Finder-MCTS: A Cognitive Spectrum Allocation Based on Traveling State Priority and Scenario Simulation in IoV

***Abstract*—With the increasing number of intelligent connected vehicles, the problem of scarcity of communication resources has become increasingly obvious. It is a practical issue with important significance to explore a real-time and reliable dynamic spectrum allocation scheme for the vehicle users, while improving the utilization of available spectrum. In this paper, we firstly model the spectrum resource allocation problem as a binary integer linear programming problem (BILP) with constraints by introducing cognitive radio into the internet of vehicles (IoV). The optimization goal is maximizing the total link capacity of vehicle users. Then, we proposed a spectrum allocation method that integrates offline learning with online search, named Finder-MCTS. This method mainly consists of two stages. Initially, Finder-MCTS gives the allocation priority of different vehicle users in the current allocation cycle based on the vehicle's local driving status and global communication status. Furthermore, Finder-MCTS can search for the approximate optimal allocation solutions online according to the priority and the environment state model of the base station, which learned offline through DNN. In the experimental section, we use SUMO to simulate real traffic flow and communication scenarios. Numerical results show that our proposed Finder-MCTS has 36.47%, 18.24%, 9.00% improvement on average than other existing methods in convergence time, link capacity and channel utilization, respectively. In addition, we verified the effectiveness and advantages of Finder in convergence time, link capacity and channel utilization, respectively, compared with two versions of MCTS.**

***Index Terms*—Internet of Vehicle (IoV), cognitive radio, dynamic spectrum allocation, Monte-Carlo tree search (MCTS)**

I. Introduction

Recently, as a promising technology, internet of vehicles (IoV) has attracted the attention of governments and enterprises around the world, to serve the smart city. The moving vehicles can be regarded as mobile terminals equipped with advanced network components, such as wireless network interfaces, on-board sensors, which provide many personalized services by accessing the internet. These vehicle services (*e.g.*, road condition broadcasts, dangerous event predictions) have high requirements for data transmission and communication quality. Although 5G technology is becoming popular and growing rapidly, the available spectrum resources have not increased simultaneously. So far, the spectrum resources of 6GHz and below 6GHz have almost been allocated [1]. Moreover, the spectrum resources at the base stations are usually allocated to the calls and traffic services of mobile phone users first. Thus, the scarcity of spectrum resources and the low utilization of frequency bands are critical issues hindering the development of IoV.

Currently, as an effective solution to the underutilized problem of spectrum resources, cognitive radio (CR) can reuse the idle spectrum resources through dynamic spectrum access technology. In CR networks, network users are divided into two types: primary users (PUs) and secondary users (SUs). PUs have the high priority to use the spectrum in the authorized frequency bands. SUs can dynamically access spectrum holes opportunistically and use available spectrum resources, which can enhance the spectrum utilization. Therefore, inspired by the CR technology, we let vehicles equipped with CR functions and form a cognitive radio-based internet of vehicles (CR-IoV). We utilize CR to help solve the low utilization of frequency bands in IoV.

In CR-IoV, the system includes PUs (composed by mobile phone users) and SUs (composed by vehicles equipped with CR functions). However, in reality, vehicle users with high mobility will cause frequent changes in the network topology. The availability of spectrum will also change with the activation time and channel occupancy of PUs. Hence, how to meet the real-time and reliable requirements when solving the dynamic spectrum allocation problem under a time-varying environment is an significant challenge.

There are many previous studies about dynamic spectrum allocation in mobile wireless networks. The most popular studies can be mainly classified into four categories: (1) traditional optimization theory-based allocation methods [2], [3]; (2) game theory-based allocation methods [4]–[6]; (3) swarm intelligence optimization-based allocation methods [7]–[11]; (4) machine learning-based allocation methods [12]–[17]. Although the above methods can solve the spectrum allocation problem, there exist many disadvantages. First, when the constraints are complex, traditional optimization theory and game theory are not suitable for quickly solving the large-scale dynamic planning problems. Second, the swarm intelligence optimization is easy to fall into the local optimum [18]. Besides, the effective parameter settings and selection in the swarm intelligence optimization is also complex. Recently, deep reinforcement learning (DRL) algorithms have been proved to solve complex dynamic decision-making problem with high-dimensional state and action space. It can learn the potential regularities in the environment with the help of the idea of trial and error, thereby assisting the intelligent decision-making. However, this type of machine learning-based method also exists some limitations, such as slow learning speed, poor convergence, and bad self-adaption ability. Thus, in this paper, we propose a new cognitive spectrum allocation method based on traveling state priority and different scenarios specially for IoV in this paper.

First, especially in IoV, we should consider the traveling/moving state of a vehicle. A vehicle that is about to leave

the coverage area of a base station should have relatively low spectrum allocation priority. Vehicle users with different traveling state, such as location, speed, acceleration, communication capabilities, should have different opportunities to obtain spectrum resources. Thus, in this paper, we consider the priority assignment based on vehicle traveling state when doing spectrum allocation.

In addition, in this proposed new method, we choose Monte-Carlo tree search algorithm (MCTS) to model our problem. Traditional model-free based deep reinforcement learning algorithms (*e.g.*, deep Q network, soft actor-critic) often require a large amount of samplings and learn strategies from past experiences with the help of neural networks. However, model-based deep MCTS can not only use deep neural networks to fit the environment model from experience data, but also can simulate a variety of possible future trajectories for evaluation through the expansion of the tree structure, so as to choose more promising directions to explore the best policy. In this paper, through designing to simulate different scenarios, we improve the learning efficiency and reduce the searching space compared with traditional MCTS methods.

Our main contributions can be summarized as follows:

• We design a priority assignment rule based on vehicle traveling state for spectrum allocation. Through defining a vehicle traveling evaluation score and a network utility score, we obtain a comprehensive priority evaluation score for each vehicle. According to the priority score, we allocate available spectrum resources from the highest priority to the lowest vehicle user, which can improve the allocation performance when doing dynamic spectrum allocation in IoV.

• Combining with the above priority score, we propose a cognitive spectrum allocation method based on traveling state priority and different scenarios specially for IoV, named Finder-MCTS. We model the problem of spectrum allocation as a binary integer linear programming problem (BILP) with constraints. Meanwhile, through designing a constraint oriented tree expansion and scenario simulation mechanism, Finder-MCTS can give an approximate optimal solution quickly and improve the link capacity of V2I (vehicle to infrastructure) communication in the network.

• We conduct a number of simulations on real-world scenarios and traces to evaluate the performance of our algorithms by SUMO. Numerical results show that our proposed Finder-MCTS has 36.47%, 18.24%, 9.00% improvement on average than other methods in convergence time, link capacity and channel utilization, respectively. In addition, Finder-MCTS also has a significant enhancement in convergence time, ALC and CUR, respectively with the aid of priority evaluation, solution space optimization and uncertainty evaluation of PUs' service duration, compared with the two versions of MCTS.

The remainder of this paper is organized as follows. In Section II, a review of related work is provided. In Section III, the system scenario and problem formalization are presented in detail. In Section IV, the priority assignment based on vehicle traveling state are described. In Section V, the Finder-MCTS method for cognitive IoV spectrum allocation are proposed. In Section VI, simulations are carried out to demonstrate the effectiveness of the proposed Finder-MCTS method. In Section VII, conclusion and future work are given.

