

Reliable Distributed Computing for Metaverse: A Hierarchical Game-Theoretic Approach

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Abstract—The metaverse is regarded as a new wave of technological transformation that provides a virtual space for people to interact through digital avatars. To achieve immersive user experiences in the metaverse, real-time rendering is the key technology. However, computing intensive tasks of real-time rendering from metaverse service providers cannot be processed efficiently on a single resource-limited mobile device. Alternatively, such mobile devices can offload the metaverse rendering tasks to other mobile devices by adopting the collaborative computing paradigm based on Coded Distributed Computing (CDC). Therefore, this paper introduces a hierarchical game-theoretic CDC framework for the metaverse services, especially for vehicular metaverse. In the framework, idle resources from vehicles, acting as CDC workers, are aggregated to handle intensive computation tasks in the vehicular metaverse. Specifically, in the upper layer, a miner coalition formation game is formulated based on a reputation metric to

select reliable workers. To guarantee the reliable management of reputation values, the reputation values calculated based on the subjective logical model are maintained in a blockchain database. In the lower layer, a Stackelberg game based incentive mechanism is considered to attract reliable workers selected in the upper layer to participate in rendering tasks. The simulation results illustrate that the proposed framework is resistant to malicious workers. Compared with the baseline schemes, the proposed scheme can improve the utility of metaverse service provider and average profit of CDC workers.

Index Terms—Blockchain, coalition game, incentive mechanism, metaverse, reliable coded distributed computing, Stackelberg game.

I. INTRODUCTION

A. Background and Motivations

THE blossom of emerging technologies, such as real-time rendering technologies, digital twin, artificial intelligence, 6 G communications and blockchain, has promoted the proliferation of the metaverse [1], [2]. The metaverse was first created in the science fiction named *Snow Crash* [3], which is a stereoscopic virtual space parallel to the physical world. Then, the successful broadcast of the famous film *Ready Player One* raises the public's attention in the metaverse again [4]. To provide immersive experiences for people in the metaverse, real-time rendering technologies (e.g., extended reality and spatial sounding rendering) are considered to be the main interaction interfaces, which might cause a large quantity of computing [5]. Edge computing extends cloud computing to the edge of networks and supports resource-limited mobile devices to offload their tasks to edge servers for processing [6]. However, the number of mobile devices connected to communication networks will increase sharply with the advent of the metaverse, which can cause congestion due to edge servers' limited resources [7]. Besides, the providers may not have dedicated computing resources for the graphic and audio rendering services in the metaverse. Considering that the intensive computation from metaverse services may be unbearable for resource-limited mobile devices [1], distributed collaborative computing has been adopted to solve computing-intensive tasks in the metaverse [8].

For the distributed computing of metaverse services, multiple mobile devices work collaboratively to complete a large-scale rendering task. One of the main challenges of the distributed computing system for metaverse services is the straggler effects. The stragglers refer to the mobile devices whose computing speed is observably slower than average due to their limited

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Fig. 1. An example of CDC in vehicular metaverse.

computing resources or poor communication link, thus causing long latency and bad immersive experience for the metaverse, especially the metaverse interactive services (e.g., online games Minecraft and Roblox). Coded Distributed Computing (CDC) is a promising distributed computing solution to alleviate the straggler effects and guarantee fault-tolerance by aggregating the extra computing resources from mobile devices [9]. CDC introduces computing redundancy to the metaverse by code techniques, and metaverse service providers (MSPs) only need to collect the computing results of rendering tasks from a subset of workers. Thus CDC can significantly reduce the computation latency and improve the data processing reliability, equivalently alleviate the straggler effects. However, there are two critical problems that need to be addressed: i) The mobile devices may be unwilling to participate in metaverse services without a reasonable incentive; ii) Some mobile devices may even misbehave to damage MSPs' benefits, thus resulting in bad user experience. How to select reliable mobile devices and incentivize them to participate in metaverse services are still challenging.

B. CDC use Case in Vehicular Metaverse

The vehicular metaverse integrates extended reality technologies and real-time motion data seamlessly to blend virtual and real space for drivers and passengers in vehicles, which is an emerging in-vehicle entertainment segment for the automotive market. WayRay's Hologractor is striving to create the metaverse vehicle, where passengers and drivers are able to interact with a different reality during the vehicle ride. Fig. 1

shows an example of CDC in the vehicular metaverse. Vehicular metaverse services present the seamless fusion of virtual and real worlds for passengers with Virtual Reality (VR) or Augmented Reality (AR) technologies, which allow passengers to entertain themselves in vehicles. Passengers can see virtual scenes or objects through front windshields and side windows with the help of metaverse Internet of Things (IoT) devices. A large amount of graphic and audio rendering in vehicular metaverse services may cause intensive computation for resource-limited vehicles. Under such conditions, those vehicles can act as MSPs to cooperate with nearby vehicles that act as workers. However, this vehicular metaverse is vulnerable to stragglers due to misbehavior and highly mobile environments, which can make some workers unable to complete computation tasks and return the results successfully. Based on the CDC technique, MSPs can decompose and assign the rendering tasks to workers, and MSPs only need to collect a subset of workers' computing results, which is beneficial for the immersive experience of users in vehicles.

C. Contributions

In this paper, we mainly investigate the use case of CDC in vehicular metaverse, but the proposed scheme is not limited to the vehicular sector. We first adopt reputation metric to assess the reliability of workers in CDC to support vehicular metaverse services, and a stable coalition of reliable workers is formed based on reputation values. Moreover, we apply a hierarchical decision making structure composed of coalition formation and Stackelberg game to design an efficient incentive mechanism for reliable CDC in the vehicular metaverse. Blockchain is used to achieve distributed secure reputation management and to maintain worker participation records in the vehicular metaverse. As blockchain can manage the interactions among entities in the metaverse by a decentralized, tamper-proof and transparent manner [10]. We summarize the contributions of this paper as follows.

- 1) We propose a novel reliable distributed collaborative computing framework for the metaverse based on CDC and blockchain technologies, which can support the immersive user experiences in the metaverse. Especially, we consider the use case in the vehicular metaverse.
- 2) We adopt the reputation values to evaluate the reliability of workers. The miners who form coalitions are responsible for the calculation of workers' reputation values, and the reputation metric is the abstraction and aggregation of multiple factors that affect the quality of coalitions.
- 3) We propose a hierarchical game-theoretic approach to investigate the reliable and sustainable CDC scheme in the vehicular metaverse. In the upper layer, the coalition game is innovatively combined with the reputation metric to choose reliable CDC workers for MSPs. In the lower layer, the Stackelberg game is formulated to motivate the reliable CDC workers to participate in metaverse services.
- 4) Numerical results indicate that the proposed hierarchical game-theoretic scheme is resistant to malicious workers.

