Leveraging Blockchain for Multi-Operator Access Sharing Management in Internet of Vehicles

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***Abstract*—Wireless service providers (WSPs) are seeking cooperation to share both resources (spectrum, infrastructures) and costs. In particular, cooperation is critical for vehicle-to-everything (V2X) applications that value quality-of-service foremost. However, cooperation is inefficient without strong trust bases. Recently, blockchain arises as a promising solution to decentralized trust, owing to its transparency and immutability. Therefore, we propose a WSP cooperation framework based on blockchain, which keeps a shared ledger on resource utilization. In this paper, we first study the WSP selection problem of vehicles by evolutionary game. Then, we make the blockchain public to vehicles to maintain its decentralization and enhance its security by crowdsourcing idle computing resources from vehicles. To deal with the mobility of vehicles, as well as to improve the consensus efficiency, we propose delegated proof-of-work (DPoW) scheme, which introduces delegate nodes for participating in the blockchain consensus on behalf of the vehicles. The alternating direction method of multipliers (ADMM) optimization framework is further used to derive optimal consensus parameters including block size, computing resource demand of delegate nodes, and prices paid for vehicles. We conduct extensive simulations to show the effectiveness of the proposed methods.**

***Index Terms*—Vehicular access, multi-operator cooperation, evolutionary game, blockchain, delegated proof-of-work.**

I. Introduction

CURRENTLY, there is a tendency that multi-operators, i.e., different wireless service providers (WSPs), are starting to seek cooperation instead of competition. Basically, resource pooling, sharing, and exchanging can lead to both expenditure savings and quality-of-service (QoS) improvement, under the condition that the total amount of resources is fixed. Furthermore, scarce resources such as bandwidth, power, and base station sites can be utilized more efficiently. As an important component of the future smart city vision, Internet of vehicles (IoV) is revolutionizing the transportation system by enabling Big Data sharing among vehicle users, road facilities, pedestrians, and transport management centers [1]. To satisfy various data-rich automotive applications, e.g., autonomous driving and in-vehicle infotainment, it is helpful for a quickly-moving vehicle to be eligible to utilize the wireless access resources from all possible WSPs, whose base stations might be unevenly distributed across different regions [2], [3]. In [4], it is demonstrated how WSPs can cooperate by providing vehicles with multiple WSP association choices. Sonkoly *et al.* implement a prototype showing large-scale service provision via multi-provider cross-domain orchestration [5]. Qian *et al.* propose a spectrum sharing method among multiple WSPs to maximize the total payoff [6].

In order to realize the benefits of WSP cooperation, different stakeholders need to manage common business agreements on the cooperation process [7], [8]. For example, if a subscriber of WSP A accesses the Internet with the resources of WSP B, WSP B must be confident that WSP A will approve the subscriber's access record so as to let it happen. However, there lacks mutual trust among WSPs. In recent years, blockchain has become an attractive solution to enhance credibility among peers and reach consensus on sharing resources [9], [10]. Basically, it is an immutable digital ledger implemented in a decentralized way (i.e., without a central repository or authority) [11], [12]. Therefore, trust is actually established on the common ledger jointly held by the originally untrusted parties, and cooperation can be effectively realized. Okon *et al.* propose to use smart contracts between multiple network WSPs and show the blockchain-based agreement can provide high availability and seamless handoff for mobile users [13].

In this paper, we propose a blockchain-enabled WSP cooperation framework for vehicular access. Based on the planned driving path, each vehicle selects the WSP that can provide the best network services through its base stations deployed across different regions. An evolutionary game approach is adopted to model the above WSP selection process and derive the optimal results. The final selection decisions are immutably recorded by the blockchain. In order to accommodate the dynamic nature of vehicles, we design a dynamic blockchain architecture, in which vehicles' idle computing resources are utilized to enhance the security of the proof-of-work (PoW) based blockchain network. Since vehicles can freely join or leave the network, we introduce a delegate node for each region. Only the delegate nodes are

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allowed to directly participate in the PoW consensus process, such that the performance of the blockchain can be guaranteed. Meanwhile, each delegate node is in charge of collecting and rewarding computing resources from vehicles in its region, so as to increase the overall computing power of the blockchain network. The key parameters regarding consensus, including block size and prices paid for vehicles by delegate nodes, are also set in an adaptive manner via the alternating direction method of multipliers (ADMM) optimization framework. The main contributions of the paper are summarized as follows.

- We propose a blockchain-enabled WSP cooperation framework for flexible vehicular access. Specifically, a vehicle can select the most suitable WSP and associate with the WSP's base stations based on its planned routes. The association records are securely stored on the blockchain and shared by all the cooperating WSPs.
- We adopt an evolutionary game model to find the optimal WSP selection decision of each vehicle, which is clear for displaying the trend of the strategies of the vehicles in a distributed way under a satisfying convergence time.
- We propose delegated Proof-of-Work (DPoW) scheme, which exploits delegate nodes to run the consensus process. Participation of vehicles is delegated by these nodes, who pay for the computing resources vehicles provide. The ADMM optimization framework is further utilized to adaptively decide key parameters involved in the consensus.

The remainder of this paper is organized as follows. Section II describes the related work. Section III introduces the system model of the proposed WSP cooperation framework. Section IV presents the evolutionary game-based WSP selection algorithm. Optimization of DPoW consensus is given in Section V. In Section VI, we show the numerical results. At last, Section VII concludes the paper.

II. Related Work

A. Multi-Operator Cooperation Scheme

There have been many kinds of researches and work in multi-operator cooperation for many services. As resources become scarce, multi-operator cooperation in the Internet of Things has gradually become an effective solution.

In the aspect of communication network, P. Luoto *et al.*, in [14] focus on the system throughput when these operators have similar traffic patterns. In [15], a non-orthogonal spectrum assignment scheme among operators is proposed using a matching game framework and stochastic geometry by Sanguanpuak *et al.* In [16], P. Luoto *et al.* propose a distributed spectrum allocation algorithm using deep learning based on Gibbs sampling. Hossain *et al.*, in [17] propose a multi-operator cooperation framework in RANs in a heuristic way.

Besides, there is also some research of multi-operator cooperation for IoT service in energy and power efficient optimization. In [18], Oikonomakou *et al.* solve a problem of energy trading among cooperative MNOs by adopting a bankruptcy game and Shapley value method. Gambn *et al.*, in [19] present a multi-operator network scenario and discuss new approaches towards their energy consumption and sharing patterns over time armed with deep learning. And in [20], a spectrum allocation and sharing scheme to minimize the power consumption among multiple operators is proposed by Opadere *et al.*

In our work, we use the evolutionary game to complete the bandwidth access process, which can share the bandwidth resources from multiple WSPs. The dynamics of interaction among the roles can be exactly captured by an evolutionary game. In an evolutionary game, a player can observe the behavior of other players, learn from the observations, and make the best choice based on his knowledge, which is useful for investigating the trend of the strategies of the players while adapting their behaviors to reach the solution in a distributed way. Besides, for the aim of describing the features of vehicle users in a more accurate way, we also propose a unique scheme to take the vehicles' mobility into account. Through this scheme, we can make bandwidth access method more efficient.

B. Blockchain Technology Application

Blockchain has become a very popular topic in recent years. The concept of blockchain first appeared in Satoshi Nakamoto's work, and now the distributed technology is applied in numerous fields including Internet of Things and Internet of Vehicles because of its trustworthiness, traceable and immutability.

For instance, Kang *et al.*, in [11] combine the blockchain and the convex optimization to provide a charging scheme for electronic vehicles. In [21], Jiang *et al.* present a blockchain-based internet of vehicles, which is used to transmit vehicle data, the work classifies the data blocks of IoV based on blockchain for IoV system. In addition, they also present how the nodes in IoV could participate in blockchains network. Cheng *et al.* in [22] propose a traffic control system based on blockchain. Li *et al.*, in [23] show a blockchain-based Internet of Vehicles advertising communication scheme structure based on cryptographic principles. An energy-efficient transaction model for the blockchain-enabled IoV is proposed in the work of [24] by Sharma *et al.*, Pustiek *et al.* in [25] put forward a blockchain-based autonomous selection of electric vehicle charging station, and Zhang *et al.* in [26] propose a blockchain-enabled framework of IoV. Besides, blockchain is also used in flying ad-hoc networks such as the work by Tan *et al.* [27].

As for [28], [29], [30], Zhang *et al.*, Liu *et al.* and Fu *et al.* solve the corresponding problem by using reinforcement learning or deep learning framework respectively. Zhang *et al.* in [28] propose a blockchain-based dueling reinforcement learning approach used in IoV. The work jointly considers the trust feature of vehicles in the blockchain circumstance, consensus nodes' number, and the computing capabilities of the edge computing as a comprehensive optimization problem.