II. Related Work

Nowadays, there are many excellent studies on dynamic spectrum allocation in cognitive radio networks. In this section, we classify and compare them from the perspective of theoretical methods.

A. Spectrum Resource Allocation Based on Traditional Optimization Theory and Game Theory

In order to solve the problem of dynamic allocation of spectrum resources in wireless communications, the traditional methods mainly include the methods based on mathematical optimization [2], [3] and the methods based on game theory [4]–[6]. For example, Martinovic *et al*. propose a cognitive radio spectrum allocation method based on integer linear programming in the work of [3], which solves the spectrum allocation problem with interference by using many complex assumptions and constraints. It is difficult or even impossible to find an optimal solution in the real cognitive radio network with the complex environment and dynamic network topology. Although the methods based on mathematical optimization have high solution accuracy, the generalization capability is insufficient.

Besides, with the goal of maximizing spectrum utilization, Yi *et al.* introduce a spectrum resource allocation method based on auction in the work of [5]. Liu *et al.* design a dynamic spectrum access method using game theory in the work of [6]. However, these methods are not fit for IoV. The high mobility of vehicles puts forward a strict requirement for the convergence of Nash equilibrium in the game theory. It is hard to reach this equilibrium point.

B. Spectrum Resource Allocation Based on Machine Learning

In recent years, with the development of statistical learning methods, many studies use machine learning to realize the dynamic spectrum allocation [12]. Among them, reinforcement learning can guide a system agent to learn the unknown environment by trial and error [19]. It can be applied to the spectrum allocation decision.

First, the multi-arm gambling machine (MAB) is not only an important random decision-making theory in the field of operational research, but also belongs to a type of online learning algorithm in reinforcement learning. The task of the agent is to select one arm to pull in each round based on the historical rewards it collected, and the goal is to collect cumulative reward over multiple rounds as much as possible. In essence, MAB is a way to optimize the reward by balancing exploration and exploitation. Li *et al.* give a survey of spectrum resource allocation by using MAB in the cognitive radio network in the work of [13]. Zhang *et al.* formulate and study a multi-user MAB problem that exploits the idea of temporal-spatial spectrum reuse in the cognitive radio network [14]. However, the MAB modeling does not consider the cost of pulling arms in the existing allocation schemes. When MAB is utilized to solve the allocation problem in a centralized

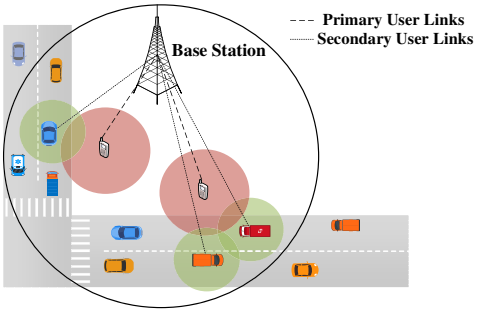


Fig. 1: System scenario of spectrum allocation in CR-IoV.

way, the scale of the arm increases exponentially with the number of users to be assigned. Therefore, the convergence of spectrum resource scheduling algorithm based on MAB cannot be guaranteed.

In addition, model-free-based deep reinforcement learning is also applied to the research of spectrum allocation. Naparstek *et al.* propose a spectrum allocation scheme based on deep learning framework under the wireless environment in the work of [15]. However, model-free-based deep reinforcement learning has problems of slow online learning speed and bad self-adaption ability.

Recently, another kind of model-based reinforcement learning, Monte-Carlo tree search algorithm (MCTS), is applied in the field of resource allocation [16], [17]. The MCTS-based allocation algorithm builds a decision tree to explore the possible solutions by expanding and pruning. Due to the expansion of the tree, the search space becomes tremendous gradually and the calculation scale is unacceptable. If this type of method is applied in IoV directly, the dynamic environment will further cause a large search tree. In addition, due to the neglect of environmental uncertainties, the random strategy adopted by Basic-MCTS in the simulation stage will produce a high variance, which reduces the search efficiency [20].

III. System Scenario and Problem Formalization

In this section, we introduce the system scenario of spectrum allocation in CR-IoV in Section III-A, and give the mathematical formalization of our optimization problem in Section **??**.

A. System Scenario

Figure 1 shows the system scenario of spectrum allocation in CR-IoV. PUs are the authorized mobile phone users in the current network, and SUs are the vehicles equipped with CR modules. When a PU occupies a channel, there is a protection area around the PU (*i.e.*, the red area in Figure 1). Any radiation from SUs falling into the protection area would interfere with the PU. Similarly, an interference radius is also generated when the SU occupies a channel (*i.e.*, the green area in Figure 1).

IV. Priority Assignment Based on Vehicle Traveling State

In Section IV-A, we describe the problem of priority assignment. In Section IV-B, we give the detailed definition of priority.

A. Problem Description

In CR-IoV, when the system carries out the spectrum allocation, the current state of vehicle traveling should be considered. For example, if a vehicle is about to leave the communication range of the current base station, it should be assigned to a low priority when the current base station allocates resources.

The traveling state of a vehicle at the current moment mainly includes direction, speed, acceleration and GPS coordinates. Besides, the traveling state also should considers the degree of geographical dispersion among vehicles and the communication capability of a vehicle.

The current state information of each vehicle is collected by the current communicating base station. Then we carry out priority evaluation for different cognitive vehicle users to distinguish the priority weights for spectrum allocation.

For a SU n who initiates a service request, from the perspectives of the global state and local state, a comprehensive priority evaluation score $Priorityscore_n$ is constructed by defining a vehicle traveling evaluation score $Travelingscore_n$ and a utility score $Utility_n$ for the SU.

B. Priority Definition Based on Vehicle Traveling State

Definition 1: Vehicle Traveling Evaluation Score

According to the GPS coordinates, speed and acceleration, we define a vehicle traveling evaluation score $Travelingscore_n$ for a cognitive vehicle n as

$$Travelingscore_n = \frac{1+cos(\theta_n)}{4} \cdot (\frac{v_{max}-v_n}{v_{max}-v_{min}} + \frac{1}{1+e^{a_n}}) \quad (1)$$

where θ_n denotes the angle between the current driving direction and the link ending at the vehicle's position and the base station's position. Notation a_n denotes the acceleration of the cognitive vehicle n. Notation v_n denotes the speed of the vehicle. Notations v_{max} and v_{min} represent the maximum and minimum values of the diving speed. We assume that the vehicle speed is within the value interval $[v_{min}, v_{max}]$.

Obviously, a relatively large angle θ_n indicates that the vehicle will travel out of the coverage range of the base station in the future. Therefore, a cognitive vehicle with large θ_n should be given a relatively low spectrum allocation priority. We use formula $\frac{1+cos(\theta_n)}{2}$ to normalize the different priorities of the angle θ_n to the value interval $[0, 1]$. In addition, a vehicle with high driving speed will quickly travel out of the coverage range of the base station in the future. Therefore, it should be given a relatively low spectrum allocation priority. The normalized formula $\frac{v_{max}-v_n}{v_{max}-v_{min}}$ is used to describe the influence of vehicle driving speed on the priority. Similarly, a vehicle with high acceleration should be given a relatively low spectrum allocation priority. To normalize the value interval to $[0, 1]$, formula $\frac{1}{1+e^{a_n}}$ is used to describe the influence

of vehicle driving acceleration on the priority. Finally, to constrain the value of $Travelingscore_n$ within the value interval $[0, 1]$, we multiply it by $\frac{1}{2}$ to the right of Eq. (1).

