \varepsilon)$$

s.t. (C6, C7, C8, C9)

(20)

Furthermore, (18) can be rewritten as

$$L(\tau, u, \varepsilon) = \sum_{i=1}^{M} \sum_{j=1}^{N} \sum_{k=1}^{N} \psi(j,m)\omega(m,k)h(P_{j,m}, P_{m,k})$$

$$+ \sum_{i=1}^{M} \sum_{j=1}^{N} \sum_{k=1}^{N} \varepsilon R_{th} + \tau P_s + \tau P_m + I_{th}(u + \bar{u})$$

(21)

where

$$h(P_{j,m}, P_{m,k}) = \frac{1}{2}(R_{j,m} + R_{m,k})(1 - \varepsilon) - P_{j,m}(\tau + u \rho_j)$$

$$- P_{m,k}(\tau + \bar{u} \rho_{m,k})$$

(22)

Since (20) can be viewed as a non-linear integer programming problem, the computational complexity of obtaining the optimal solution is extremely high. Therefore, to reduce the complexity, the optimization problem is divided into three subproblems: power allocation, subcarrier pairing, and relay selection.

### 3.1.1 Power allocation

Regardless of optimal relay selection and subcarrier pairing, the optimal power allocation for each cognitive link can be achieved by solving the convex optimization problem. At this time, the objective function is

$$\max_{P_{j,m}, P_{m,k}} h(P_{j,m}, P_{m,k})$$

s.t. $P_{j,m} \geq 0, P_{m,k} \geq 0$

(23)

In the process of solving (23), the gradient descent method [33] is used to ensure the convergence of the algorithm. As a result, for any initial values $\tau^0, \tau^0, u^0, \bar{u}^0, \varepsilon^0$, the dual variables at the $(i+1)^{th}$ iteration can be written as

$$\tau^{i+1} = \tau^i + \delta^i \left( \sum_{m=1}^{M} \sum_{j=1}^{N} P_{j,m} - P_{j} \right)$$

(24)

### 3.1.2 Relay selection

When the power of each pair of subcarriers have been down, the following assignment strategy is employed to select the best relay. For each pair of subcarriers $(j, k)$ which have assigned, traversing every relay $m \in \{1, \ldots, M\}$ and selecting the $m$th relay to maximise the function $b(P_{j,m}^*, P_{m,k}^*)$ which is $m = \arg \max b(P_{j,m}^*, P_{m,k}^*)$, then ending the process until all possible relays are assigned.

### 3.1.3 Subcarrier pairing

When the optimal relay selection and power allocation have been done, subcarrier pairing can be acquired by solving the problem (23) following the similar procedure in power allocation.

$$\max_{\psi(j,m) \geq 0, \omega(m,k) \geq 0} \sum_{i=1}^{M} \sum_{j=1}^{N} \sum_{k=1}^{N} \psi(j,m)\omega(m,k)h(P_{j,m}^*, P_{m,k}^*)$$

$$+ \sum_{i=1}^{M} \sum_{j=1}^{N} \sum_{k=1}^{N} \varepsilon R_{th} + \tau P_s + \tau P_m + I_{th}(u + \bar{u})$$

s.t. C6, C7

(29)

### 3.2 Suboptimal resource allocation algorithm

The algorithm in Section 3.1 achieves the optimal approximate solution, but it results in a high computational complexity for the RA algorithm at the same time. In this section, a suboptimal algorithm is proposed to solve the problem efficiently.
The different subcarrier, power and relay resources are allocated jointly. Compared with the optimal solution, it has lower computational complexity.

The suboptimal algorithm addresses the RA problem into two steps. At first, subcarrier pairing and relay nodes selection scheme are proposed with the initial average power values. Then, the power allocation scheme with alternate iteration is utilized to improve system performance.