Besides, for the security framework in blockchain, Aman *et al.* in [31], [32] demonstrate the blockchain framework in internet of vehicles. In [31], a mutual authentication protocol that needs fewer authentication requests and significantly low overhead for IoVs is designed to ensure privacy preservation and efficiency. And in [32], they illustrate a decentralized and scalable protocol and A reliable framework for via the blockchain public-key infrastructure features and smart contracts in IoV. A dynamic consensus algorithm that is suitable for IoV is also proposed.

The traditional blockchain framework usually has a fixed block size and block generation time, which is not flexible

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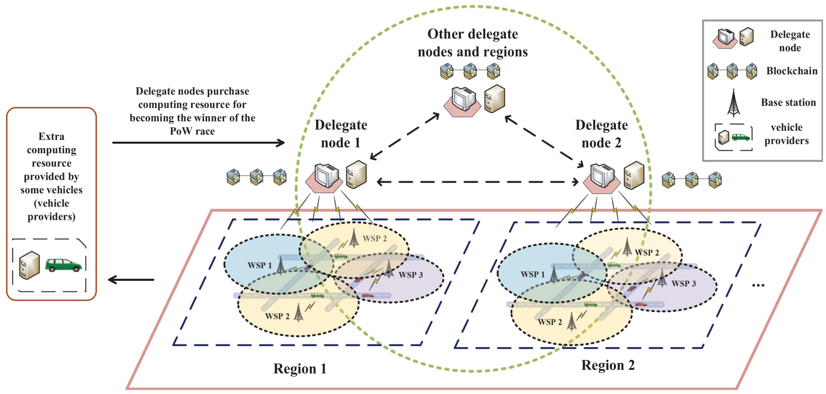

Fig. 1. A Blockchain-enabled multi-operator access sharing management system for Internet of Vehicles.

enough. Therefore, in our scheme, we propose a blockchain-enabled structure and an adaptive block size scheme. As for the consensus mechanism, we design a DPoW consensus protocol to create a more robust network. In the DPoW process, we motivate vehicle users to provide some extra computing resources with the delegate nodes in their own region to help strengthen the robustness of the network, which is a multi-leader game. Then the winner delegate node will complete the block generation work.

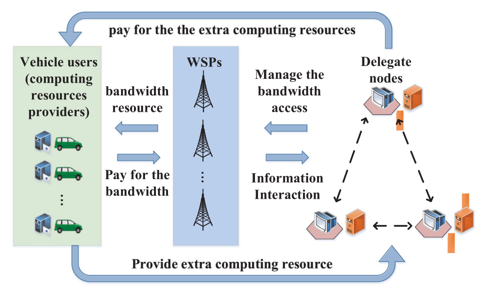

Fig. 2. The relationship of each role in our framework.

III. System Model

A. Scenario

We consider a multi-WSP scenario, where each WSP has several base stations (BSs) deployed in different regions, as shown in Fig. 1. The major roles in the system are described as below.

Vehicle user: On the one hand, vehicle users in each region require bandwidth resources. A vehicle user is a subscriber to a specific WSP, but it can access the Internet via other WSPs owing to the WSP cooperation. In this work, we assume that a vehicle user always associates with the nearest base station of the WSP it currently selects. On the other hand, vehicles are equipped with powerful computing devices, so they can also provide their idle computing resources to enhance the security of the blockchain network. We use M to represent the set of vehicle users, i.e. $\mathrm{M} = \{u_1, u_2, \ldots, u_{\|\mathrm{M}\|}\}$.

Wireless service provider: There are $\|W\|$ WSPs (i.e. operators) in our scenario. The base stations of WSPs are unevenly distributed in each region. Besides, we assume that the each WSP has fixed bandwidth resources, which are exploited by all its BSs. We use $\mathrm{W} = \{wsp_1, wsp_2, \ldots, wsp_{\|W\|}\}$ to represent the WSP set.

Base station: Base stations (BS) are operated by their WSPs and provide vehicular access services. The bandwidth resources of each base station are shared by all its associated vehicles. We suppose that interference mainly comes from the other base stations owned by the same WSP in this region. We use b_k^l to stand for the l-th base station of the k-th WSP.

Delegate node: The delegate node is basically a powerful server deployed at the edge cloud in each region. On the one hand, it serves as the information hub to facilitate WSP selection in the region, and the delegate node is used to interact with all the vehicles and base stations in the corresponding region. On the other hand, it delegates the vehicles in the region to participate in the blockchain consensus process. Besides, the vehicles can support the delegate node by offering idle spectrum computing resources for better security of the system. Delegate nodes work in a decentralized way and ADMM is run on each node to get the optimal consensus parameter values. Data stored on the nodes are shared by all the cooperating WSPs. Delegate nodes are denoted by a set $\mathrm{AN} = \{an_1, an_2, \ldots, an_{\|AN\|}\}$.

Blockchain: We maintain the public nature of blockchain. In other words, it essentially allows all vehicles to participate in the consensus. The total computing power is thereby increased by crowdsourcing from vehicles' idle resources. Prices are also paid for solving the PoW quiz. Actually, it is more like a dynamic mining farm organized by the delegate node, which is introduced to deal with the mobility of vehicles. And the relationships among all the roles are shown in Fig. 2

B. Process of WSP Cooperation

In each region, at a certain time, the delegate node first gathers necessary status information of vehicles and determines the vehicle-WSP association by an evolutionary game. Each association pair is regarded as a "transaction" of the blockchain and is disseminated to all the delegate nodes. A fee is included in each transaction as an economic incentive to WSP cooperation and the corresponding blockchain. A valid block is formed by solving the PoW puzzle after collecting a certain number of transactions. The generated block is then propagated in the blockchain network and will be finalized after it is validated by other nodes. The winning node, i.e., the block proposer, will

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be rewarded by the total fees included in each transaction of the block. All the delegate nodes jointly determine the block size and prices paid for vehicles' computing resources through the ADMM. Clearing between the cooperating WSPs is based on the immutable transaction data stored on the blockchain.

IV. Evolutionary Game Enabled WSP Selection

A. Bandwidth Access Model Based on Evolutionary Game Method

In this section, we propose the bandwidth access scheme. We divide the scheme into the following parts:

Population: The set of all users that subscribe to a certain WSP is denoted as a population. Since there are $\|W\|$ WSPs, there will be $\|W\|$ populations in our system.

Strategy space: Every vehicle user can decide which WSP to access, the strategy space can be written as $S = \{s_1, s_2, \ldots, s_{\|W\|}\}$

Population state: In an evolutionary game, we assume that the ratio of users choosing each strategy is expressed as $\mathbf{y}=\{y_{s_1}, y_{s_2} \ldots, y_{s\|W\|}\}$. Obviously, we have $\sum_{n=1}^{\|W\|} y_{s_n}=1$.

Payoff function: The payoff function π_{s_n} is used to quantify the satisfaction profit or benefit that users can obtain from a certain strategy, namely a mapping from y to the payoff function.

We denote λ_{w_k} as the density of the base station of the k-th WSP in each region in our scheme, and use λ_u to stand for the vehicle users' density. When each vehicle user has determined to select and subscribe a specific WSP, it associate to a nearest base station operated by this WSP. Then we define the expected signal to noise ratio (SINR) $\bar{\gamma}_j$ of these vehicle users at time t as

$$\bar{\gamma}_j = \mathrm{E}\left[\frac{P_{W_n}^l h_l\left(D_{b_n^l}^j(t)\right)^{-\alpha}}{\sum\limits_{k\neq l} P_{W_n}^k h_k\left(D_{b_n^k}^j(t)\right)^{-\alpha} + \sigma^2}\right], \tag{1}$$

In Eq. (1), $P_{W_n}^l$ is the power transmitted by the l-th base station from n-th WSP, σ^2 is the power density of Additive White Gaussian Noise (AWGN), we denote α as the path-loss exponent. $D_{b_n^l}^j(t)$ is the distance of the accessed l-th base station of wsp_n (i.e. b_n^l) and the vehicle user j at time t, and h_l stands for the Rayleigh fading effect.

The inteference in our model can be divided into two parts. The first part is from the same operators' other base stations, and the second part of the interference is the white Gaussian noise. Then we use the signal-to-noise ratio to get the expected rate of the vehicle users $\bar{R}(t)$ by making use of the Shannon formula as follows:

$$\bar{R}(t) = \mathrm{E}\left\{B_j \log_2[1 + \gamma_j(t)]\right\}, \tag{2}$$

where B_j is the bandwidth allocated to the j-th vehicle user.