Definition 2: Network Utility Score

We define a network utility score for a cognitive vehicle user to evaluate its communication capability. For a cognitive vehicle n, its network utility score is defined as follows:

$$Utility_n = \log_2(1+SNR_n) \cdot \frac{\sum\limits_{1\leq n,n'\leq N, n'\neq n} Dispersion_{n,n'}}{N-1} \quad (2)$$

where SNR_n denotes the signal-to-noise ratio of the user n to receive the signal from the base station. Formula $\sum\limits_{1\leq n,n'\leq N, n'\neq n} Dispersion_{n,n'}$ represents the global dispersion of user n within the coverage area of the base station.

For the numerator of Eq. (2), we give the following detailed definition. The $Dispersion_{n,n'}$ between two SUs n and n' is defined as follows:

$$Dispersion_{n,n'} = \begin{cases} 1 & D_{n,n'} > \varepsilon_n \\ 0 & others \end{cases} \quad (3)$$

where ε_n is a dispersion threshold; Notation $D_{n,n'}$ represents the average dispersion time between two SUs n and n'. First, the threshold ε_n is obtained by taking the median value of $\{D_{n,n'} | 1 \leq n' \leq N, n' \neq n\}$. Second, the average dispersion time $D_{n,n'}$ is defined as

$$D_{n,n'} = \frac{\int_0^T \beta_{n,n'}(t)dt}{\tau_{n,n'}} \quad (4)$$

In Eq. (4), the communication dispersion state between two vehicles n and n' is defined as $\beta_{n,n'}(t)$. When there exists communication interference between vehicle n and n', we let $\beta_{n,n'}(t) = 0$. It means that the two are in an 'encounter' state. On the contrary, when $\beta_{n,n'}(t) = 1$, it means that the two are in a 'scattered' state. Thus, in a time window T, the numerator of Eq. (4) represents the total dispersion time between user n and user n'. Besides, $\tau_{n,n'}$ in the denominator denotes the total number of times that user n and user n' are in the 'scattered' state in time window T. Obviously, the higher the value of $D_{n,n'}$, the longer the time that the two users n and n' are in the 'scattered' state. Thus, we conclude that the higher the global dispersion $\sum\limits_{1\leq n,n'\leq N, n'\neq n} Dispersion_{n,n'}$, the greater the probability that a user has the chance to reuse the channel, which further leads to a high network utility.

To sum up, a vehicle with a large network utility score in Eq. (2) means that its global communication capability is strong, so the vehicle should be given a high spectrum allocation priority.

Definition 3: Comprehensive Priority Evaluation Score

According to the vehicle traveling evaluation score $TravelingScore_n$ and network utility score $Utility_n$, we construct a comprehensive priority evaluation score $PriorityScore_n$ for the secondary vehicle user n below,

$$Priorityscore_n = Travelingscore_n \cdot Utility_n \quad (5)$$

For a secondary vehicle user who requests to access the base station, the base station calculates the priority score of this SU by collecting the vehicle's information. We rank all the scores from the largest to the smallest. Therefore, we can obtain a priority order list $Priorityscore\_list$ for all the SUs in the current allocation task, which will be used in the following Section V.

V. Finder-MCTS Algorithm for Cognitive IoV Spectrum Allocation

In the introduction, we mentioned that our paper will use MCTS to solve the problem of efficient spectrum allocation for CR-IoV. MCTS is a classic reinforcement learning algorithm based on tree search. To distinguish it from the method proposed in our paper, we call the classic MCTS as Basic-MCTS. The Basic-MCTS offers a concise computation framework by recursively using a tree policy to expand the search tree towards high-reward nodes, and a default policy to perform the simulations for updating the estimated rewards and other statistics [21]. However, due to the continuous expansion of search actions, the search scale of Basic-MCTS is often very large, which greatly affects its search speed. In addition, due to the neglect of environmental uncertainties, the random strategy adopted by Basic-MCTS in the simulation stage will produce a high variance, which reduces the search effect of Basic-MCTS.

To improve the search speed and obtain an optimal solution, we propose an algorithm named Finder-MCTS in this section. First, we reduce the search scale of the tree horizontally by using the comprehensive priority evaluation score defined in Definition 3 above. Meanwhile, the constraints defined in Section **??** are also considered to reduce the search scale of the tree vertically. Second, the uncertainty of the SUs' spectrum occupation activities are included into the simulation strategy. We give the bias estimation of reward in different scenarios in the simulation stage so as to approximate the real environment and accelerate the convergence of tree search.

Thus, in Finder-MCTS, the first step is to use Markov decision process (MDP) to construct Monte-Carlo tree computation framework (Section V-A). Then, with respect to the state prediction, we give a DNN-based environment state predictor–ESP (Section V-B). Finally, we describe the detailed steps of Finder-MCTS algorithm (Section V-C).

A. Finder-MCTS's Computation Framework

The problems solved by the MCTS are commonly formalized by the Markov decision process (MDP), in which we take the base station as the spectrum scheduling agent and use the link capacity formulated in Eq. (**??**) as the value of the reward Q when a SU occupies a channel. Let $\mathcal{S}$ and $\mathcal{A}$ denote the MDP state space and action space, respectively. $\mathcal{F} : \mathcal{S} \times \mathcal{A} \to \mathcal{S}$ denotes the MDP transition function from a state-action pair to the next state. The state transition function f_{ESP} is given by a deep neural network (DNN) simulator in Section V-B. The definitions of the MDP state space and action space are described as follows,

$$\mathcal{S} = \{s_v | s_v = (\lambda_v, \varphi_v)\} \quad (6)$$

$$\mathcal{A} = \{a_m | 1 \leq m \leq M\} \quad (7)$$

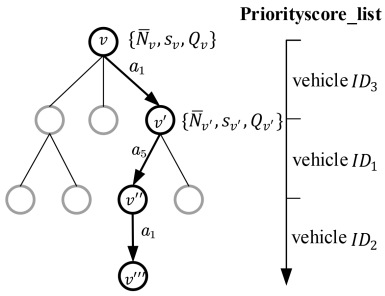


Fig. 2: An example of search steps in Finder-MCTS.

In Eq. (6), the MDP state is composed of two parts: λ_v denotes a vector of bandwidth resource usage of M channels in the base station, and φ_v denotes the number of service requests to be allocated in the current system. In addition, in Eq. (7), the action space is a set composed of whether the number of M channels are allocated, in which the action a_m denotes that the agent allocates the channel m to a vehicle that enters into the priority-based allocation sequence and is ready to be scheduled by the base station currently.

A Monte-Carlo search tree consists of nodes and edges. A node v is a tree node that corresponds to the **MDP state** s_v, and the edge connecting a parent node and a child node in the tree represents an action that causes the state transition. Each node v in the tree holds a **node state**, which contains three types of statistics: visit count ($\overline{N}_v$), MDP state (s_v), and cumulative reward (Q_v) received by node v.