The MSP can obtain higher utility and CDC workers can obtain higher profits with the proposed scheme than those of the baseline schemes.

The structure of this paper is shown as follows. Related works about CDC and metaverse services are introduced in Section II. The system model and problem formulations of the proposed reliable CDC scheme for the vehicular metaverse are presented in Section III. The worker selection process based on the reputation model and coalition game is presented in Section IV. Stackelberg game-based incentive mechanism is introduced in Section V. Section VI shows performance evaluation of reliable worker selection and CDC incentive mechanism. Section VII gives the conclusion of this paper.

II. RELATED WORKS

A. Coded Distributed Computing

The research on CDC mainly focuses on mitigating the straggler effects and minimizing the communication cost. Coding theories are the popular methods to solve above issues. In [11], the authors explore the usage of coding theory to alleviate the straggler effect in matrix multiplication and reduce communication bottlenecks in data shuffling. The theoretical analysis proves that the coded schemes can obtain significant gains compared with uncoded schemes. In [12], the authors study the distributed matrix multiplication problem in heterogeneous environments, where a coding framework is designed to accelerate distributed matrix multiplication with straggling devices. In [13], the authors consider that the straggler phenomenon of wireless distributed computing networks is caused by local computation and wireless transmission. In [14], a coded computing framework for federated learning is proposed, which uses structured coding redundancy to alleviate the straggler effects and speed up the training procedure. In [15], the authors design the incentive mechanism for the CDC tasks by formulating a game-theoretic approach. In [16], the authors design platforms' incentive mechanisms to encourage workers' participation in the coded machine learning. However, the existing works ignore the reliability of CDC workers when study CDC, which might negatively impact the performance of CDC. Besides, reliable CDC incentive mechanism for the metaverse has not been studied.

B. Metaverse Services

Metaverse-related research is still in its infancy. There are some works studying the metaverse services in graphic or audio rendering, extended reality technologies etc. In [17], the authors propose a vision of the metaverse native communications that includes encrypted address-based access model and blockchain. In order to realize the audio/visual and virtual/reality congruence in metaverse services, the authors in [18] design the 6-degree-of-freedom interactive audio engines based on objects. In [19], the authors give a comprehensive survey on computational arts that blend virtual and physical environment in the metaverse. The authors in [20] design a brain-to-speech scheme for smart

communication in the real world, which is also presented as a potential application in the metaverse. The authors in [21] propose an operating system for the metaverse based on extended reality, which integrates hardware, computer vision and extended reality specific network. In [22], the authors propose a blockchain-based framework for the metaverse. The sharding scheme is used to improve the scalability of blockchain networks. The above works have not considered the metaverse services in vehicular networks. As metaverse might have a profound impact in the automotive field, a great deal of research needs to be done on the vehicular metaverse, including the distributed computing that is meaningful for the user immersive experience in the vehicular metaverse.

III. SYSTEM MODEL AND PROBLEM FORMULATIONS

A. System Model

The vehicular metaverse mainly includes the virtual world, physical world and interaction layer. Passengers can immerse themselves in the fusion of virtual and real scenarios through the interaction layer. The immersive user experience is a significant part of the interaction layer [4]. To achieve immersive user experiences in the metaverse services (e.g., projecting avatars into passengers' seats or enjoying the virtual attractions through interactive holographic windscreens), high fidelity rendering technologies (e.g., graphic and spatial sound rendering) are adopted to create 3D or holographic digital media, which require intensive matrix computation tasks to be processed by onboard units or devices in vehicles. Those vehicles can choose to execute rendering tasks by collaborating with other vehicles within a limited communication distance. In the metaverse, vehicles that distribute large-scale matrix computation tasks (e.g., projection and shadow mapping in graphic rendering [23]) are called MSPs. The vehicles that execute the computing tasks of metaverse services are called workers. RodeSide Units (RSUs) with sufficient computation and storage resources in vehicular networks act as miners to execute the blockchain consensus algorithm. In addition, miners are motivated to join the reputation calculation, and miners that have contributed to the reliable worker selection will be rewarded by the blockchain (e.g., receiving tokens or obtaining resource rewards).

Fig. 2 shows the whole CDC process in the vehicular metaverse, including the worker selection phase and CDC rendering task execution phase. In the worker selection phase, miners calculate workers' reputation values and form coalitions to select reliable workers for the MSP. Then, the MSP can obtain reliable worker information from the distributed ledger of the blockchain. In the CDC task execution phase, the MSP distributes the rendering tasks to the selected workers. The workers process the computation tasks and transmit the final results to MSPs via OFDMA-based wireless transmission links. Then the MSPs update workers' reputation values and record the updated values on the blockchain. Besides, the miners collect the transaction information for the blockchain and all the resource interaction information (e.g., workers contribute their computing resources to MSPs) between the MSPs and workers