B. Payoff Function of Vehicle Users

Vehicle users are highly mobile when communicating with cellular base stations. To better reflect the network service level and estimate the link rate, we propose the concept of payoff function of vehicles, which is based on the expected driving path for these vehicle users.

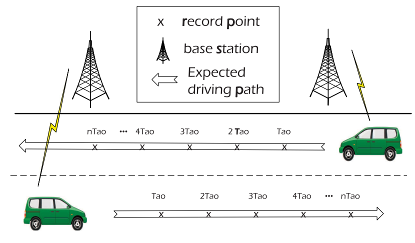

Fig. 3. Illustration of vehicle expected driving path.

As illustrated in Fig. 3, in the evolutionary game, the vehicle user j has his expected driving path L_j with his own speed v_j. For the aim of reflecting the mobility feature of vehicle users more accurately, we adopt an expected driving path for a certain duration instead of just a fixed position.

We assume that each vehicle user is firstly located at the starting point of his expecting driving path, and we define the time $t = 0$ currently. These vehicle users are driving along their planned driving path. Firstly, they arrive at the first record point at $t = \tau$, and then at $t = 2\tau$, they arrive at the second record point, etc. We totally consider and set A record points into the model. At the starting points of these vehicles, each vehicle estimates his locations in the future time for the calculation of his payoff function. The amount of record points is defined as A. Then combined with Eq. (1) and (2), the average payoff function for each strategy will be written as follows:

$$\pi_{s_n} = E\left\{\frac{1}{A+1}\sum_{t=0}^{A} B_{s_n}\log_2[1 + \gamma_{s_n}(t)]\right\}, \tag{3}$$

where

$$\bar{\gamma}_{s_n} = \mathrm{E}\left[\frac{P_{W_n}^l h_l\left(D_{b_n^l}^{s_n}(t)\right)^{-\alpha}}{\sum\limits_{k\neq l} P_{W_n}^k h_k\left(D_{b_n^k}^{s_n}(t)\right)^{-\alpha} + \sigma^2}\right],$$

Then the mean user rate while each vehicle user j crosses through these A record points can be depicted by the payoff function π_{s_n}. For vehicle user j, the payoff function can be shown as:

$$\pi_j = \frac{1}{A+1}\sum_{t=0}^{A} B_j \log_2\left[1 + \frac{P_{w_n} h_j\left(D_{b_n^l}^j(t)\right)^{-\alpha}}{\sum\limits_{k\neq j} P_{w_n} h_k\left(D_{b_n^k}^j(t)\right)^{-\alpha} + \sigma^2}\right]. \tag{4}$$

Eq. (3) and (4) illustrate the payoff function of vehicle users, i.e. the vehicle users' mean rate which is combined with the information of present locations and future locations (there are totally A+1 points). The payoff function described the communication condition of vehicle users more accurately, because of the consideration of both vehicle's current location and expected driving path.

C. Replicator Dynamics and the Formulation of ESS

For the aim of describing the dynamical behavior of vehicle users, the replicator dynamics is proposed in this section as follows:

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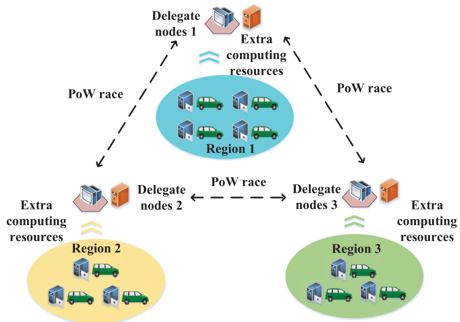

Fig. 4. The DPoW framework.

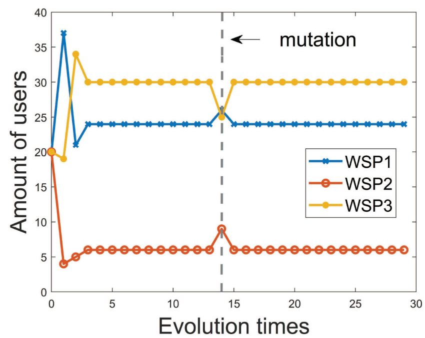

Fig. 5. The dynamics before and after the mutation of the population share with $(\lambda_{w_1}, \lambda_{w_2}, \lambda_{w_3}) = (3, 3, 6)$ and $\lambda_u = 60$.

$$\begin{aligned} \dot{y}_{s_k} &= \delta y_{s_k}(\pi_{s_k} - \bar{\pi}(\mathbf{y})) \\ &= \delta y_{s_k}(y_{s_k} - \sum_{s_k}^{'} \in \mathbb{S} y_{s_k'} \pi_{s_k'}(\mathbf{y})), \forall k \in W. \end{aligned} \tag{5}$$

In Eq. (5), $\delta > 0$ denotes the update rate of strategy, $\bar{\pi}(\mathbf{y})$ stands for the all populations' mean payoff. From the replicator dynamics, we can obtain that the percentage growth rate of the population share of each strategy is proportional to the difference between the strategy's payoff and the population's average payoff. It can be illustrated as a natural selection model in biology, and also as an imitation model in economics. [4]. Armed with replicator dynamics, we will be able to obtain N first-order equations. With the assistance of the above equations, each vehicle user could find the fixed point, and it is also the evolutionary equilibrium (EE) point. If the state of EE is accomplished, each of the vehicle users won't change his strategy. And in what follows, we depict the definition of evolutionary stable strategy (ESS).

Definition 1 (ESS) : The strategy $\bar{\mathbf{y}}$ is an evolutionary stable strategy (ESS) for any arbitrary different population state $\mathbf{y} \neq \bar{\mathbf{y}}$ if we have the condition in Eq. (6)

$$\bar{\pi}(\bar{\mathbf{y}}, (1-\varepsilon)\bar{\mathbf{y}} + \varepsilon\mathbf{y}) > \bar{\pi}(\mathbf{y}, (1-\varepsilon)\bar{\mathbf{y}} + \varepsilon\mathbf{y}), \tag{6}$$

where $\bar{\pi}(\bar{\mathbf{y}}, (1-\varepsilon)\bar{\mathbf{y}} + \varepsilon\mathbf{y})$ and $\bar{\pi}(\mathbf{y}, (1-\varepsilon)\bar{\mathbf{y}} + \varepsilon\mathbf{y})$ is the average payoff in state of $\bar{\mathbf{y}}$ and $\mathbf{y}$ under the population state $(1-\varepsilon)\bar{\mathbf{y}} + \varepsilon\mathbf{y}$ with ε as a mutation constant respectively.

Actually, due to the complexity involved in calculating the channel rates in Eq. (4), it is very hard to solve the proof of the ESS. To this end, we seek to use simulation results (Fig. 5 and Fig. 6) to demonstrate the stability and convergence of our

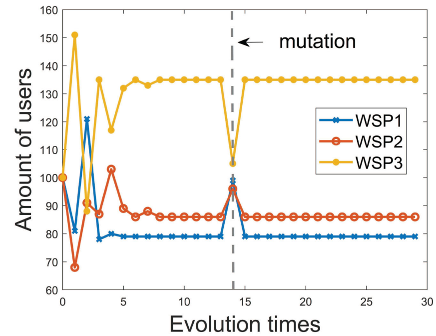

Fig. 6. The dynamics before and after the mutation of the population share with $(\lambda_{w_1}, \lambda_{w_2}, \lambda_{w_3}) = (4, 3, 6)$ and $\lambda_u = 300$.

Algorithm 1: WSP Selection Algorithm.

1: **Initialization** Each vehicle user selects a WSP to subscribe in a random manner, and accesses the base station of the WSP which is neraest to the vehicle. And we set the iterative time $t = 0$.
2: **loop**
3: Vehicle users calculate their own payoff π_j in the current strategy state by equation. (4) respectively, then they upload the results to the delegate node of this region AN.
4: Delegate node AN obtains all of the user rate from vehicles in the region, then it calculates the mean payoff $\bar{\pi}(\mathbf{y})$, broadcasts the results to all vehicle users in this region.
5: **if** For each vehicle user j, $\pi_j < \bar{\pi}(\mathbf{y})$ **then**
6: Vehicle user i changes his original strategy, and selects a new WSP k to subscribe, where $k = \arg\max(\pi_{s_k})$ for each user j.
7: **End if**
8: Vehicle uploads their new strategies to AN, and AN updates and calculates the data.
9: $t = t + 1$
10: **Until** No vehicle user will change his strategy or the maximum number of iteration is reached.
11: **End loop**

evolutionary game. It is shown that for the proposed evolutionary game, no one will change his strategy under fairness and stable circumstances.