The specific search steps are shown in Figure 2.

1) Create a root node of the search tree and initialize the node state. Assume that the root node is denoted by v and the node state is $\{\overline{N}_v, s_v, Q_v\}$.

2) Allocate the spectrum resources for vehicles according to the priority order list $Priorityscore\_list$ defined in Definition 3, and extend the child node while update the node state. Each layer's tree expansion represents the spectrum allocation for a vehicle and each allocation process involves many iterations. Take the root node v in Figure 2 as an example. When the channel assignment action of vehicle ID3 is a_1, the search tree extends down to the child node v' and update the node state through iterative calculation (*i.e.*, $s_{v'} = f_{ESP}(s_v, a_1)$).

3) When the tree expansion reaches to the termination condition of iteration (*i.e.*, the second users or the available spectrum resources are all allocated), an optimal channel allocation matrix A^* in the current allocation period is returned. For example, assume that when reaching to the node v''' in Figure 2, the iteration ends. The black arrow lines direct an allocation path $v \to v' \to v'' \to v'''$. Then the corresponding actions constitute a feasible allocation policy set $\{a_1, a_5, a_1\}$, which can be converted to a channel allocation matrix $A_{N\times M}$ as an output.

B. DNN-based Environmental State Predictor—ESP

Due to the uncertainty of the PUs' spectrum occupancy activities, when the tree is expanded from one node to the next in Section V-A, the expansion will be not stable, *i.e.*, given a state and an action, the next state is uncertain. This uncertainty is caused by the unknown environment of IoV. Therefore, to limit the expansion scale of the MCTS tree horizontally and speed up the search, it is necessary to gradually learn to approach to the real environment of IoV when doing spectrum allocation. This section presents an offline environment state predictor (named ESP) based on a deep neural network (DNN).

Note that, to obtain the ESP, enough training data are needed. Thus, first during the cold start phase of Finder-MCTS (*i.e.*, the algorithm just starts running), we do not rely on ESP. This does not affect the channel allocation solution of Finder-MCTS. After a period of time in the cold start phase, our base station can obtain and cumulate large numbers of 'state-action transition pairs'. Subsequently, we input these 'state-action transition pairs' into ESP continuously as the training data to obtain a state transition function f_{ESP}, which is an offline training process. Once we have the f_{ESP}, the Finder-MCTS could converge fast due to the reduction in branching. The above training is done by DNN.

The network structure of DNN consists of one input layer and three hidden layers. In this paper, we set the learning rate of DNN to 0.05 and the activation function of DNN is the rectified linear unit function (ReLU). To optimize the neural network parameters, we use the mini-batch gradient descent method [22]. In the DNN, the training label is the state $s_{v'}$, which is the state of the corresponding expansion child node v' of node v. ESP is used to obtain the prediction state $\widehat{s}_{v'}$. The loss function of ESP is,

$$loss_{ESP} = \frac{1}{B}\sum_{B}(\|s_{v'} - \widehat{s}_{v'}\|_2) \tag{8}$$

where B represents the batch size of mini-batch gradient descent. In the experiment we set $B = 64$, with indicating that 64 samples are selected in each iteration. Notation $\|.\|_2$ represents the L2 norm. When $loss_{ESP}$ converges, we let the DNN network parameter w_{ESP} update.

After we obtain the ESP function, based on the selected action a_m and MDP state s_v, ESP can give the MDP state of its expanded node $\widehat{s}_{v'}$,

$$\widehat{s}_{v'} = f_{ESP}(s_v, a_m|w_{ESP}) \tag{9}$$

C. Finder-MCTS Algorithm Based on Action Space Pruning and Scenario Simulation

Finder-MCTS requires to execute the following four steps: selection, expansion, simulation, and backpropagation iteratively to complete an computation process, which are shown in Figure 3. In Figure 3, the black circles indicate the nodes involved in each step and the red arrow lines indicate the actions corresponding to each step. In subfigure (c), policy usually refers to the random selection action extended at each step of the simulation process. We usually call step (a) selection and step (b) expansion as the tree policy; step (c) simulation and step (d) backpropagation as the default policy. Specifically, the detailed procedures and descriptions are give in Figure 4 and in the following steps (a)-(d).

(a) **Selection**. Each iteration starts from the root node. When the algorithm has to choose to which child node it will

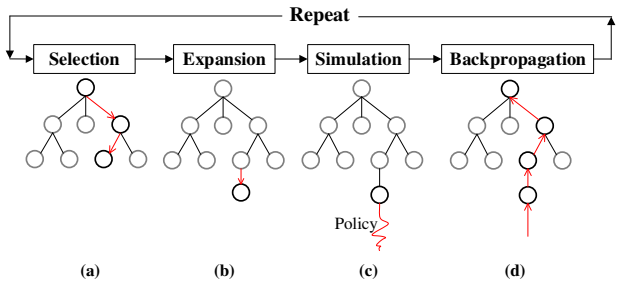


Fig. 3: An iterative computation process of Finder-MCTS.

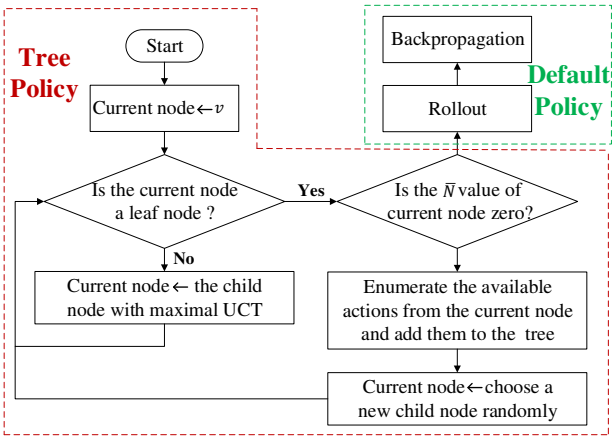


Fig. 4: The flow chart of Finder-MCTS.

descend, it tries to find a good balance between exploitation and exploration. We use the upper confidence bound for tree (UCT) [23] to recursively select child nodes. The selection criterion of the optimal child node is:

$$\underset{v' \in child(v)}{\arg\max} \left(\frac{Q_{v'}}{\overline{N}_{v'}} + c \cdot \sqrt{\frac{\ln(\overline{N}_v)}{\overline{N}_{v'}}} \right) \tag{10}$$

where $c \geq 0$ is a weight coefficient used to adjust the exploitation and exploration. We set $c = 0.8$ in the experiment through many tests. Notation $child(v)$ represents the set of child nodes with v as the parent in the tree. $\overline{N}_{v'}$ and $\overline{N}_v$ represent the total number of times that the child node v' and its parent node v have been visited iteratively. $Q_{v'}$ represents the cumulative reward obtained by node v'. Note that, the selected child node should be expandable (*i.e.*, have unvisited child node) and represent a non-terminal state. Next, the algorithm treats the child node with the largest value of UCT as the current node for the next expansion.