3.2.1 Subcarrier pairing and relay selection

Let $S$, $D$ denote the unallocated subcarriers set at the source node and destination node respectively, and $C$ denote all available relays set in the system. Assuming that the available power of cognitive source is equally distributed to all subcarriers and the interference to PUs caused by each subcarrier channel is equal at the same time. According to (1), the transmitted power of each subcarrier in cognitive source represents:

$$P_{j,m} = \min \left\{ \frac{P_j}{N}, \frac{I_{th}}{N\rho_j} \right\}$$

(31)

Meanwhile, according to (2), to maximise the transmission rate of communication link, the transmitted power of the $k$th subcarrier in the $m$th relay represents:

$$P_{m,k} = \min \left( \frac{P_m}{N^2}, \frac{I_{th}}{N\rho_{m,k}} \right)$$

(32)

The algorithm is described detailedly in Table 1.

3.2.2 Power allocation

As mentioned, the algorithm discussed above assumes that the available power of the cognitive source is allocated to each subcarrier equally, as proposed in [34]. So subcarrier pairing and relay selection for maximising system capacity can be achieved by the average power distribution algorithm. The computational complexity of the scheme in [34] is greatly reduced in comparison with the optimal RA algorithm. However, since the channel states are quite different between diverse cognitive links, the average allocation mechanism is not always optimal which results in the degradation of the system performance.

For balancing the complexity and performance of the RA algorithm, an alternative algorithm is proposed to allocate power. In the process of subcarrier pairing and relay selection, we know that the allocated link must guarantee the rate requirement, so the RA problem can be re-expressed as:

$$\max \sum_{j=1}^{M} \sum_{m=1}^{N} \sum_{k=1}^{N} \frac{1}{2} [R(j, m) + R(m, k)]$$

s.t $C1, C2, C3, C4, C8, C9$

(33)

Similar to the power allocation in Section 3.1, the Lagrangian function of problem (33) is

$$L(P, T) = \frac{1}{2} (R(j, m) + R(m, k)) - \lambda \left( \sum_{m=1}^{N} P_{j,m} - P_j \right)$$

$$- \mu \left( \sum_{m=1}^{N} P_{m,k} - \rho_j H_{m,k} \right)$$

$$- \bar{\mu} \left( \sum_{m=1}^{N} P_{m,k} - \rho_j H_{m,k} \right)$$

(34)

where $P = \{P_{j,m}, P_{m,k}\}$ represents power allocation set; $T = \{T_1, T_2\}$ represents time-slot allocation set. And $\{\lambda, \bar{\lambda}, \mu, \bar{\mu}, \gamma\}$ denotes the Lagrange multipliers of the constraints $C1, C2, C3, C4, C9$. The sub-optimal time-slot and power allocation can be calculated according to KKT conditions:

$$T_1^* = \frac{1 - 2\gamma}{2} T$$

$$T_2^* = \frac{1 + 2\gamma}{2} T$$

### TABLE 1 Subcarrier pairing and relay selection algorithm

**Algorithm 1**

**Step 1**: Parameter initialisation

a) assignable subcarriers set in source node:

$$S = \{j | j = 1, 2, ..., N\}$$

b) assignable subcarriers set in destination node:

$$D = \{k | k = 1, 2, ..., N\}$$

c) available relays in system: $C = \{C_m | m = 1, 2, ..., M\}$

**Step 2**: For $j = 1$ to $N$

a) for each relay $C_m \in C$, $P_j$ allocates to every subcarrier equally, according to equation (1)

$$P_{j,m} = \min \left\{ \frac{P_j}{N}, \frac{I_{th}}{N\rho_j} \right\}$$

b) for each relay $C_m \in C$ and subcarriers in cognitive destination $k$, the transmitted power of the $k$th subcarrier in the $m$th relay, $P_{m,k}$ is allocated to every subcarrier equally, as proposed in [34]. So subcarrier pairing and relay selection for maximising system capacity can be achieved by the average power distribution algorithm. The computational complexity of the scheme in [34] is greatly reduced in comparison with the optimal RA algorithm. However, since the channel states are quite different between diverse cognitive links, the average allocation mechanism is not always optimal which results in the degradation of the system performance.