The operation of WSP selection algorithm is explained below. The delegate node works as the information interaction hub in the region. Due to the features of the evolutionary game method, the algorithm has a satisfying convergence speed. Besides, the delegate node in our model only needs to calculate the mean rate of all vehicle users in his region. as for the individual user rate of vehicles, it will be accomplished by each vehicle user distributedly and respectively. Our algorithm can avoid large complexity on the delegate node. In other words, the calculating task is shared by all the vehicle users.

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V. Optimization of DPoW

A. ADMM Introduction and Basics

ADMM is known as a parallel tool for solving large-scale optimization problems, and it is also very excelled at solving algorithms in a distributed manner compared with other convex algorithm. The ADMM method also has the advantages of fast convergence. So it is widely used to solve an extremely large scale optimization problem [33]. In addition, the ADMM method is proved that it is able to converge to the stationary solutions if the objective function is convex and separable [34]. Even if for the non-convex function, the convergence of ADMM can still be assured under certain conditions. In the consensus optimization problem, we consider the case with only one global variable, and the objective and constraint terms are divided into N parts:

$$\begin{array}{ll} \min & \sum_{i=1}^{N} f_i(x_i) \\ s.t. & x_i - z = 0, i = 1, \ldots, N. \end{array} \tag{7}$$

In this model, every processor collaborates to develop a global utility, and the constraint is the local variables should agree to be equal, i.e. the local variable x_i should all reach the global variable z. And by deriving the augmented Lagrangian function, we can obtain the resulting equation, which is shown as

$$\begin{cases} L_\rho(x,z,\lambda) = \sum_{i=1}^{N} \left(f_i\left(x_i\right) + \lambda_i^T\left(x_i - z\right) + (\rho/2)\left\|x_i - z\right\|_2^2 \right) \\ x_i^{k+1} = \underset{x_i}{\operatorname{argmin}} \begin{pmatrix} f_i\left(x_i\right) + \lambda_i^{kT}\left(x_i - z^k\right) \\ +(\rho/2)\left\|x_i - z^k\right\|_2^2 \end{pmatrix} \\ z^{k+1} = \frac{1}{N}\sum_{i=1}^{N}\left(x_i^{k+1} + (1/\rho)\lambda_i^k\right) \\ \lambda_i^{k+1} = \lambda_i^k + \rho\left(x_i^{k+1} - z^{k+1}\right) \end{cases} \tag{8}$$

In Eq. (8), $L_\rho(x,z,\lambda)$ is the Lagrangian function, and the x_i, z^k, λ_i denote the local variable, global variable and multipliers respectively. In the following section, we explain the solution based on the ADMM method respectively. Based on the ADMM algorithm, we solve our problem in the following sections in a distributed way.

B. Delegated PoW Consensus Mechanism

We consider a PoW-based consensus mechanism [35] [36] [37] [38]. PoW protocol is widely used in public blockchains, such as Bitcoin and Etherum, due to the high-security level it can provide. The protocol is a puzzle race, it requires participating nodes to solve a hard problem called hash puzzle, which will consume a lot of computing resources. The probability that a node i finds the answer to a question, i.e. p_{i_PoW}, is proportional to the ratio of computing resources it owns, as shown in Eq. (9):

$$\begin{array}{l} p_{i\_PoW}\left(f_{i\_PoW}, F_{-i\_PoW}\right) = \frac{f_{i\_PoW}}{\sum_j f_{j\_PoW}}, \\ \sum_j p_{j\_PoW} = 1. \end{array} \tag{9}$$

Based on PoW, we further propose the delegated PoW consensus mechanism tailored for the vehicular scenario. Similar to the delegated proof-of-stake mechanism, the delegate node attends PoW race on behalf of the vehicles in its region, as shown in Fig. 4. The delegate nodes solicit extra idle computing resources from the vehicles, who will be rewarded based on the computing resource it provides.

After successfully writing a block onto the blockchain, the delegate node will obtain an amount of transaction fee as a reward for its work. However, the block may become invalid (i.e., orphaned) due to the PoW mechanism. We can quantify the block generation reward of delegate node i as

$$R_i^G = \eta^G\left(1 - P_{orphan}\right)R^B. \tag{10}$$

In Eq. (10), η^G and R_i^B shows that if an delegate node completes the task, it will receive a η^G percentage of block reward R_i^B. And P_{orphan} is the orphaning probability. The orphaning probability is influenced by the amount of transactions (block size) S_B and block generation time T_G, We assume the block times follow a Poisson distribution, then the orphaning probability can be given as

$$P_{orphan} = 1 - e^{-\frac{\xi S_B}{T_G}}. \tag{11}$$

The block reward R_i^B is divided into 2 parts, i.e. a fixed reward R_{basic} and a variable reward, which is determined by the amount of the transactions, i.e. the block size. Therefore, we can model the block reward as

$$R_i^B = R_{basic} + \varepsilon_i\frac{S_B}{\sigma}. \tag{12}$$

ε_i is a given parameter which is depended on the communication condition of the node and the network, and σ denotes the average size of a transaction. So the block reward for delegate node i can be rewritten as

$$R_i^G\left(S_B\right) = \eta^G e^{-\frac{\xi S_B}{T_G}}\left(R_{basic} + \varepsilon_i\frac{S_B}{\sigma}\right). \tag{13}$$

In Eq.(13), we can see that the expression is comprised of two parts, $\eta^G e^{-\frac{\xi S_B}{T_G}}$ and $(R_{basic} + \varepsilon_i\frac{S_B}{\sigma})$. When the block size S_B becomes larger, the first part will become smaller because the orphaning probability of an extremely large block are usually high, which decreases the utility. However, the later part will get larger as the block size becomes larger since there are more profit of transactions in one block, and vice versa. Then the problem becomes a trade off optimization problem and thus the block size become a variable that need to be optimized.

Let x_{ik} denote the computing resource demand of delegate node i from vehicle k, and each delegate node will decide on computing resource from vehicles in its own region, denoted by $\mathbf{x}_i = \{x_{i1}, x_{i2}, \ldots, x_{in}\}$. And for convenience, we define $\mathbf{X}_{-i}$ as the computing resource demand of all other delegate nodes except node i. Then we define the total computing power of delegate node i as

$$x_i^{total} = C_{init}^i + \sum_{j\in M}\omega_{ij}x_{ij}, \tag{14}$$

We assume that each delegate node i has an initial computing resources which is denoted as C_{init}^i. Then, each delegate node will have a percentage of computing power

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$$\alpha_i(\mathbf{x}_i, \mathbf{X}_{-i}) = \frac{x_i^{\text{total}}}{\sum_{m\in AN} x_m^{\text{total}}} = \frac{C_{init}^i + \sum_{j\in M}\omega_{ij}x_{ij}}{\sum_{m\in AN} C_{init}^m + \sum_{i\in AN}\sum_{j\in M}\omega_{ij}x_{ij}}, \tag{15}$$

since $\alpha_i(x_i, X_{-i})$ is the percentage of computing power, such that $\sum_{i\in N}\alpha_i(x_i, X_{-i}) = 1$. ω_{ij} in Eq. (13) and Eq. (14) is the probability of delegate node i to choose vehicle user j for the computing resource purchase, and $\sum_{j\in M}\omega_{ij} = 1$. For each delegate node, according to incentive mechanism method [39], we have

$$\omega_{ij} = \frac{b_{ij}}{\sum_{m\in M} b_{im}}, \tag{16}$$

where b_{ij} is the difference of the highest price $p_{\max}$ and the marginal price p_{ij}. In other words, b_{ij} is also the motivation of unit price decrease on computing service demand, i.e.

$$b_{ij} = p_{\max} - p_{ij}. \tag{17}$$

Combined with Eq. (16) and (17), once the value of ω_{ij} becomes larger, the delegate node i will obtain the computing resource at a lower price from vehicle user j. And it is reasonable that the delegate nodes are more likely to purchase computing resources from vehicle j when ω_{ij} increases. Therefore, this results in price competition among vehicle users.