(b) **Constraint Oriented Expansion**. Finder-MCTS judges whether the number of visits of the current node is 0. If visit count $\overline{N} = 0$, the algorithm goes to step (c) directly. If the visit count $\overline{N} \neq 0$, the algorithm enumerates the available actions. However, if it is just a simple enumeration, the number of available actions in the next layer is M. As the tree expands, a huge search tree will be built. The computational complexity grows geometrically with the number of SUs to be allocated. Thus, here we give the constraint oriented expansion.

In the constraint oriented expansion, we prune the action space according to the constraint conditions defined in Section **??**-2) so as to obtain all available actions from the current node. And then add new nodes to expand the tree and let the current node be a new child node which is randomly selected after expansion.

Specifically, we use $\mathcal{A}(n, v)$ represent the set of available actions starting from the node v, which is used for the next round of channel allocation for the n-th SU. That is to say $\mathcal{A}(n, v)$ is an interference-free action space of a SU. The detailed implementation steps of the constraint oriented expansion are described in Algorithm 1.

In Algorithm 1, we use three main steps to perform action pruning. First, considering the channel availability, we introduce the channel availability matrix L to prune the set of actions. We map the elements of $l_{n,m} = 1$ in the channel availability matrix for vehicle n to the available action set (Lines 2-6 in Algorithm 1). Second, considering that the vehicle ID_n currently to be allocated should not share the same channel with a vehicle having communication interference, we introduce the SU-SU interference matrix C for the tree pruning. The algorithm traverses the elements in the channel allocation matrix A and makes a judgement on whether $a_{n',m} = 1$ and $c_{n,n',m} = 1$ hold at the same time. If they hold at the same time, a_m is removed from the action set (Lines 7-15 in Algorithm 1). Next, in each iteration, the algorithm needs to make a judgement on whether constraint (1) and constraints (5-a) $\sim$ (5-g) hold. If the available channel m for the vehicle currently to be allocated does not satisfy these constraints, action a_m needs to be removed from the set of actions (Lines 16-20 in Algorithm 1). Finally, If $\mathcal{A}(n, v) = \emptyset$, the algorithm will skip the current allocation and wait for the next round of allocation (Lines 21-23 in Algorithm 1).

(c) **Simulation Based on Different Scenarios**. From the above step (b), we know that if the visit count of the current node is zero, we will perform a simulation from the current node (*i.e.*, the newly expanded node, denoted by $\widetilde{v}$)[1] to the terminal node (denoted by $\widetilde{v}_\Delta$). Here, the terminal node refers to the node that the descending arrives at when the SUs or the available channel resources have been all allocated. Usually, the simulation uses a random search strategy to generate a reward $Q_{\widetilde{v}_\Delta}$ at the final leaf node $\widetilde{v}_\Delta$. However, the time-varying property of PUs' spectrum occupancy activities makes the actual available spectrum resources uncertain. This uncertainty will have potential impacts on the reward evaluation for the SU to be allocated in IoV.

Therefore, in this paper, the duration of network service for a PU (denoted by τ) is included in the simulation when doing reward evaluation. Reference [24] pointed out that the duration of network service for PU in each channel obeys a log-normal distribution. The probability density function (PDF) is:

$$f(\tau; \mu, \sigma) = \frac{1}{\tau\sigma\sqrt{2\pi}} e^{\frac{-(\ln\tau - \mu)^2}{2\sigma^2}} \qquad (\tau > 0) \tag{11}$$

The parameters (μ, σ) are in milliseconds (ms) and the values used in this paper are $(2.47, 1.88)$ [24].

[1]We use symbol $\sim$ to label the nodes in the stage of simulation.

Algorithm 1 Constraint Oriented Expansion for Vehicle ID_n

Input:
L - channel availability matrix
C - SU-SU interference constraint matrix
A - channel allocation matrix
γ_m - the maximum allowable interference level of channel m
ϕ_m - the available bandwidth of channel m
$\delta_{m,k}$ - the maximum allowable interference power of PU k on channel m
Output:
$\mathcal{A}(n,v)$ - the action space/set of vehicle ID_n under the current node v
$Function\ Action(n,v)$
$\mathcal{A}(n,v) \leftarrow \emptyset$
for each $l_{n,m}$ in the n-th row of matrix L **do**
  if $l_{n,m} = 1$ **then**
    $\mathcal{A}(n,v) \leftarrow a_m$
  end if
end for
for each $c_{n,n',m}$ in $1 \sim n$ columns of the n-th row of matrix C **do**
  for each $a_{n',m}$ in A **do**
    if $c_{n,n',m} = 1$ and $a_{n',m} = 1$ **then**
      if $a_m \in \mathcal{A}(n,v)$ **then**
        remove a_m from $\mathcal{A}(n,v)$
      end if
    end if
  end for
end for
for each a_m in $\mathcal{A}(n,v)$ **do**
  if the available channel m for the vehicle ID_n does not satisfy the constraint (1) and constraints (5-a) $\sim$ (5-g) **then**
    remove a_m from $\mathcal{A}(n,v)$
  end if
end for
if $\mathcal{A}(n,v) = \emptyset$ **then**
  the algorithm does not perform the allocation for vehicle ID_n and waits for the allocation of the next user according to the $Priorityscore\_list$
end if

Through random sampling from the above distribution, we can obtain different scenarios of the service durations for the PUs at each layer in the simulation stage. Each sampling corresponds to a scenario. Since there are infinite scenarios when sampling, here we sample number of χ times at each layer of simulation to control the computation scale. Thus, a scenario set is formed, denoted by $\tilde{\pi} = \pi^1, \pi^2, ..., \pi^i, ..., \pi^\chi$,. In the experiment, we set $\chi = 9$. Next, we define a stochastic bonus to adjust the reward evaluation according to different service durations, the resource supply and demand situation, and the utilities of SUs.

Definition 4: Stochastic Bonus

Assume that the channel m matches the vehicle ID_n and the tree expands from node $\widetilde{v}$ to node $\widetilde{v}'$ in the simulation stage. Then, we define a stochastic bonus for node $\widetilde{v}$ as $\mathop{\mathbb{E}}_{i \in \tilde{\pi}}(H^{\tilde{v}}_{n,m}(i))$, in which $\mathbb{E}$ represents the expectation of stochastic bonus obtained by vehicle ID_n in χ scenarios. We have

$$H^{\tilde{v}}_{n,m}(i)) = \tanh(Utility_n) \cdot \tau_i^{-1} \cdot \left(\frac{g_m}{Count(L_m) - Count(A_m)} \right) \tag{12}$$

where τ_i $(1 \le i \le \chi)$ denotes one of the samplings based on distribution $f(\tau; \mu, \sigma)$. The larger the value of τ_i, the longer the channel occupied by the PUs in this sampling. It indicates the bonus of vehicle ID_n when doing allocation will be low. Notation $Utility_n > 0$ represents the network utility score of vehicle ID_n (Definition 2), which reflects the communication capability of vehicle ID_n and is used as a weight coefficient here. We utilize the hyperbolic tangent function $\tanh(\cdot)$ to normalize the value of $Utility_n$ to the interval $[0, 1]$. When the $Utility_n$ is large, the weight coefficient is closer to 1, which indicates that the vehicle ID_n with strong communication ability tends to have high bonus. Besides, $\frac{g_m}{Count(L_m) - Count(A_m)}$ measures the remaining minimum average bandwidth available to vehicle ID_n currently. g_m denotes the remaining channel bandwidth of the m-th channel which is based on the available bandwidth threshold ϕ_m. $Count(L_m)$ records the number of elements in the m-th column with value of 1 in matrix L. Thus $Count(L_m) - Count(A_m)$ describes the maximum number of allowable access vehicles on channel m without considering the interference matrix C and the available bandwidth ϕ_m.