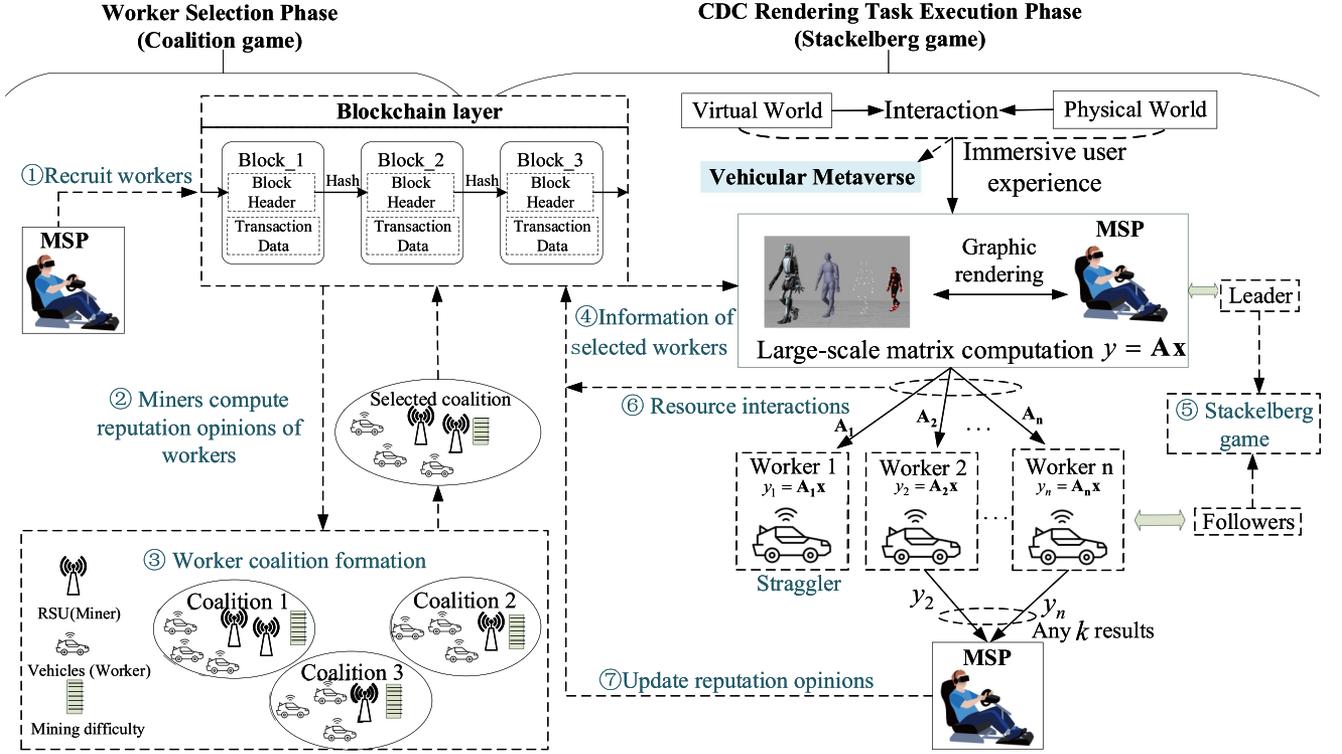


Fig. 2. System model: Worker selection and CDC rendering task execution in vehicular metaverse.

are recorded on the blockchain. The detailed CDC process are given as follows.

Step 1: The MSP sends a transaction to blockchain to recruit workers that are willing to serve for rendering tasks in the vehicular metaverse. The transaction contains the requirements of the MSP, such as the reputation threshold T_{th}^{com} of workers.

Step 2: The workers that are willing to help the MSP with metaverse services send transactions to respond to the MSP. The worker set is denoted as $\mathbb{W} = \{1, 2, \dots, w, \dots, W\}$. In the metaverse, users have many perception dimensions in immersive experience due to computations of graphic rendering and sound generation. Such perception can be qualitative and the subjective logical model is suitable. To select trustable workers, the blockchain needs to obtain the compositive reputation opinions of workers based on the subjective logical model [24]. Miners are stimulated to compute workers' compositive reputation opinions. The set of miners is denoted as $\mathbb{M} = \{1, 2, \dots, m, \dots, M\}$. Miners have no idea about the reliability of workers before they compute reputation values of workers. Each miner randomly selects several workers and computes workers' compositive reputation opinions. The number of workers selected by miner m is denoted as $|\mathbb{W}_m|$. The workers whose compositive reputation opinions are lower than T_{th}^{com} are discarded by miners, and T_{th}^{com} is set based on MSPs' service requirements [24]. We assume that the number of discarded workers is much smaller than those of workers that are not abandoned by miners. The set of workers selected by miner m is denoted as $\mathbb{W}_m = \{\mathcal{W}_{m,1}, \mathcal{W}_{m,2}, \dots, \mathcal{W}_{m,w}, \dots, \mathcal{W}_{m,|\mathbb{W}_m|}\}$, where $\mathcal{W}_{m,w}$ is the identity number of the w -th worker selected by miner m .

Step 3: In order to increase a likelihood to be rewarded by blockchain, miners that obtain workers' compositive reputation opinions form coalitions. The coalition members in each coalition contain miners and their corresponding worker sets. When the coalition is selected by blockchain, the compositive reputation values of workers in the selected coalition will be recorded on blockchain. Another benefit for the coalition formation is that multiple reliable workers evaluated by their reputation can offer larger computational resources to the MSP.

Step 4: The blockchain returns selected workers' information, including the location information and reputation opinions, to the MSP.

Step 5: The MSP distributes the rendering tasks to the selected workers based on Stackelberg game. In the game, the MSP acts as the leader to determine the reward strategy, and workers act as followers to adjust computing speed strategy. Specifically, we consider that MSP P_i needs to render 2D images in RGB color into the needed Field of Views (FoV). The number of pixels is denoted as n_p , and the resolution of the required FoV is $n_p \times n_p$. With the CDC technology, the MSP allocates the rendering task to workers. The Maximum Distance Separable (MDS) code is adopted to alleviate the straggler effects in the distributed computing [9]. The rendering task of MSP P_i is expressed as $y_i = A_i x_i$, and $A_i \in \mathbb{R}^{(3 \times 2 \times n_p) \times n_p}$, where "3" is the number of colors in RGB model, which contains red, green and blue colors, "2" is the number of viewpoints [25]. MSP P_i first divides the rendering matrix A_i into K equal-sized submatrices in $\mathbb{R}^{\frac{(3 \times 2 \times n_p)}{K} \times n_p}$. Then, based on (N, K) MDS code, the MSP gets N encoded submatrices with the same size $\frac{(3 \times 2 \times n_p)}{K} \times n_p$.

Each submatrix is allocated to a worker. MSP P_i can reconstruct the final rendering result when receiving the results from any K ($K < N$) workers, which can mitigate straggler effects.

Step 6: The resource interactions between the MSP and workers are recorded on blockchain. Then, the workers can receive the deserved reward from the MSP.

Step 7: After finishing CDC rendering tasks, the MSP updates the local reputation opinions of workers on blockchain.

In the process of reliable worker selection, the interactions among MSPs, miners and blockchain database might cause unbearable delays for metaverse services. To realize efficient CDC rendering task execution and to enhance immersive vehicular metaverse experience, MSPs can select workers with the help of blockchain before the generation of rendering tasks. Then once MSPs have CDC computing tasks, MSPs can interact with the selected workers directly.