Given the pricing profiles of all vehicle users $\mathbf{P} = \{\mathbf{p}_1, \mathbf{p}_2 \cdots, \mathbf{p}_{\|M\|}\}$ in a region, computing service demand from all other delegate nodes X_{-i} and Eq. (12), we have the concept of the utility of delegate nodes, i.e.

$$\begin{aligned} &u_i(\mathbf{x}_i, \mathbf{X}_{-i}, \mathbf{P}, S_B) \\ &= R_i^G(S_B) \times \frac{C_{init}^i + \sum_{j\in\mathcal{M}}\omega_{ij}x_{ij}}{\sum_{m\in AN} C_{init}^m + \sum_{i\in\mathcal{A}N}\sum_{j\in\mathcal{M}}\omega_{ij}x_{ij}} - \sum_{j\in\mathcal{M}} p_{ij}\omega_{ij}x_{ij} \\ &= R_i^G(S_B) \times \alpha_i(\mathbf{x}_i, \mathbf{X}_{-i}) - \sum_{j\in\mathcal{M}} p_{ij}\omega_{ij}x_{ij}. \end{aligned} \tag{18}$$

Then the delegate node i will decide on its computing resource need by finding a solution of a optimization problem, and we write the optimization problem of each delegate node as follows:

$$\begin{aligned} &\underset{\mathbf{x}_i, S_B}{\text{maximize}}\, u_i(\mathbf{x}_i, \mathbf{X}_{-i}, \mathbf{P}, S_B) \\ &s.t. \begin{cases} \mathrm{C}_1: x_{ij} \geq 0 \\ \mathrm{C}_2: \sum_{j\in\mathcal{M}} x_{ij} \leq D_{\max} \\ \mathrm{C}_3: 0 \leq S_B \leq S_{\max}. \end{cases} \end{aligned} \tag{19}$$

$D_{\max}$ in C_2 denotes the maximum service demand of one delegate node due to some budget and resource limitation. $S_{\max}$ in C_3 is the maximum block size limitation, which makes sure that the block size does not exceed the block limit. Considering the pricing of other vehicle users and the computing resource demand of delegate nodes, each vehicle user j determines its pricing profile p_j while maximizing its profit. So we define the profit for each vehicle user as follows:

$$\psi_j(\mathbf{p}_j, \mathbf{P}_{-j}, \mathbf{X}) = \sum_{i\in AN}\omega_{ij}(p_{ij}x_{ij} - cx_{ij}). \tag{20}$$

Algorithm 2: DPoW Optimization Process Based on ADMM.

1: **Initialization** the global variable $S_B^{(0)}$, the initial Lagrange multiplier $\lambda(an)$ for each delegate node; initial price $p_{ij} \in [0, p_{\max}], \forall i \in AN, \forall j \in M$
2: **Repeat** To find the global consensus solution on adaptive block size S_B:
3: Each delegate node an updates his local block size $\{\hat{S}_B(an)\}^{t_B+1}$ by solving problem (23), updates the global variables $\{\hat{\mathbf{S}}_B\}^{t_B+1}$ as (24), and updates the Lagrange multiplier $[\lambda(an)]^{t_B+1}$ as (25).
4: $t_B = t_B + 1$
5: **Until** stopping criteria (26) and (27) are satisfied. The optimal block size S_B^* is obtained.
6: **Repeat**: **(inner loop)** each delegate node observes the set prices p_{ij}, to decides the computing service demand x_{ij}^q by maximizing the utility function $u1_i'(\mathbf{x}_i)$ through (29) and (30).
(outer loop) WSPs observe the delegate nodes behaviors x_{ij}^q, employ ADMM to maximize their profit function $\psi_j'(\mathbf{p}_j)$ through (31).
7: $q = q + 1$;
8: **Until** stopping criteria (32) is satisfied. The optimal computing service demand $\mathbf{x}_i^*$ and the optimal pricing $\mathbf{p}_j^*$ is obtained.
9: **End**

Accordingly, the optimization problem of each vehicle user is defined as follows:

$$\begin{aligned} &\underset{\mathbf{p}_j}{\text{maximize}}\, \psi_j(\mathbf{p}_j, \mathbf{P}_{-j}, \mathbf{X}) \\ &s.t.\, \mathrm{C}_4: 0 \leq p_{ij} \leq p_{\max}. \end{aligned} \tag{21}$$

Combined with Eq. (19) and (21), it is a multi-leader (vehicle users as providers in computing resources) problem, which should be solved in a large-scale network. Therefore, we resort to the ADMM algorithm to obtain the solution in a decentralized way. For Eq. (11), since block size S_B is relatively independent compared to other variables, so we decompose the problem into two parts for convenience, namely 1) adaptive block size optimization and 2) demand and price optimization.

The overall DPoW optimization process is given in Algorithm 2. And the specific method of optimization will be illustrated in the following sections. When the block is generated, it will be added to the blockchain at each delegated node distributedly, and it is traceable and convenient to search the corresponding information for each vehicle.

C. Adaptive Block Size Optimization

In this section, we only focus on the optimization of block reward $R_i^G(S_B)$ in Eq. (13). Block size is a global consensus variable which is optimized in each delegate node at a distributed manner. So intuitively, we can introduce a local copy of S_B, i.e. $\hat{\mathbf{S}}_B = \{\hat{S}_B(an)\}$, and then we try to make these copies reach consensus. For the objective function, we use the sum of block reward $R_i^G(S_B)$ of N delegate nodes as the optimization goal. In conclude, we can rewrite the adaptive block size optimization

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TABLE I
MAIN SYMBOLS AND PARAMETERS

Symbols Associated with Evolutionary Game	
M	The set of vehicles.
$u_1, u_2, \ldots, u_{\|M\|}$	The vehicles.
W	The set of WSPs
$wsp_1, wsp_2, \cdots, wsp_{\|W\|}$	The WSPs.
b_k^l	The l-th base station of the k-th WSP.
AN	The set of delegate nodes.
$an_1, an_2, \cdots, an_{\|AN\|}$	The delegate nodes.
S	The set of the strategy space of the vehicles
$s_1, s_2, \ldots, s_{\|W\|}$	The strategies for the vehicles.
$\mathbf{y}$	The set of the ratio of users choosing each strategy.
$y_{s_1}, y_{s_2} \ldots, y_{s_{\|W\|}}$	The ratio of users choosing each strategy.
π_{s_n}	The payoff function of the vehicle users.
λ_{w_k}	The density of the base station of the k-th WSP in each region.
λ_u	The vehicle users' density.
$\bar{\gamma}_j$	The expected signal to noise ratio (SINR) .
$P_{W_n}^l$	The power transmitted by the l-th base station from n-th WSP.
σ^2	The power density of Additive White Gaussian Noise (AWGN).
α	The path-loss exponent.
h_l	The Rayleigh fading effect.
$D_{b_n^l}^j(t)$	The distance of the accessed l-th base station of wsp_n (i.e. b_n^l) and the vehicle user j at time t.
$\bar{R}(t)$	The expected rate of the vehicle users.
B_j	The bandwidth allocated to the j-th vehicle user.
A	The amount of record points.
Symbols Associated with the DPoW Scheme	
P_{orphan}	The orphaning probability.
η^G	Percentage of block reward.
S_B	The block size.
T_G	The block generation time.
R_{basic}	The fixed block reward.
ε_i	A given parameter which is depended on the communication condition of the node and the network.
σ	The average size of a transaction.
x_{ik}	The computing resource demand of delegate node i from vehicle k.
x_i^{total}	The total computing power of delegate node i.
C_{init}^i	The initial computing resources of each delegate node i.
α_i	The percentage of computing power.
$p_{\max}$	The highest price.
p_{ij}	The marginal price.
b_{ij}	The difference of the highest price $p_{\max}$ and the marginal price p_{ij}.
ω_{ij}	The probability of delegate node i to choose vehicle user j for the computing resource purchase.
$D_{\max}$	The maximum service demand of one delegate node due to some budget and resource limitation.
$S_{\max}$	The maximum block size limitation.

problem as

$$\begin{aligned} &\min_{S_B} R_i^G(S_B) \\ &= \begin{cases} -\sum\limits_{i\in N} \eta^G e^{-\frac{\xi S_B}{T_G}} \left(R_{basic} + \varepsilon_i \frac{S_B}{\sigma}\right), \text{if } \mathrm{C}_3 \text{ holds} \\ \infty, \text{otherwise.} \end{cases} \\ &s.t.\ \mathrm{C}_5 : \hat{S}_B(an) = S_B \end{aligned} \tag{22}$$

The problem in (22) can be regarded as a global variable consensus optimization according to [39]. First, we obtain the augmented Lagrangian for (22) as

$$\min_{\hat{\mathbf{s}}_B} \left\{ \begin{array}{c} R_i^G(S_B) + [\lambda(an)]^{t_B} \left(\hat{S}_B(an) - S_B^{t_B}\right) \\ +\frac{\rho}{2} \left|\hat{S}_B(an) - S_B^{t_B}\right|_2^2 \end{array} \right\}. \tag{23}$$

The superscript t_B is the number of iterations, and we can find that (13) is a non-convex problem because of U_i, so we try to find a sub-optimal solution by Newton's method. Then we obtain the updating of global variables and Lagrange multiplier to achieve a global consensus as follows:

$$S_B = \frac{1}{\|AN\|\,\rho} \sum_{n=1}^{N} [\lambda(an)]^{t_B} + \frac{1}{\|AN\|} \sum_{n=1}^{N} \left[\hat{S}_B(an)\right]^{t_B} \tag{24}$$

$$[\lambda(an)]^{t_B+1} = [\lambda(an)]^{t_B} + \rho \left(\left[\hat{S}_B(an)\right]^{t_B+1} - S_B^{t_B+1} \right) \tag{25}$$

We update the global block size in Eq. (24), and update the Lagrange multiplier step by step in Eq. (25) respectively. Next, we give the stopping criterion of the iteration as follows:

$$\left\| \hat{S}_B(an)^{[t_B+1]} - S_B^{[t_B+1]} \right\|_2 \le \varepsilon_{primal}, \forall an \tag{26}$$

$$\left\| S_B(an)^{[t_B+1]} - S_B(an)^{[t_B]} \right\|_2 \le \varepsilon_{dual}, \forall an \tag{27}$$

Specifically, the residuals for both primal and dual conditions for delegate node n in iteration $t_B + 1$ should be small enough. ε_{primal} and ε_{dual} are respectively the pre-defined tolerances of the primal and dual conditions.