In summary, if a vehicle with strong communication capability, the PUs with low service durations, and the remaining resources are enough, the stochastic bonus will be high.

Based on the above Eq. (12), we have an adjusted reward $Q_{\widetilde{v}}$ for node $\widetilde{v}$ in the simulation stage,

$$Q_{\widetilde{v}} = r_{(n,m)} + \mathop{\mathbb{E}}_{i \in \tilde{\pi}}(H^{\widetilde{v}}_{n,m}(i)) \tag{13}$$

where $r_{n,m}$ refers to the immediate reward that channel m is allocated to vehicle ID_n (defined in Eq.(**??**)). For simplicity, we use notation $Q_{\widetilde{v}}$ with omitting the label of n and m.

When the simulation reaches to the terminal node $\widetilde{v}_\Delta$, we can get the simulation cumulative reward $Q_{\widetilde{v}_\Delta}$ of all nodes on the simulation path from $\widetilde{v}$ to $\widetilde{v}_\Delta$. We have

$$Q_{\widetilde{v}_\Delta} = \sum_{\widetilde{v}}^{\widetilde{v}_\Delta} \{ r_{n,m} + \mathop{\mathbb{E}}_{i \in \tilde{\pi}}(H^{\widetilde{v}}_{n,m}(i)) \} \tag{14}$$

(d) **Backpropagation**. The aim of backpropagation is to update the empirical information of the prior exploration before the next iteration, , which is shown in Figure 5. When an iteration reaches to the terminal node $\widetilde{v}_\Delta$, according to Eq. (14), we get the simulation cumulative reward $Q_{\widetilde{v}_\Delta}$ for backpropagation.

VI. Experimental Results and Analysis

In this section, first we give the detailed simulation settings, including the vehicular dataset generation and some parameters in our proposed method. Second, we compare Finder-MCTS with other types of methods in terms of channel utilization ratio (CUR), average link capacity (ALC), and convergence time. Finally, we test the performance of Finder-MCTS compared with other MCTS algorithms' variations.

A. Simulation Settings

Our experiments are done by using the simulation of urban mobility (SUMO) simulator. All the simulations are conducted in a PC with Intel Core CPU i9-9820X 3.50GHz processor, 64GB RAM. We export a map of area near Pudong Airport in Shanghai from OpenSteetMap, which is shown in Figure 6. The latitude of the experimental area is between [31.19177, 31.19742]. The longitude is between [121.31134, 121.31853].

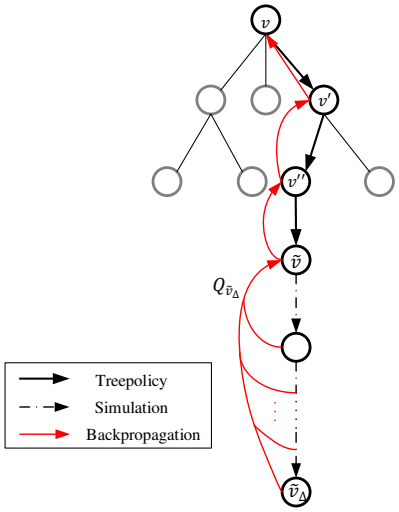


Fig. 5: Backpropagation of Finder-MCTS.

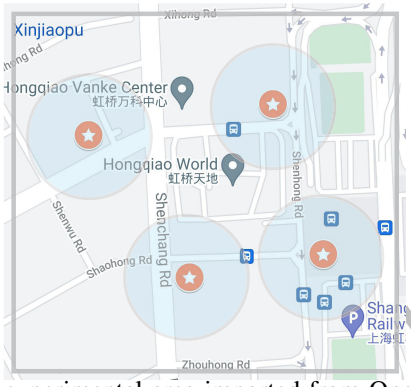


Fig. 6: The experimental area imported from OpenStreetMap.

In this area, we randomly select four base stations (depicted by red star marks). The locations of these base stations and different communication radius are listed in TABLE I. Each base station can observe the traffic flows and obtain the passing vehicles' information, including the vehicle ID, location, speed, timestamp and acceleration.

Assume that each base station has $M = 5$ available spectrum channels. The bandwidth of each channel is set to 10MHz. We import 200 cognitive vehicles into the simulation scene. Each vehicle randomly proposes a service request to the base station with probability of 50% at each allocation time window. Suppose that the duration of network service for each vehicle is equal to the allocation time window. In SUMO, we set the parameters for the different types of vehicles in TABLE II. Compared with the moving vehicle, a PU can be regarded as a static point in the experiment. We set a total of $K = 50$ fixed points as PUs under the four base stations. Each PU randomly occupies a part of the communication bandwidth (MHz), which subjects to $U[1, 3]$ uniform distribution. At each allocation time window, we randomly let 70% PUs occupy the nearest base station's available channels. The the duration of network service for a PU is chosen according to Eq.(11).

Algorithm 2 Finder-MCTS

Input:
$Priorityscore\_list$
Output:
optimal channel allocation matrix A^*
$Function\ Finder-MCTS(v, Priorityscore\_list)$
load network f_{ESP}
create root node v with state s_v
create channel allocation buffer $\Lambda_{L,C}$
while node v is a terminal node **do**
  initialize a matrix $A_{N\times M}$ with all elements equaling to 0
  $\widetilde{v} \longleftarrow Treepolicy(v)$
  $Q_{\widetilde{v}_\Delta} \longleftarrow Simulation(s_{\widetilde{v}}, \widetilde{v})$
  if $a_m = 1$ for vehicle ID_n **then**
    $a_{n,m}$=1
  else
    $a_{n,m}$=0
  end if
  update and put $A_{N\times M}$ in $\Lambda_{L,C}$
  $Backpropagation(v, Q_{\widetilde{v}_\Delta})$
end while
return $A^* = \underset{A_{N\times M}\in\Lambda_{L,C}}{argmax}\ \{U(A_{N\times M}, R)\}$
$Function\ Treepolicy(v)$
while v is nonterminal **do**
  if v is not a leaf node **then**
    $v' \leftarrow Bestchild(v)$
    $Treepolicy(v')$
  else
    if $\overline{N}_v = 0$ **then**
      $\widetilde{v} \leftarrow v$
    else
      $Expand(v)$
    end if
  end if
end while
$Function\ Bestchild(v)$
return $\underset{v'\in child(v)}{argmax}\ (\frac{Q_{v'}}{\overline{N}_{v'}} + c\cdot\sqrt{\frac{ln(\overline{N}_v)}{\overline{N}_{v'}}})$
$Function\ Expand(v)$
execute $Action(n, v)$
choose $a_m \in \mathcal{A}(n, v)$ randomly
generate a new child v' of node v
initialize $Q_{v'} = 0$
$s_{v'} = f_{ESP}(s_v, a_m)$
$Treepolicy(v')$
$Function\ Simulation(\widetilde{v})$
initialize $i = 0$,$Q_{\widetilde{v}}$=0
while $\widetilde{v}$ is not a terminal node $\widetilde{v}_\Delta$ **do**
  choose $a_m \in \mathcal{A}(n, \widetilde{v})$ randomly
  $s_{\widetilde{v}'} \leftarrow f(s_{\widetilde{v}}, a_m)$,$\widetilde{v}' \leftarrow \widetilde{v}$
  calculate $r_{n,m}$ according to Eq. (**??**)
  $Q_{\widetilde{v}'} \leftarrow Q_{\widetilde{v}} + r_{n,m} + Bonus$ ($Bonus$ is calculated based on Eq. (12)-(14))
  $i \leftarrow i + 1$
end while
return $Q_{\widetilde{v}_\Delta}$ when node $\widetilde{v}$ reaching to the terminal node $\widetilde{v}_\Delta$
$Function\ Backpropagation(v, Q_{\widetilde{v}_\Delta})$
while node v is not null **do**
  $\overline{N}_v \leftarrow \overline{N}_v + 1, Q_v \leftarrow Q_v + Q_{\widetilde{v}_\Delta}$
  $v \leftarrow parent\ \ of\ \ v$
end while