B. Transmission Model

We consider that the CDC rendering task execution mainly contains computing the tasks and transmitting the computing results to the MSP. Here we establish the transmission model that vehicle workers transmit the rendering task computation results to the MSP, where we adopt the orthogonal frequency division multiple access (OFDMA) scheme. MSP P_i uses a set of resource blocks for the wireless transmission, and there is no interference between workers, this assumption is typically to simply the analysis, but the model can still be straightforwardly extended with interference [26]. We also consider the effects of mobility on channel gain between the MSP P_i and workers. To estimate an accurate mobile channel gain, the channel state information of mobile link is broadcast to workers with a period of T_c . The channel states of the wireless mobile links in the previous and current time interval are denoted as g and \hat{g} , respectively. The relationship between g and \hat{g} is $g = \varpi \hat{g} + \kappa$, where $\varpi = J_0(2\pi f_D T_c)$ ($0 < \varpi < 1$) is the channel correlation coefficient. $J_0(\bullet)$ is the zero-order Bessel function. f_D is the maximum Doppler frequency and is expressed as $f_D = |\Delta v| f_c / 3 \times 10^8$. $|\Delta v|$ is the relative vehicle speed between the MSP and workers. f_c is the carrier frequency at 5.9 GHz. κ is the channel discrepancy coefficient that follows $\mathcal{CN}(0, 1 - \varpi^2)$ [27], [28]. Then the channel gain model between MSP P_i and worker w is expressed as

$$\mathcal{H}_{iw} = G_{iw} \left((\varpi_{iw} \hat{g}_{iw})^2 + |\kappa_{iw}|^2 \right), \quad (1)$$

where G_{iw} is the large-scale fading effect between MSP P_i and worker w . The signal-to-noise between MSP P_i and worker w is expressed as

$$\eta_{iw} = \frac{p_w \mathcal{H}_{iw}}{\tilde{\sigma}^2}, \quad (2)$$

where p_w is the transmitting power of worker w , $\tilde{\sigma}^2$ is the variance of the Gaussian noise. The data rate between worker w and MSP P_i is expressed as

$$c_{iw} = B \log_2(1 + \eta_{iw}). \quad (3)$$

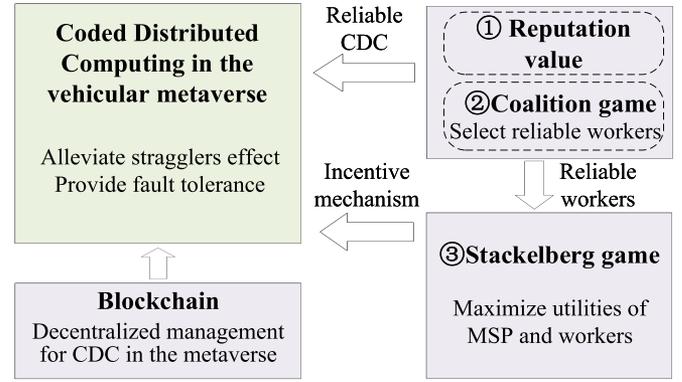


Fig. 3. Hierarchical game-theoretic CDC framework for blockchain assisted vehicular metaverse.

The communication delay of worker w is expressed as

$$T_w^{com-u} = \frac{s_w}{c_{iw}}, \quad (4)$$

where s_w is the packet size of computation results transmitted by worker w .

C. Computation Model

The computation time of each worker follows a 2-parameter shifted exponential distribution [11], [12]. Then, the cumulative distribution function of the time T_w^{cmp} that worker w finishes the rendering task is expressed as

$$\Pr(T_w^{cmp} \leq t) = 1 - e^{-\mu_w \left(\frac{t}{l} - a_w\right)}, \forall t \geq a_w l, \quad (5)$$

where μ_w is the average computation speed of worker w , a_w is the start-up time to begin the rendering task computation, l is the amount of rendering task allocated to each worker, and $l = 3 \times 2 \times n_p / K$. The probability density function of the above distribution is

$$f(t) = \frac{\mu_w}{l} e^{-\mu_w \left(\frac{t}{l} - a_w\right)}. \quad (6)$$

The average computation time for worker w is expressed as

$$\begin{aligned} \mathbb{E}(T_w^{cmp}) &= \int_0^{+\infty} t \frac{\mu_w}{l} e^{-\mu_w \left(\frac{t}{l} - a_w\right)} dt, \\ &= \frac{l e^{a_w \mu_w}}{\mu_w}. \end{aligned} \quad (7)$$

The average rendering task execution time of worker w is expressed as

$$\mathbb{E}(T_w) = \mathbb{E}(T_w^{com-u}) + \mathbb{E}(T_w^{cmp}). \quad (8)$$

D. Hierarchical Game-Theoretic CDC Framework for Vehicular Metaverse

The outline of the proposed hierarchical game is shown in Fig. 3. Blockchain is utilized to achieve the decentralized management for CDC in the vehicular metaverse. In order to realize reliable and sustainable CDC in the vehicular metaverse, we adopt a hierarchical game-theoretic approach based on coalition formation and Stackelberg game. The coalition-Stackelberg

game makes the proposed framework suitable for reliable CDC in the vehicular metaverse. The description of the hierarchical game-theoretic approach is shown as follows:

- 1) Upper layer: In the upper layer, the coalition formation game is adopted to investigate the cooperative interactions among miners that contribute to the computation of workers' compositive reputation values. The miners compute workers' compositive reputation values based on reputation opinions stored on blockchain. Then the miners form coalitions by maximizing the coalition utility that includes workers' compositive reputation values and cost. In order to be selected by blockchain, each miner prefers to form coalitions with other miners to obtain higher coalition utility. Besides, considering the coalition formation cost, the grand coalition may not be stable. This is due to the fact that a high communication overhead discourages all miners to participate and act as a coalition. The coalition with the highest coalition utility will be selected by blockchain, and the workers in the selected coalition will have the chance to join the CDC task execution.
- 2) Lower layer: In the lower layer, the Stackelberg game is used to incentivize workers selected in the upper layer to allocate more computing resource to the MSP's CDC rendering tasks. In the Stackelberg game, the MSP acts as a leader to adjust the reward to workers who finish the computing tasks in time, the workers act as followers to adjust the average computing speed. The strategies of workers also affect their local reputation values updated by the MSP.
- 3) Interactions between upper and lower layers: In the upper layer, the miners that compute workers' compositive reputation values form coalitions. The coalition with the highest coalition utility will be selected by the blockchain, and the workers in the selected coalition will join the Stackelberg game in the lower layer. For the Stackelberg game, the MSP decides reward strategy, and the selected coalitions of workers, which are formed in the upper layer, contribute their computing resources to maximize their utilities. Besides, to increase the probability of being selected in the next round of the coalition formation game, the workers should consider their local reputation values when adjusting the computing resource strategy. The hierarchical game approach ensures that the CDC rendering tasks can be executed by reliable workers and maximize the MSP's utility. Without forming coalitions, the MSP may not be able to identify reliable workers, which may degrade the utility of the MSP. Meanwhile, the selected reliable workers are incentivized to contribute their computing resources to the CDC rendering tasks from vehicular metaverse services.