D. Demand and Price Optimization

In the following, we explain the demand and price optimization based on ADMM. Since $R_i^G(S_B)$ is discussed in Section V.B, in this section, we will give a scheme on the demand of delegate nodes and the price of vehicle users' optimization. Based on Eq. (19) and section V.B, we regard $R_i^G(S_B)$ as a constant in this section. Then the demand and price optimization

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problem can be rewritten as

$$\begin{aligned}&\underset{\mathbf{p}_j}{\operatorname{maximize}}\, \psi_j' (\mathbf{p}_j, \mathbf{P}_{-j}, \mathbf{X}) \\ &s.t.\, \mathrm{C}_4 : 0 \le p_{ij} \le p_{\max}. \\ &\begin{cases} \mathbf{x}_i = \arg\max u_i (\mathbf{x}_i, \mathbf{X}_{-i}, \mathbf{P}) \\ s.t. \begin{cases} \mathrm{C}_1 : x_{ij} \ge 0 \\ \mathrm{C}_2 : \sum\limits_{j\in\mathcal{M}} x_{ij} \le D_{\max} \end{cases} \end{cases}\end{aligned} \tag{28}$$

We regard the optimization problem as a two-stage optimization problem, stage 1 is an inner loop for delegate nodes of the ADMM based algorithm (the iteration process is denoted as t), and stage 2 is the outer loop of the algorithm (the iteration process is denoted as q). The specific illustration is shown as follows:

Stage 1) demand optimization for delegate nodes: In this stage, each delegate node $i \in AN$ first observes the price p_{ij}^q provided by vehicles firstly at each iteration q, decides on the computing service obtained from each vehicle to maximize its utility $u_i(x_i)$, and the inner loop is formed by delegate nodes, they aim to maximize their own individual utilities to obtain more profit, and each delegate node update its demand x_i as follows:

$$\begin{aligned}&\mathbf{x}_i^{(q)}(t_C+1) \\ &= \arg\max \left\{ \begin{aligned}&\left(u_i\left(\mathbf{x}_i^{(q)}\right)\right) + \lambda_i^{(q)}(t_C)\left(\sum_{j=1}^{M} x_{ij} - D_{\max}\right) \\ &+\frac{\rho}{2}\sum_{j=1}^{M}\left\| \sum_{k=1,k\neq i}^{AN} x_{kj}^q\left(\hat{t}_C\right) + x_{ij} - D_{\max}\right\|_2^2\end{aligned}\right\}.\end{aligned} \tag{29}$$

In the Eq. (29), $\hat{t}_C = t_C + 1$ if $i > k$, and $\hat{t} = t_C$ if $i < k$. And $\rho > 0$ is the penalty factor. Besides, the lagrange multiplier λ has the updating rule as follows:

$$\lambda_i^{(q)}(t_C+1) = \lambda_i^{(q)}(t_C) + \rho\left(\sum_{j=1}^{M} x_{ij}^{(q)}(t_C+1) - D_{\max}\right). \tag{30}$$

By Eq. (29) and (30), the delegate node will obtain the values of service demand that can maximize their utilities in each inner loop.

Stage 2) price optimization for vehicle providers: In this stage, each WSP will adjust the values of $\mathbf{p}_j$ by maximizing its profit function by adopting ADMM in the outer loop as

$$p_j^{q+1}(t_C+1) = \arg\max \psi_j\left(\mathbf{p}_j^q\right). \tag{31}$$

Then the priceing profile will be transmitted to all delegate nodes, which is a preparation for the next iteration ($t_C + 2$ and $q + 2$). And the stop criterion of the outer loop is

$$\left\|\sum_{j\in\mathcal{M}} \Pi_j\left(p_j^{(q)}\right) - \sum_{j\in\mathcal{M}} \Pi_j\left(p_j^{(q-1)}\right)\right\|_2 \le \varepsilon_{out} \tag{32}$$

ε_{out} is the pre-defined threshold of the outer loop stop criterion.

Theorem 1: The utility function of the delegate node $i \in AN$ in Eq. (18) is a concave function.

Proof: We calculate the first-order and the second-order derivative of (18) with respect to x_{ij}, which can be written as Eq. (33), Eq. (34) and Eq. (35)

$$\frac{\partial u_i}{\partial x_{ij}} = R_i^G(S_B) \times \frac{\partial \alpha_i}{\partial x_{ij}} - \sum_{j\in\mathcal{M}} \omega_{ij} p_{ij}, \tag{33}$$

$$\frac{\partial^2 u_i}{\partial x_{ij}^2} = R_i^G(S_B) \times \frac{\partial^2 \alpha_i}{\partial x_{ij}^2}, \tag{34}$$

where we have α_i as follow:

$$\alpha_i = \frac{C_{init}^i + \sum\limits_{j\in\mathcal{M}} \omega_{ij} x_{ij}}{\sum\limits_{m\in\mathcal{AN}} C_{init}^m + \sum\limits_{i\in\mathcal{AN}}\sum\limits_{j\in\mathcal{M}} \omega_{ij} x_{ij}}. \tag{35}$$

Since $R_i^G(S_B)$ is a constant for x_{ij}, we only need to solve the derivative of α_i in Eq. (33) and (34). First, we take the first-order derivative of α_i for delegate node i as

$$\begin{aligned}\frac{\partial \alpha_i}{\partial x_{ij}} &= \frac{\partial\left(\frac{C_{init}^i + \sum_{j\in M}\omega_{ij}x_{ij}}{\sum_{m\in N} C_{init}^m + \sum_{i\in AN}\sum_{j\in M}\omega_{ij}x_{ij}}\right)}{\partial x_{ij}} \\ &= \frac{\left\{\begin{aligned}&\sum_{j\in M}\omega_{ij}\left(\sum_{k\in AN} C_{init}^k + \sum_{i\in AN}\sum_{j\in M}\omega_{ij}x_{ij}\right) - \\ &\left(C_{init}^i + \sum_{j\in M}\omega_{ij}x_{ij}\right)\sum_{j\in M}\omega_{ij}\end{aligned}\right\}}{\left(\sum\limits_{m\in AN} C_{init}^m + \sum\limits_{i\in AN}\sum\limits_{j\in M}\omega_{ij}x_{ij}\right)^2} \\ &= \sum_{j\in M}\omega_{ij}\frac{\sum\limits_{m\in AN, m\neq i} C_{init}^m + \sum\limits_{a\in AN, a\neq i}\sum\limits_{b\in M}\omega_{ab}x_{ab}}{\left(\sum\limits_{m\in AN} C_{init}^m + \sum\limits_{i\in AN}\sum\limits_{j\in M}\omega_{ij}x_{ij}\right)^2}.\end{aligned} \tag{36}$$

Then we take the second-order derivative of α_i, the Equation can be expressed as Eq. (37), shown at the bottom of the next page.

From Eq. (37), we can obtain that $\frac{\partial^2 \alpha_i}{\partial x_{ij}^2} < 0$, so the concavity of the utility function of each delegate node has been proved. ■

Theorem 2: The utility function of vehicle user $j \in M$ in Eq. (20) is also a concave function.