For balancing the complexity and performance of the RA algorithm, an alternative algorithm is proposed to allocate power. In the process of subcarrier pairing and relay selection, we know that the allocated link must guarantee the rate requirement, so the RA problem can be re-expressed as:

$$\max \sum_{j=1}^{M} \sum_{m=1}^{N} \sum_{k=1}^{N} \frac{1}{2} [R(j, m) + R(m, k)]$$

s.t $C1, C2, C3, C4, C8, C9$

(33)

Similar to the power allocation in Section 3.1, the Lagrangian function of problem (33) is

$$L(P, T) = \frac{1}{2} (R(j, m) + R(m, k)) - \lambda \left( \sum_{m=1}^{N} P_{j,m} - P_j \right)$$

$$- \mu \left( \sum_{m=1}^{N} P_{m,k} - \rho_j H_{m,k} \right)$$

$$- \bar{\mu} \left( \sum_{m=1}^{N} P_{m,k} - \rho_j H_{m,k} \right)$$

(34)

where $P = \{P_{j,m}, P_{m,k}\}$ represents power allocation set; $T = \{T_1, T_2\}$ represents time-slot allocation set. And $\{\lambda, \bar{\lambda}, \mu, \bar{\mu}, \gamma\}$ denotes the Lagrange multipliers of the constraints $C1, C2, C3, C4, C9$. The sub-optimal time-slot and power allocation can be calculated according to KKT conditions:

$$T_1^* = \frac{1 - 2\gamma}{2} T$$

$$T_2^* = \frac{1 + 2\gamma}{2} T$$
3.3 Complexity analysis

1) In the optimal RA algorithm in Section 3.1, which is an optimal RA algorithm using the principle in [32] and is derived for the considered cognitive IoV system model is called “ISB[32]+ORA”. Each iteration solving the optimal power allocation requires calculation $O(MN^2)$. When the times of iteration are $A$, the calculation of power allocation is $A(MN^2)$. For $N^2$ possible subcarrier pairs, each pair needs to calculate $M$. So the calculation of subcarrier pairing and relay selection are $O(MN^2)$, and the total complexity is $O((A + 2)(MN^2))$. Since $A$ is generally large, the algorithm in the literature is computationally intensive, and is not applicable to systems with higher real-time requirements.

2) If the subcarrier pairing and relay selection use our proposed algorithm (Algorithm 1), the power is evenly distributed in [34], which is called “Shaat[34]+SPRS”. For each subcarrier in the cognitive source needs to be calculated $MN$ times, the total calculations are $O(MN^2)$, which is reduced greatly.

3) The suboptimal RA algorithm (Algorithm 1, 2, 3) which is called “SRA” under our study needs to calculate $MN^2$ times for subcarrier pairing and relay selection. Each iteration for power needs $N$, iteration number is $B$ and less than $A$, the times of power allocation are $BN$. Therefore, the total complexity is $O(MN^2 + BN)$ which achieves the goal of pursuing the balance between complexity and performance.

In Table 4, the complexity of the three algorithms is summarised.

4 PERFORMANCE EVALUATION

In this section, the simulation results are presented for the proposed RA algorithms to solve joint subcarrier pairing, relay selection and power allocation problems. The performance of
the RA algorithms are evaluated using Monte Carlo simulation. In the following simulation, “SRA” are compared with the algorithm in [35], which is denoted as the “Salem[35]”.

It is assumed that there is a geographical region, covered by a primary system and a cognitive IoV system. The amplitude of the multipath channel fading is independent Rayleigh distributed random variables and the path loss exponent is $L = 3.5$. The cognitive bandwidth $B = 20$ MHz; the total number of subcarriers $N = 64$, so the available bandwidth for each subcarrier is 0.3125 MHz. It is supposed that both the busy and vacant probability of each subcarrier are equal to 0.5. The maximum number of candidate relays $M = 5$. The total timeslot length is $T_s = 5 \mu s$; the noise variance is assumed to be $\sigma^2 = 10^{-4}$.