IV. RELIABLE WORKER SELECTION FOR VEHICULAR METAVERSE

In the worker selection phase, we mainly focus on two problems. The first one is how to obtain the overall reputation

opinions from the interaction histories between MSPs and workers. Subjective logic is a popular tool to model the reliability of entities in the vehicular metaverse, as it quantifies belief, disbelief and uncertainty [29]. Based on the subjective logic model, both direct and indirect reputations from other MSPs are combined to derive reputation opinions of workers. The second problem is how to select reliable workers based on reputation opinions of workers in a distributed way. With the subjective logic model, the reputation calculation of workers may not be efficient for MSPs. On the one hand, MSPs need to process the rendering tasks in time with limited capabilities. On the other hand, if MSPs select reliable workers, MSPs need to search all the local and recommended reputation opinions of workers on the blockchain and compute the workers' compositive reputation opinions, which might be a burden for the MSPs. As miners are trustable entities in blockchain-enabled metaverse systems, the miners are motivated to select reliable workers for the MSPs, and the miners that contribute to the reliable worker selection will be rewarded by blockchain. For the formulated hierarchical game design, the subjective logic model based reputation calculation is used in the upper layer. Each miner in \mathbb{M} selects several workers from \mathbb{W} to compute workers' compositive reputation opinions based on the stored direct reputation opinions and subjective logic model. Then, the miners form coalitions and the miner coalition with the highest coalition utility will be selected by blockchain. In this section, the subjective logic model is introduced, then the miner coalition formation game is formulated.

A. Subjective Logic Model-Based Reputation Calculation

1) *Local Opinions for Subjective Logic*: The MSPs' direct reputation opinions to all workers are recorded on blockchain. MSP P_i sends a transaction to blockchain to recruit workers. Then, the workers that are willing to help MSP P_i send transactions to respond to MSP P_i . Miners compute the workers' compositive reputation opinions by combining the direct reputation opinions updated by MSP P_i , and those updated by other MSPs on blockchain. MSP P_i 's direct reputation opinions are considered to be local reputation opinions, and other MSPs' direct reputation opinions are considered to be recommended reputation opinions.

The local opinion of MSP P_i to worker w in the subjective logic model is expressed as a vector $R_{i \rightarrow w}^{local} = \{b_{i \rightarrow w}^{local}, d_{i \rightarrow w}^{local}, u_{i \rightarrow w}^{local}\}$, where $b_{i \rightarrow w}^{local}$ represents belief, $d_{i \rightarrow w}^{local}$ represents disbelief and $u_{i \rightarrow w}^{local}$ represents uncertainty. Here $b_{i \rightarrow w}^{local}, d_{i \rightarrow w}^{local}, u_{i \rightarrow w}^{local} \in [0, 1]$, and $b_{i \rightarrow w}^{local} + d_{i \rightarrow w}^{local} + u_{i \rightarrow w}^{local} = 1$. Based on the subjective logic model in [30], belief, disbelief and uncertainty expression for reputation opinions can be mapped from the representation of the uncertain probability of events, which can be represented by the beta distribution, and is decided by the number of positive events and negative events. So $b_{i \rightarrow w}^{local}, d_{i \rightarrow w}^{local}$ and $u_{i \rightarrow w}^{local}$ are represented as follows:

$$\begin{cases} b_{i \rightarrow w}^{local} = \frac{\sigma_1 p_{i \rightarrow w}}{\sigma_1 p_{i \rightarrow w} + \sigma_2 q_{i \rightarrow w} + 2}, \\ d_{i \rightarrow w}^{local} = \frac{\sigma_2 q_{i \rightarrow w}}{\sigma_1 p_{i \rightarrow w} + \sigma_2 q_{i \rightarrow w} + 2}, \\ u_{i \rightarrow w}^{local} = \frac{2}{\sigma_1 p_{i \rightarrow w} + \sigma_2 q_{i \rightarrow w} + 2}, \end{cases} \quad (9)$$

where $p_{i \rightarrow w}$ and $q_{i \rightarrow w}$ are the numbers of positive and negative interactions between MSP P_i and worker w , respectively. The MSP regards the resource interaction between itself and a worker as a positive event if the worker is not a straggler in the CDC, and returns the effective computation results that is important for enhancing immersive experience of the vehicular metaverse services (e.g., graph resolution or audio playback resolution). The weights of positive and negative interaction are denoted as σ_1 and σ_2 , respectively, and $0 < \sigma_2 < \sigma_1 < 1$. The local reputation value $T_{i \rightarrow w}^{local}$ is expressed as

$$T_{i \rightarrow w}^{local} = b_{i \rightarrow w}^{local} + \gamma u_{i \rightarrow w}^{local}, \quad (10)$$

where $\gamma \in [0, 1]$ is the effective coefficient of uncertainty on the reputation of worker w .