Proof: Similarly, we take the first and the second-order derivative of (20) with respect to p_{ij}, and it can be shown as follows:

$$\psi_j(\mathbf{p}_j, \mathbf{P}_{-j}, \mathbf{X}) = \sum_{i\in N} \frac{p_{\max} - p_{ij}}{\sum\limits_{k\in M} p_{\max} - p_{ik}}(p_{ij}x_{ij} - cx_{ij}). \tag{38}$$

From Eq. (30), we only need to focus on the concavity of $\frac{p_{\max}-p_{ij}}{\sum_{k\in M} p_{\max}-p_{ik}} p_{ij}$. For convenience, we denote $\sum_{k\in M, k\neq j}(p_{\max} - p_{ik}) + p_{\max}$ as Θ. Since $p_{\max} - p_{ik} > 0$, we obtain that $\sum_{k\in M, k\neq j}(p_{\max} - p_{ik}) + p_{\max} > p_{\max} > p_{ij}$,

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i.e. $\Theta > p_{\max} > p_{ij}$. And firstly, we take the first-order derivative of the expression:

$$\begin{aligned}
&\frac{\partial\left(\frac{p_{\max}-p_{ij}}{\sum\limits_{k\in M} p_{\max}-p_{ik}}p_{ij}\right)}{\partial p_{ij}} = \frac{\partial\left(\frac{p_{\max}-p_{ij}}{\sum\limits_{k\in M,k\neq j}(p_{\max}-p_{ik})+p_{\max}-p_{ij}}p_{ij}\right)}{\partial p_{ij}}\\
&=\frac{\partial\left(\frac{p_{\max}-p_{ij}}{\Theta-p_{ij}}p_{ij}\right)}{\partial p_{ij}}=\frac{(p_{\max}-2p_{ij})(\Theta-p_{ij})+\left(p_{\max}p_{ij}-p_{ij}^2\right)}{(\Theta-p_{ij})^2}\\
&=\frac{p_{ij}^2-2p_{ij}\Theta+p_{\max}\Theta}{(\Theta-P_{ij})^2}
\end{aligned} \tag{39}$$

Then we take the second-order derivative of Eq. (39), which is expressed as

$$\begin{aligned}
&\frac{\partial^2\left(\frac{p_{\max}-p_{ij}}{\sum\limits_{k\in M} p_{\max}-p_{ik}}p_{ij}\right)}{\partial p_{ij}^2}\\
&=\frac{2\left(p_{ij}-\Theta\right)\left(\Theta-p_{ij}\right)^2+2\left(p_{ij}^2-2p_{ij}\Theta+p_{\max}\Theta\right)\left(\Theta-p_{ij}\right)}{\left(\Theta-p_{ij}\right)^4}\\
&=\frac{2\left(p_{ij}-\Theta\right)\left(\Theta^2-p_{\max}\Theta\right)}{\left(\Theta-p_{ij}\right)^4}=\frac{2\left(p_{ij}-\Theta\right)\left(\Theta-p_{\max}\right)\Theta}{\left(\Theta-p_{ij}\right)^4}<0
\end{aligned} \tag{40}$$

Since we can obtain that $\frac{\partial^2(\frac{p_{\max}-p_{ij}}{\sum_{k\in M} p_{\max}-p_{ik}}p_{ij})}{\partial p_{ij}^2} < 0$, the concavity of the utility function of each WSP is proved. ∎

In our model, the idle computing resources of vehicles are used for the improvement of security. And to deal with the dynamic of vehicles, we propose delegated proof-of-work (DPoW) scheme, which is an adaption of PoW (Proof of Work) and DPoS (delegated Proof of Stake), and it introduces delegate nodes for participating in the blockchain consensus. Each delegate node is responsible for gathering computing resources from vehicles in the region it delegates.

Sybil attack: A Sybil attack is a kind of attack that a small number of entities counterfeit multiple peer identities to compromise a disproportionate share of the system. In our model, as the same as PoW, for every individual who takes part in the mining and block generation, essential computation ability is necessary for our model. Thus it is difficult for one individual to manipulate several accounts simultaneously, which guarantees the security in the Sybil attack.

Double-spending attack and selfish mining: Both double-spending attacks and selfish mining make use of huge computing ability to obtain some profit they do not deserve or disturb other honest miners in the normal mining process. In traditional PoW protocol, it is possible when some individuals take charge of multitudinous computing ability. Nevertheless, The computing ability is comprised of many vehicles in that region at that time, which is extremely dynamic and variable. Thus it seems more difficult for one node to have stable and numerous computing abilities all the time. Besides, we add a protocol that is used in conventional PoW to avoid the attack, which is called the unpredictable deterministic tie-breaking method. It rewards a random delegate node from the nodes who complete the mining process if there is more than one node accomplish the assignment simultaneously, which will destroy the motivation of these attacks. Since the block generated by the node will not definitely be admitted.

TABLE II
VALUES AND ARGUMENTS

Parameter	Value
Number of Operators (WSPs)	3
Number of delegate nodes	5
Available bandwidth for each WSP	10 MHz
Noise power density	-174 dBm/Hz
Path-loss exponent	4
Transmission power of base station P_{W_n}	46 dBm
The number of record points A	3
The maximum price in PoW $p_{\max}$	50
The maximum extra computing resources demand in PoW $D_{\max}$	100
The penalty factor ρ	1

VI. NUMERICAL RESULTS

We evaluate the evolutionary game method for WSP selection firstly in this section. Then, we analyze the DPoW optimization scheme and analyze the security. Some main values and arguments are displayed in Table II.

$$\begin{aligned}
\frac{\partial^2\alpha_i}{\partial x_{ij}^2} &= \frac{\partial\left(\frac{\partial\alpha_i}{\partial x_{ij}}\right)}{\partial x_{ij}}\\
&=\sum_{j\in M}\omega_{ij}\left\{\begin{array}{l}\frac{0\times\left(\sum\limits_{m\in AN}C_{init}^m+\sum\limits_{i\in AN}\sum\limits_{j\in M}\omega_{ij}x_{ij}\right)}{\left(\sum\limits_{m\in AN}C_{init}^m+\sum\limits_{i\in AN}\sum\limits_{j\in M}\omega_{ij}x_{ij}\right)^4}\\
-\frac{\left(\sum\limits_{m\in AN,m\neq i}C_{init}^m+\sum\limits_{a\in AN,a\neq i}\sum\limits_{b\in M}\omega_{ab}x_{ab}\right)\left(\sum\limits_{m\in AN}C_{init}^m+\sum\limits_{i\in AN}\sum\limits_{j\in M}\omega_{ij}x_{ij}\right)\times 2\sum\limits_{j\in M}\omega_{ij}}{\left(\sum\limits_{m\in AN}C_{init}^m+\sum\limits_{i\in AN}\sum\limits_{j\in M}\omega_{ij}x_{ij}\right)^4}\end{array}\right\}\\
&=-2\left[\sum_{j\in M}\omega_{ij}\right]^2\frac{\sum\limits_{m\in AN,k\neq i}C_{init}^m+\sum\limits_{a\in AN,a\neq i}\sum\limits_{b\in M}\omega_{ab}x_{ab}}{\left(\sum\limits_{m\in AN}C_{init}^m+\sum\limits_{i\in AN}\sum\limits_{j\in M}\omega_{ij}x_{ij}\right)^3}<0.
\end{aligned} \tag{37}$$

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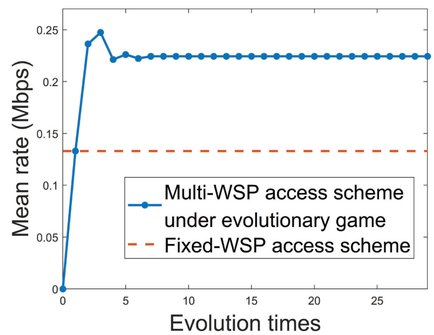

Fig. 7. The average rate dynamic of the proposed scheme and the fixed scheme.

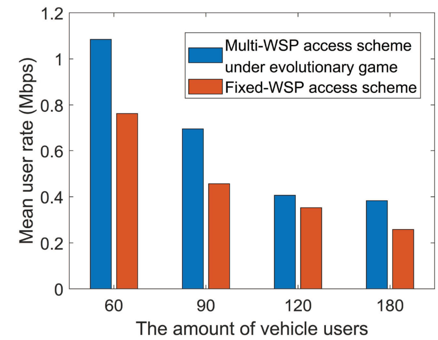

Fig. 8. The average rate of the proposed scheme and the fixed scheme under different amounts of vehicle users.

A. Evaluation of Multi-WSP Selection Scheme for Vehicle Users

The vehicles' dynamic behaviors can be clearly depicted by using the evolutionary game method. Firstly, without loss of generality, we take a 200 m $\times$ 200 m square area as an example to simulate. And we assume that there are totally 3 operators, many base stations, and a lot of vehicle users. As for these base stations, we assume that they are distributed in this region in a random manner at the density of $\lambda_{w_1}, \lambda_{w_2}$ and λ_{w_3} for the BSs possessed by WSP1, WSP2 and WSP3 respectively. The vehicles are distributed also in a random manner an intersection with the density of λ_u. All vehicle users will subscribe to a random WSP, choose the nearest base station of the WSP to access firstly, and drive along their planned driving path. And then the evolutionary game will be launched, vehicle users will choose a better strategy that will provide the most benefit at present.