Figure 2 illustrates the impact of the relay location on the system throughput and compares the “Salem[35]” with “SRA”, where the distance between cognitive source and destination is fixed to 2000 m, while the distance between the cognitive source and the relay varies from 400 to 1600 m. The transmission power of the cognitive source and the relay $P_s = P_m = 5$ dBm, the interference threshold $I_{th} = 0$ dBm and the rate-guarantee threshold $R_{th} = 0$ Bit/s/Hz. It is observed that the system capacity of the “SRA” is superior, with good robustness against distance. This is because the “SRA” can increase the available transmission rate for each subcarrier pair by adaptively arranging timeslot length before and after the relay according to the distance.

Figure 3 shows the achieved system throughput of the different algorithms under different available power budgets, where $P_s = P_m = 0$ dBm, $I_{th}$ changes from $-20$ to 20 dBm, the rate-guarantee threshold $R_{th} = 0$ Bit/Hz/s. From the simulation results, we can see that “SRA” outperforms the “Shaat[34]+SPRS” and achieves a near optimal performance with much less computational complexity compared with “ISB[32]+ORA”. Additionally, we can observe that the overall throughput grows with the increase of interference threshold, and all the algorithms have a near performance in the low interference threshold region. Furthermore, the gaps among the “SRA” with the other two schemes are increased with the increasing interference threshold.

Figure 4 depicts the achieved system throughput of the different algorithms under different rate-guarantee thresholds, where $P_s = P_m = -3$ dBm, $I_{th} = 0$ dBm, $R_{th}$ changes from 0 to 0.1. Obviously, the system throughput decreases as rate-guarantee threshold grows for all the algorithms. This is because the rate provided by some allocated subcarriers may be too low to a practical usage. In order to ensure communication requirements, these poor quality links are discarded. In addition, the
“SRA” performs much better than “Shaat[34]+SPRS” and the gap between “ISB[32]+ORA” and “SRA” is very small. So the “SRA” provides a good approximation to the “ISB[32]+ORA”.

Figure 6 illustrates the system throughput of the sub-optimal algorithm vs. the different number of relays, where $I_{th} = 0$ dBm, $R_{th} = 0$, $P_s = P_m$ changes from $-20$ to $10$ dBm. In the same power budget, the throughput increases with the number of relays increases, especially when comparing with the signal relay, the multiple relays transmission system performances much better. For the reason of cognitive users distribute randomly in communication system, the channel stations between communication links are different and the suboptimal algorithm is always to find the optimal relay to communicate. Therefore the more relays are used, the better communication links can be received, the system throughput also increases. At the same time, we can see that when $M>5$, the growth rate of system performance is gradually reduced. Obviously, the more relays are used, the more complex of the network system will be. In a practical application environment, we must balance the number of relays and the performance of system.

5 | CONCLUSION

In this paper, the relay-added asymmetric time-slot RA algorithm for cognitive IoV is investigated. The optimisation objective maximises the throughput of cognitive IoV networks among different subcarriers and relays. The RA problem has been solved by dividing it into three subproblems, including subcarrier pairing, relay selection and power allocation, which is modelled as a MBINP. To solve those problems, the dual decomposition method is utilized to design an optimum RA algorithm. Additionally, suboptimal RA algorithm has been proposed to reduce the high computational complexity in the optimum RA algorithm. The suboptimal RA algorithm can arrange the appropriate relay and the subcarrier pairing quickly by averaging the power allocation among the cognitive sources and relays, and then an alternative optimization mechanism is utilised to obtain the updated power allocation. From the simulation results, it can be concluded that the asymmetric time-slot RA algorithm can achieve a larger throughput and is more robust than the symmetric one. Additionally, the proposed suboptimal RA algorithm not only can obtain the maximum system capacity close to the optimal RA algorithm, but can also reduce the complexity of the algorithm significantly, which can meet the higher transmission rate, reliability, and coverage requirements of CR-IoV networks.
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