B. Comparison with Other Types of Methods

First, after the simulations are all done in the four base stations, we compare the average CUR, ALC, and convergence time of the proposed Finder-MCTS with three other methods, shown in Figure 7. From the average CUR performance in Figure 7 (a), we can see that Finder-MCTS performs the best, the second-best is game theory-based method, and the worst is PSO-based method. From the average ALC performance

TABLE I: Information of the four base stations.

Name	Latitude	Longitude	Communication Radius
BS1	31.19554	121.31274	500m
BS2	31.19604	121.31619	500m
BS3	31.19327	121.31462	500m
BS4	31.19363	121.31713	500m

TABLE II: Parameters used in SUMO.

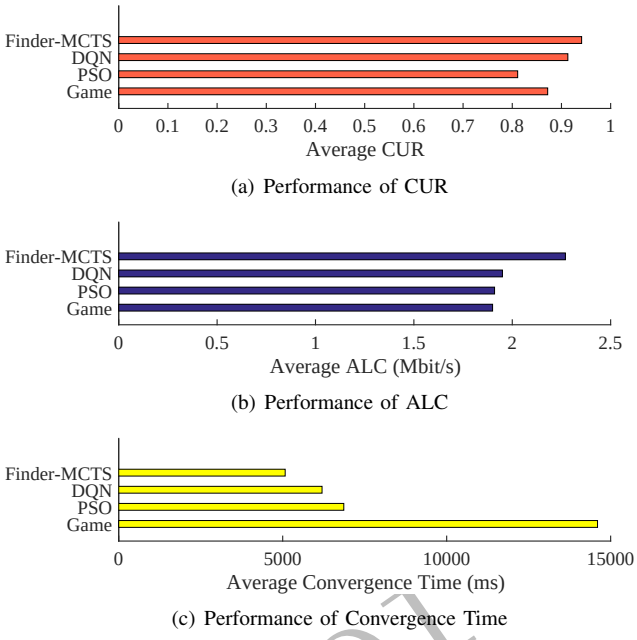
Parameters	Car	Bus	Truck
the maximum speed	15(m/s)	13(m/s)	10(m/s)
the minimum speed	1(m/s)	1(m/s)	1(m/s)
the minimum gap between vehicles	2.5(m)	2.5(m)	2.5(m)
the maximum acceleration	3(m/s^2)	1.5(m/s^2)	1.5(m/s^2)
the maximum deceleration	7.5(m/s^2)	4(m/s^2)	4(m/s^2)
the maximum deceleration for emergency breaking	9(m/s)	7(m/s)	7(m/s)

in Figure 7 (b), we can see that Finder-MCTS performs the best, the second-best best is DQN-based method, and the worst is game theory-based method. From the average convergence time performance in Figure 7 (c), we can see that Finder-MCTS performs the best, the second-best best is DQN-based method, and the worst is game theory-based method.

Based on the above results, we give the following analysis. Because the convergence of the Nash equilibrium solution is negatively related to the size of the problem, the game theory-based method's convergence performance is poor. When the game theory-based method reaches convergence, the CUR performance of the system can be approximately optimal, however the equilibrium of the multi-user game makes the ALC value relatively low. Besides, the PSO-based method is easy to fall into the local optimal solution, its average CUR and average ALC perform relatively poor. Since the complicated parameters' setting of PSO, its average convergence time becomes longer as the scale of the problem becomes larger. Moreover, after the exploration of actions through reinforcement learning, DQN-based method can obtain a higher quality spectrum allocation solution, and the performance of average CUR and ALC is second only to Finder-MCTS. However, the convergence time of DQN-based method is higher than Finder-MCTS due to the long-term exploration and value updating, although enough experience information learned through online learning can speed up the convergence time of DQN to some extent. By contrast, Finder-MCTS based on offline training and online learning has an average 36.47% improvement in convergence time than other methods. In terms of ALC, Finder-MCTS has an average advantage of 18.24% over other methods. At the same time, the channel utilization

TABLE III: The parameters use in BILP.

Parameter	Notion	Value
the maximum allowable interference level on channel m	γ_m	-114dBm
the level of background noise on channel m	N_m	1dB
[minimum transmission power, maximum transmission power]	$[\overline{P}^{min}_{m,n}, \overline{P}^{max}_{m,n}]$	[20,25] dBm
the maximum allowable interference power of PU k on channel m	$\delta_{m,k}$	5dB



(a) Performance of CUR

(b) Performance of ALC

(c) Performance of Convergence Time

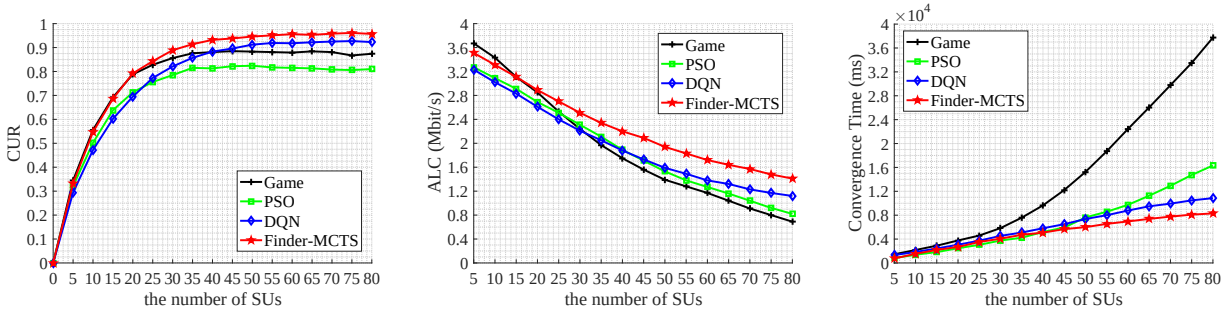
Fig. 7: Comparison with three other methods in terms of average CUR, ALC and convergence time.

of Finder-MCTS is 9.40% higher than other methods on average.