The population state trend are displayed in Fig. 5 and 6. In Fig. 5 and Fig. 6, and the parameters are $(\lambda_{wsp_1}, \lambda_{wsp_2}, \lambda_{wsp_3}) = (3, 3, 6)$ and $\lambda_u = 60$, $(\lambda_{wsp_1}, \lambda_{wsp_2}, \lambda_{wsp_3}) = (4, 3, 6)$ and $\lambda_u = 300$ respectively. From Fig. 5 and 6, we obtain that the EES (evolutionary equilibrium state) will be completed whitin 7 iterations. Satisfying convergence time gurantees that these vehicle users will be able to access bandwidth with low latency. Besides, we artificially added some system mutations around the 15th iteration by changing the selection of WSP of some vehicle users, as given in Fig. 5. The results show the robustness of the system in that all the vehicles' selection will return to the original ESS.

Then, we show the average user rate between flexible multi-WSP selection under the proposed WSP cooperation framework and fixed WSP selection. Fig. 7 shows the dynamics of the mean user rate, and we still can know that the convergence speed of the evolutionary game is fast. Fig. 8 compares the mean rate with different amounts of vehicle users. We can obtain that our multi-WSP selection scheme always has a higher average rate. The reason is obvious since vehicle users can choose the WSP with better services considering the planned driving path. The bandwidth resources are used more efficiently through cooperation.

B. Evaluation of DPoW Optimization

We demonstrate the influence of block size on the utility of delegate nodes in Fig. 9. It illustrates that a larger or smaller block size will lead to lower utility. Although larger block size means more transactions and rewards, it also causes high orphaning probability. Thus, the block reward for delegate nodes can be optimized by choosing the appropriate block size. Besides, we find out that the block reward of delegate nodes will become larger with longer block generation time. It is because that the longer block generation time will lead to a lower orphaning probability for each block.

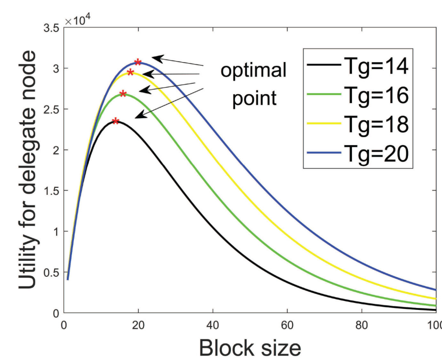

Fig. 9. Block rewards of delegate nodes and the optimal block sizes under different Tg.

VII. Conclusion

In this paper, we have proposed a WSP cooperation framework where vehicle users can freely select WSPs for better QoS. The evolutionary game approach finds the optimal user-WSP pairs with fast convergence speed. The records are immutably stored on the blockchain, laying the foundation of WSP cooperation. The proposed delegated PoW enhances the security of blockchain without degrading consensus performance, by allowing delegate nodes to participate in the consensus on behalf of vehicles with the vehicles' idle computing resources. Adaptive block size and ADMM schemes are adopted to increase delegate nodes' utilities. In our future work, we will consider a more flexible WSP cooperation framework by allowing vehicles to freely select base stations in a cell-free and fully-decoupled manner. Also, the computing power may be highly variable with the number of serving vehicles. A potential mitigation approach is to reserve computing resources at the delegate node so as to maintain a minimal computing power of the system, which needs to be considered in the future.

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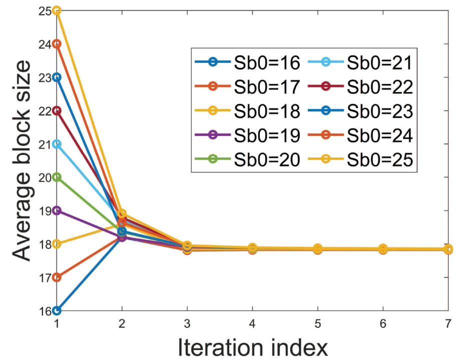

Fig. 10. The trend of global block size when selecting different initial value of local block size.

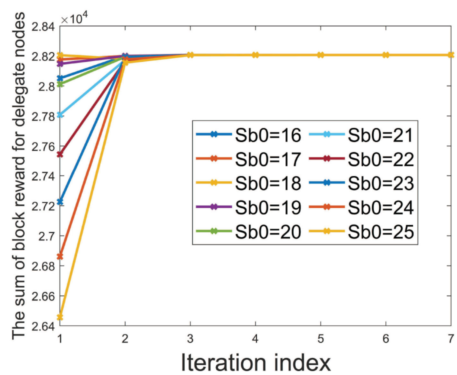

Fig. 11. The trend of block reward when selecting different initial value of local block size.

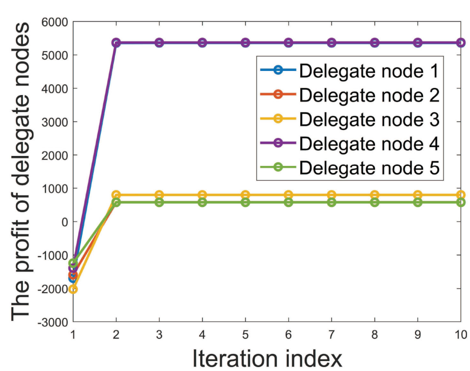

Fig. 12. The trend of the profit function of the delegate nodes.

Fig. 10 and Fig. 11 show the convergence of the adaptive block size scheme. Fig. 10 shows that the block size will converge to an optimal value within 4 iterations with different initial block sizes (Sb_0), demonstrating the effectiveness of ADMM. A similar trend is shown in Fig. 11 concerning block reward. Fig. 11 also shows the converged block reward is larger than the initial block rewards.Soliciting computing resources from vehicles is indispensable for DPoW. Since the profit functions of the delegate node and vehicles are both concave, the ADMM method is suitable. The leaders (vehicles) provide computing resources at a flexible price and the followers (delegate nodes) demand extra computing resources. Fig. 12 shows the trend of the profit function of the delegate nodes, demonstrating a fast convergence speed. The profit trends of the 5 recorded vehicles

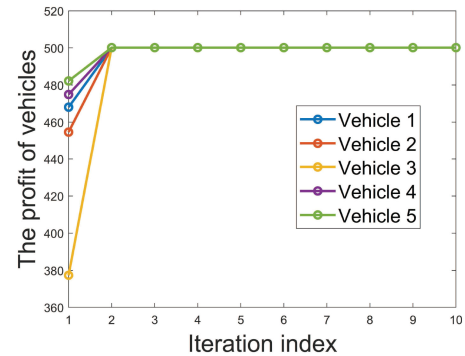

Fig. 13. The trend of the profit function of the vehicle providers.

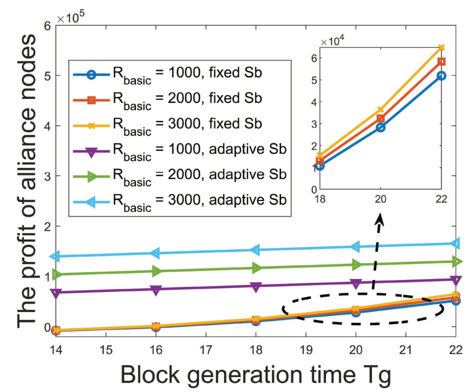

Fig. 14. The profit of delegate node under different schemes.

are shown in Fig. 13, and we can also find the convergence speed is fast. Fig. 14 shows the profits of delegate nodes with different fixed reward R_{basic} and under different schemes. First, our adaptive block size scheme makes delegate nodes obtain more profits. It is because optimal choices on block size can be made according to transaction amounts and block generation time T_g. Second, the delegate node prefers longer T_g, which brings them better profits. However, transaction delays will also be larger, which is not acceptable.

A. The Convergence and Complexity of the Consensus Optimization

The performance of our ADMM consensus model is shown in Figs. 10 and 11. We can obtain that the block size will converge to a global consensus value within 6 steps. Firstly, the curve varies very violently, and the trend after iteration 4 is extremely slight, which verifies the quick convergence in our model. In our simulation, we take the stopping criterion threshold in Eq. (26) and (27) as 10^{-2}. We obtain satisfying results from the threshold which is suitable for this algorithm.

Next we analyze the complexity of our block size consensus algorithm. Armed with ADMM, the distributed way in solving the problem, we can obtain that each delegate node has the complexity of $O(I^{poly})$, I denotes the number of iteration, and $poly > 1$ is a parameter which shows the polynomial complexity of solving the optimization problem. Compared with a centralized manner, which has the complexity of $O(\|AN\|^{poly})$, the distributed method of our model has a simpler complexity since the number of delegate nodes (about 20-100) is usually large than the iteration (about 10-30).

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