2) *Recommended Opinions*: Apart from MSP P_i 's local reputation opinions, miners also need to search for selected workers' direct reputation opinions updated by other MSPs on blockchain to obtain the recommended reputation opinions. Suppose that miner m receives a number of \mathfrak{R} recommended opinions of w on blockchain. \mathfrak{R} is also the number of recommenders. For recommender $r \in \mathfrak{R}$, the weight factor ω_r is given as [31]

$$\omega_r = \frac{b_{i \rightarrow r} \times (b_{r \rightarrow w}^{local} + d_{r \rightarrow w}^{local})}{\sum_{r \in \mathfrak{R}} b_{i \rightarrow r} \times (b_{r \rightarrow w}^{local} + d_{r \rightarrow w}^{local})}, \quad (11)$$

where $b_{r \rightarrow w}^{local} + d_{r \rightarrow w}^{local}$ represents the familiarity value between recommender r and worker w . The higher familiarity value means that the recommended opinions of recommender r on worker w is more convincing. $b_{i \rightarrow r}$ is the social tie strength between MSP P_i and the recommender. When MSP P_i and the recommender have the same worker set, we consider that the strength of social ties between MSP P_i and the recommender is strong [32]. The sets of workers that have provided computing services for MSP P_i and recommender r are denoted as $\Gamma(P_i)$ and $\Gamma(r)$, respectively. Then, $b_{i \rightarrow r}$ is expressed as [32]

$$b_{i \rightarrow r} = \frac{|\Gamma(P_i) \cap \Gamma(r)|}{|\Gamma(P_i) \cup \Gamma(r)|}. \quad (12)$$

The overall recommended reputation opinion of w is denoted as $R_{i \rightarrow w}^{rec} = \{b_{i \rightarrow w}^{rec}, d_{i \rightarrow w}^{rec}, u_{i \rightarrow w}^{rec}\}$. The recommended reputation opinion of worker w is the combination of all the recommenders' local opinions with their weight ω_r , $r \in \mathfrak{R}$. $b_{i \rightarrow w}^{rec}$, $d_{i \rightarrow w}^{rec}$ and $u_{i \rightarrow w}^{rec}$ are represented as follows:

$$\begin{cases} b_{i \rightarrow w}^{rec} = \sum_{r \in \mathfrak{R}} \omega_r b_{r \rightarrow w}^{local}, \\ d_{i \rightarrow w}^{rec} = \sum_{r \in \mathfrak{R}} \omega_r d_{r \rightarrow w}^{local}, \\ u_{i \rightarrow w}^{rec} = \sum_{r \in \mathfrak{R}} \omega_r u_{r \rightarrow w}^{local}. \end{cases} \quad (13)$$

3) *Combining Local Opinions With Recommend Opinions*: Based on the local opinion and recommended opinions from other MSPs. Miner m can obtain the final compositive reputation opinion of MSP P_i to worker w . The compositive reputation opinion of MSP P_i to worker w is represented as $R_{i \rightarrow w}^{com} = \{b_{i \rightarrow w}^{com}, d_{i \rightarrow w}^{com}, u_{i \rightarrow w}^{com}\}$. According to [24], $b_{i \rightarrow w}^{com}$, $d_{i \rightarrow w}^{com}$, $u_{i \rightarrow w}^{com}$ are

expressed as follows:

$$\begin{cases} b_{i \rightarrow w}^{com} = \frac{b_{i \rightarrow w}^{local} u_{i \rightarrow w}^{rec} + b_{i \rightarrow w}^{rec} u_{i \rightarrow w}^{local}}{u_{i \rightarrow w}^{local} + u_{i \rightarrow w}^{rec} - u_{i \rightarrow w}^{rec} u_{i \rightarrow w}^{local}}, \\ d_{i \rightarrow w}^{com} = \frac{d_{i \rightarrow w}^{local} u_{i \rightarrow w}^{rec} + d_{i \rightarrow w}^{rec} u_{i \rightarrow w}^{local}}{u_{i \rightarrow w}^{local} + u_{i \rightarrow w}^{rec} - u_{i \rightarrow w}^{rec} u_{i \rightarrow w}^{local}}, \\ u_{i \rightarrow w}^{com} = \frac{u_{i \rightarrow w}^{rec} u_{i \rightarrow w}^{local}}{u_{i \rightarrow w}^{local} + u_{i \rightarrow w}^{rec} - u_{i \rightarrow w}^{rec} u_{i \rightarrow w}^{local}}. \end{cases} \quad (14)$$

The compositive reputation value of MSP P_i to worker w is expressed as

$$T_{i \rightarrow w}^{com} = b_{i \rightarrow w}^{com} + \gamma u_{i \rightarrow w}^{com}. \quad (15)$$

For the initialization of workers' reputation values, the numbers of positive and negative interactions between MSPs and workers are set as 0. Then the initial reputation values of workers can be obtained based on the above model. Based on compositive reputation opinions, MSPs can recruit more workers with high reputation values, promoting the finish of CDC rendering tasks. After finishing a computing task, the MSP updates the selected workers' direct reputation opinions on blockchain.

B. Coalition Formation Game Formulations

In the proposed model, miners cooperate to select reliable workers for vehicular metaverse services. To achieve suitable cooperative strategies for miners, the coalition game theory is used. The combination of coalition game and reputation metric makes the coalition more multi-dimensional from the decision making perspective. The formulated model could be suitable than classical coalition formation game that relies only on a single value of utility, which may not be known precisely in reality. The cooperative worker selection problem among miners is modeled as a coalition formation game with non-transferable utility (NTU), which means that the value or the utility of a coalition cannot randomly be divided between coalition members [33] [34]. Next, we give the definition of coalition partition for the coalition formation game.

Definition 1: A group of mutually disjoint coalitions in \mathbb{M} is represented as $\Pi = \{\mathcal{G}_1, \mathcal{G}_2, \dots, \mathcal{G}_o, \dots, \mathcal{G}_O\}$, where $\mathcal{G}_o \cap \mathcal{G}_{o'} = \phi$ for $o \neq o'$, O is the number of coalitions. If the group covers all the players in \mathbb{M} , i.e., $\cup_{o=1}^O \mathcal{G}_o = \mathbb{M}$, the group is called a coalition partition of \mathbb{M} [35].