Second, since the number of SUs in the coverage area of each base station is time-varying, it is necessary to observe the performance changes under different SUs' scales. The results are shown in Figure 8. Here, notice that in Figure 8, each depicted point in the curve is an averaged value statistically. For example, as to the results that distribute in the scale interval $(p_1, p_2]$ of x-axis, we average these results and depict the averaged value corresponding to point p_2.

Figure 8 (a) shows the relationship between the number of SUs and CUR. In general, as the number of SUs increases, the CUR curve increases until it gradually converges. In addition, we find that when the number of SUs is small, the game theory can give a solution with high CUR. However, with the increase of SUs, Finder-MCTS and DQN-based method show obvious advantages in resource utilization. The reason behind that is when the scale of SU becomes large, the combination of historical experiences and online exploration can greatly improve the quality of the solution. In contrast, the game theory-based equilibrium quality for large-scale SU problem has declined. Also, the PSO-based method often converges to a local optimal solution and its CUR performance cannot be guaranteed.

Figure 8 (b) depicts the relationship between the number of SUs and ALC. It is obvious that as the number of SUs increases, the ALC value decreases since the available spectrum resources of the base station side are limited. Besides, we find that when the number of SUs is small, the game-based method shows a good performance in ALC. However, as the number of SUs increases, Finder-MCTS shows an obvious advantage. This because when the scale of SUs becomes large, finding an optimal solution is hard for the game-based method.



(a) Performance of CUR (b) Performance of ALC (c) Performance of Convergence Time

Fig. 8: Performance comparison with varying the number of SUs.

Moreover, since the PSO-based method is hard to reach the global convergence, the ALC performance is relatively low with the number of SUs increasing.

Figure 8 (c) shows the simulation results of the relationship between the number of SUs and the convergence time. First, we can see that the convergence time of game theory-based and PSO-based method shows an obvious growth trend as the number of SUs increases, while the convergence time based on DQN and Finder-MCTS rises moderately. The main reason is that the Finder-MCTS and DQN-based methods gradually fit the channel state model after continuous learning, thereby greatly improving the search efficiency. The convergence time of Finder-MCTS is reduced by 65.23% and 18.85% compared with the game theory-based method and the PSO-based method. In the long run, Finder-MCTS shows a short and gentle convergence time performance in the dynamic environment.

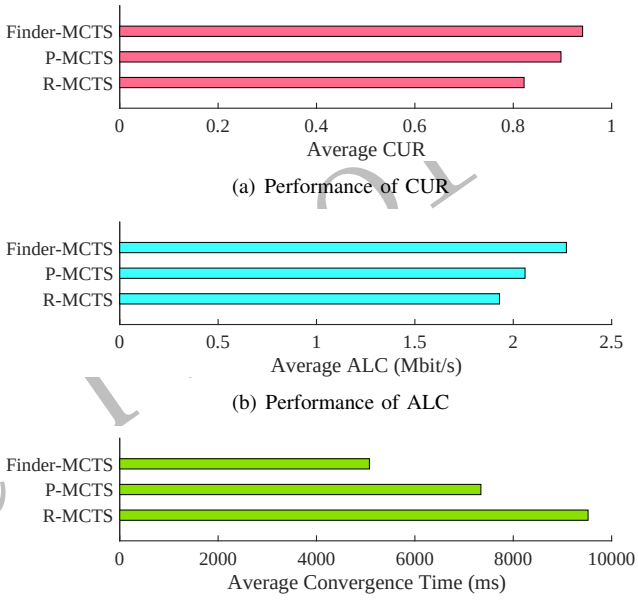
All above phenomena verify the advantage of Finder-MCTS in solving spectrum allocation in IoV. Finder-MCTS can effectively complete the rapid learning of the approximate optimal allocation solution in a time-varying environment, which greatly improves the available spectrum utilization ratio of the current base station system.

C. Comparison with Other MCTS Algorithms' Variations

In this part, we compare Finder-MCTS with other MCTS algorithms' variations. We show why we consider the priority mechanism and simulation under different scenarios.

We set two basic types of MCTS-based spectrum allocation modes: random-order-based allocation mode and priority-based allocation mode, which are called as R-MCTS and P-MCTS respectively. In R-MCTS, compared with Finder-MCTS, both priority and the uncertainty of PUs' service durations are not taken into consideration. In P-MCTS, compared with Finder-MCTS, only the uncertainty of PUs' service durations is not taken into consideration. The simulation results are shown in Figure 9. We can see that Finder-MCTS performs the best, the second-best is P-MCTS, and the worst is R-MCTS. According to the above results, we give the following analysis.

From Figure 9 (a), we can see that the CUR performance of P-MCTS is superior than R-MCTS. This gap illustrates that the introduction of priority evaluation will improve the ratio of the spectrum utilization (about 5.90% increase). Meanwhile,



(a) Performance of CUR

(b) Performance of ALC

(c) Performance of Convergence Time

Fig. 9: Comparison with two types of MCTS algorithms' variations in terms of average CUR, ALC and convergence time.

Finder-MCTS has the best CUR performance. In the long run, the service duration τ of PU on each channel will give each allocated SU differentiated stochastic bonus. Hence, based on the uncertainty of the channel state occupied by the PUs, we introduce the factor τ that affects the supply-demand ratio of spectrum resources into the reward evaluation during each expansion step of the simulation process. We learn about Finder-MCTS is better (about 4.08% increase) than P-MCTS on ALC. Hence, we can conclude that the optimization of the stochastic simulation process contribute to improve spectrum usage efficiency of CR-IoV from a global perspective.

Figure 9 (b) depicts the different performances of the three methods in ALC performance. With the help of priority evaluation, P-MCTS has increased by 6.73% compared with R-MCTS. The ALC performance of Finder-MCTS has increased by 10.19% compared with P-MCTS by evaluating the uncertainty of PUs' service durations.

Figure 9 (c) shows the average convergence time of three methods. Owing to the priority evaluation, P-MCTS has a 22.89% advantage than R-MCTS. This characterizes the positive impact of the differentiation priority evaluation on the algorithm convergence time. Secondly, under the same setting, with the help of reduction of action space in each descending layer, Finder-MCTS achieves a faster convergence speed (about 46.69% increase and 30.86% increase) than R-MCTS and P-MCTS.

VII. Conclusion

In this paper, we investigate the spectrum allocation in CR-IoV by modeling a optimization problem to maximize the link capacity of vehicle users while guaranteeing no interference between users. What's more, we propose Finder-MCTS to solve the optimization problem. We show that Finder-MCTS can learn to adapt and update allocation strategy for transmission with dynamic network settings. At last, the simulation results prove that Finder-MCTS is more efficient in convergence speed, and it achieves considerable performance gain in spectrum utilization and link capacity comparing to other popular strategies especially when the number of vehicle users gets larger. Besides, we have also confirmed the effectiveness of priority evaluation of vehicle users, solution space optimization and uncertainty evaluation of the PUs' service duration by comparing with the performance of classic MCTS. In the future work, we will further study the cooperative problem of multiple base stations while guaranteeing spectrum allocation efficiency and consider migrating our proposed method from the virtual to the real life.

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