The proposed NTU coalition game is modeled as $\mathbb{G} = \{\mathbb{M}, \Pi, u\}$, where \mathbb{M} is the player set made up of miners, Π is a coalition partition of \mathbb{M} , and u is the utility function. The blockchain returns the compositive reputation opinions of the workers in the coalition with the highest utility. We denote the coalition of miners as $\mathcal{G}_o \in \mathbb{M}$, and o is the index of the coalition. The worker set for the coalition \mathcal{G}_o is denoted as $\cup_{m \in \mathcal{G}_o} \mathbb{W}_m$, and the number of workers in $\cup_{m \in \mathcal{G}_o} \mathbb{W}_m$ is denoted as $|\cup_{m \in \mathcal{G}_o} \mathbb{W}_m|$. For the calculation of workers' reputation opinions, the contribution value of the coalition \mathcal{G}_o is expressed as

$$Q(\mathcal{G}_o) = \rho_c \frac{|\cup_{m \in \mathcal{G}_o} \mathbb{W}_m|}{W} + \rho_r \frac{\sum_{m \in \mathcal{G}_o} \sum_{w=1}^{|\mathbb{W}_m|} T_{i \rightarrow w}^{com}}{|\cup_{m \in \mathcal{G}_o} \mathbb{W}_m|}, \quad (16)$$

where $|\cup_{m \in \mathcal{G}_o} \mathbb{W}_m|/W$ is the percent of workers that the coalition \mathcal{G}_o has computed, and the second term $\sum_{m \in \mathcal{G}_o} \sum_{w=1}^{|\mathbb{W}_m|} T_{i \rightarrow w}^{com}/|\cup_{m \in \mathcal{G}_o} \mathbb{W}_m|$ is the average reputation

values of workers in the coalition \mathcal{G}_o . ρ_c and ρ_r are the coefficients that maintain the importance of the above two parts on the contribution value.

The communication cost among miners increases with the growth of the number of miners in the coalition, because forming a miner coalition requires negotiation and information exchange that may bring the cost and reduce the gains from forming the coalition [36]. For the coalition \mathcal{G}_o , the communication cost $\mathcal{C}(\mathcal{G}_o)$ should reflect the negotiation and information exchange overhead, which are determined by the number of miners in the coalition \mathcal{G}_o . The communication cost $\mathcal{C}(\mathcal{G}_o)$ should satisfy the following requirements. Firstly, the communication cost $\mathcal{C}(\mathcal{G}_o)$ increases monotonically with respect to $|\mathbb{M}_o|$ that is the number of miners in the coalition \mathcal{G}_o . Secondly, the slope of $\mathcal{C}(\mathcal{G}_o)$ becomes steeper with the increase of $|\mathbb{M}_o|$. To satisfy above requirements, the logarithmic barrier penalty function is adopted to model the coalition cost [37]. The communication cost $\mathcal{C}(\mathcal{G}_o)$ is expressed as

$$\mathcal{C}(\mathcal{G}_o) = \begin{cases} -\log \left(1 - \left(\frac{|\mathbb{M}_o| - \delta}{M} \right)^2 \right), & \text{if } |\mathbb{M}_o| \geq 2, \\ 0, & \text{otherwise,} \end{cases} \quad (17)$$

where δ is used to avoid an infinite value of $\mathcal{C}(\mathcal{G}_o)$ when $|\mathbb{M}_o| = M$, and $\delta = 0.1$ [37]. Then, the coalition utility of the coalition \mathcal{G}_o is expressed as

$$u(\mathcal{G}_o) = Q(\mathcal{G}_o) - \delta \mathcal{C}(\mathcal{G}_o), \quad (18)$$

where δ is the communication cost coefficient.

For the coalition \mathcal{G}_o , whether the miners in \mathcal{G}_o can be rewarded by blockchain depends on the coalition utility $u(\mathcal{G}_o)$. We notice that, in the proposed coalition game, the coalition utility $u(\mathcal{G}_o)$ is not divisible among the miners, and the utility of each miner in the coalition \mathcal{G}_o is equal to $u(\mathcal{G}_o)$, instead of a fraction of $u(\mathcal{G}_o)$. Hence, the proposed coalition formation game has non-transferable utility. Each miner can choose the suitable coalition based on the received utility. The definition of preference order is given as follows.

Definition 2: A preference operator \triangleright is adopted to compare $\Pi_1 = \{\mathcal{G}_1^1, \dots, \mathcal{G}_O^1\}$ and $\Pi_2 = \{\mathcal{G}_1^2, \dots, \mathcal{G}_O^2\}$ that are partitions of the same subset $\mathbb{A} \subseteq \mathbb{M}$ (i.e., the players in Π_1 and Π_2 are the same). Then, $\Pi_1 \triangleright \Pi_2$ implies that partition Π_1 is better than partition Π_2 for subset \mathbb{A} [38].

Different orders can be adopted to compare relationships between partitions. We adopt Pareto order in this paper to compare the preference relation between two partitions.

Definition 3: For the two partitions $\Pi_1 = \{\mathcal{G}_1^1, \dots, \mathcal{G}_O^1\}$ and $\Pi_2 = \{\mathcal{G}_1^2, \dots, \mathcal{G}_O^2\}$, the utility of miner m in the partition $\Pi_1 = \{\mathcal{G}_1^1, \dots, \mathcal{G}_O^1\}$ and $\Pi_2 = \{\mathcal{G}_1^2, \dots, \mathcal{G}_O^2\}$ are denoted as $u_m(\Pi_1)$ and $u_m(\Pi_2)$, respectively. The partition Π_1 is better than Π_2 by the Pareto order, which is denoted as $\Pi_1 \triangleright \Pi_2$, if and only if

$$u_m(\Pi_1) \geq u_m(\Pi_2) \quad \forall m \subseteq \Pi_1, \Pi_2, \quad (19)$$

with at least one strict inequality ($>$) for a miner m .

A coalition formation algorithm based on the simple rules of merge and split is proposed by using the Pareto order. The coalition formation process usually needs to execute many rounds, and all the coalitions are involved in each round to make sure

Algorithm 1: Coalition formation algorithm for miners in the proposed model:

Input: Player set $\mathbb{M} = \{1, 2, \dots, m, \dots, M\}$. Workers selected by miners $W_m = \{\mathcal{W}_{m,1}, \mathcal{W}_{m,2}, \dots, \mathcal{W}_{m,|W_m|}\}$, $1 \leq m \leq M$;

Output: The coalition with the highest coalition utility;

- 1: Initialization: The initial partition of miners Π_0 , where all the miners are disjoint. Each miner selects several workers and computes selected workers' compositive reputation value;
 - 2: Each coalition computes coalition utility according to utility function (18);
 - 3: Merge mechanism: The Coalition \mathcal{G}_o tries to merge with \mathcal{G}_o' based on the merge rule;
 - 4: Split mechanism: The Coalition \mathcal{G}_o tries to split with \mathcal{G}_o' based on the split rule;
 - 5: Until: Merge and split iteration terminates, and the final coalition partition is obtained;
 - 6: Return: The coalition with the highest coalition utility.
-

that the utilities of coalitions increase or remain stable. The rules of merge and split are given as follows [39]:

- 1) Merge Rule: For any set of coalitions $\{\mathcal{G}_1, \dots, \mathcal{G}_o, \dots, \mathcal{G}_O\}$, where $\{\cup_{o=1}^O \mathcal{G}_o\} \triangleright \{\mathcal{G}_1, \dots, \mathcal{G}_o, \dots, \mathcal{G}_O\}$, merge $\{\mathcal{G}_1, \dots, \mathcal{G}_o, \dots, \mathcal{G}_O\}$ into $\{\cup_{o=1}^L \mathcal{G}_o\}$, which is denoted as $\{\mathcal{G}_1, \dots, \mathcal{G}_o, \dots, \mathcal{G}_O\} \rightarrow \{\cup_{o=1}^O \mathcal{G}_o\}$.
- 2) Split Rule: For any coalitions $\cup_{o=1}^O \mathcal{G}_o$, where $\{\mathcal{G}_1, \dots, \mathcal{G}_o, \dots, \mathcal{G}_O\} \triangleright \{\cup_{o=1}^O \mathcal{G}_o\}$, split $\{\cup_{o=1}^O \mathcal{G}_o\}$ into $\{\mathcal{G}_1, \dots, \mathcal{G}_o, \dots, \mathcal{G}_O\}$, which is denoted as $\{\cup_{o=1}^O \mathcal{G}_o\} \rightarrow \{\mathcal{G}_1, \dots, \mathcal{G}_o, \dots, \mathcal{G}_O\}$.

The coalitions will merge or split if these actions yield a preferred collection according to the pareto order. By using the Pareto order, a coalition will split only if the split operation makes at least one miner's utility improved without decreasing other miners' utilities. Similarly, the coalitions will merge only if at least one miner's utility can be increased without hurting other miners' utilities. With merge-and-split rules, a stable coalition partition can be obtained, as any coalition formation algorithm designed with the merge-and-split rules always converges [35]. Algorithm 1 is the coalition formation algorithm for miners. In Algorithm 1, the complexity mainly depends on the merge-and-split process. In the worst case, the total number of merge operations is $O(M^3)$. In practical systems, a large coalition is formed after the first merge, so the merge operation requires a lower number of operations. For the worst case of the split process, the total number of split operations is given by the Bellman number, which increases exponentially with the number of miners in the coalition. The split operation is only performed over each miner coalition, reducing the complexity of split operations. In summary, the complexity of the merge-and-split process is affordable for the practical miner coalition systems.

For the designed coalition formation game \mathbb{G} , the grand coalition of all the miners seldom forms due to the communication cost. Besides, the participation of miners that obtain the low

reputation values of workers may degrade the coalition utility, which also prevents the grand coalition formation. Next, we use the defection function \mathbb{D}_{hp} to analyze the stability of the final coalition partition.

Definition 4: A partition $\Pi = \{\mathcal{G}_1, \mathcal{G}_2, \dots, \mathcal{G}_o, \dots, \mathcal{G}_O\}$ is stable if no coalition \mathcal{G}_o is incentivized to change the current partition Π by joining another coalition $\mathcal{G}_{o'}$, where $\mathcal{G}_o \cap \mathcal{G}_{o'} = \phi$, for $o \neq o'$, or trying to split into smaller disjoint coalitions [35].

Definition 5: A partition of coalitions $\Pi = \{\mathcal{G}_1, \mathcal{G}_2, \dots, \mathcal{G}_o, \dots, \mathcal{G}_O\}$ is \mathbb{D}_{hp} -stable if it meets the following two conditions:

- 1) For $o \in \{1, \dots, O\}$ and each partition $\{R_1, \dots, R_p\}$ of coalition \mathcal{G}_o , we have $\{R_1, \dots, R_p\} \not\triangleright \mathcal{G}_o$;
- 2) For $S \in \{1, \dots, O\}$, we have $\bigcup_{o \in S} \mathcal{G}_o \not\triangleright \{\mathcal{G}_o \mid o \in S\}$, where $\not\triangleright$ is the opposite rule of \triangleright .

Theorem 1: The coalition partition under the proposed scheme is \mathbb{D}_{hp} -stable.

Proof: We first consider Condition 1. $\Pi = \{\mathcal{G}_1, \mathcal{G}_2, \dots, \mathcal{G}_o, \dots, \mathcal{G}_O\}$ is the final partition obtained from the coalition formation algorithm. If for $o \in \{1, \dots, O\}$ and any partition $\{R_1, \dots, R_p\}$ of \mathcal{G}_o , there is $\{R_1, \dots, R_p\} \triangleright \mathcal{G}_o$, then the partition \mathcal{G}_o will split, which is in contradiction with the fact that Π is the stable partition resulting from the merge-and-split iteration. For Condition 2, we still consider the same final coalition set $\Pi = \{\mathcal{G}_1, \mathcal{G}_2, \dots, \mathcal{G}_o, \dots, \mathcal{G}_O\}$. If for each $S \in \{1, \dots, O\}$, there has $\bigcup_{o \in S} \mathcal{G}_o \not\triangleright \{\mathcal{G}_o \mid o \in S\}$, then the partition Π can be modified through the merge rule, which is also in contradiction with the fact that Π is the stable partition. Thus, the coalition partition under the proposed scheme is \mathbb{D}_{hp} -stable.

V. STACKELBERG GAME-BASED INCENTIVE MECHANISM FOR VEHICULAR METAVERSE

After the worker selection phase, MSP P_i obtains the information of workers in the selected coalition \mathcal{G}_o . MSP P_i selects N workers from the coalition \mathcal{G}_o based on workers' reputation opinions. The set of selected workers is denoted as $\mathbb{W}_{\text{sel}} = \{1, 2, \dots, w, \dots, N\}$, and $\mathbb{W}_{\text{sel}} \subseteq \mathcal{G}_o$. In the CDC rendering task execution phase shown in Fig. 2, MSP P_i divides the matrix A_i into K equal-sized submatrices $\mathbb{R}^{\frac{(3 \times 2 \times n_p)}{K} \times n_p}$, and then MSP P_i has N encoded submatrices with the same size $\frac{(3 \times 2 \times n_p)}{K} \times n_p$ based on the (N, K) MDS code. Each submatrix is allocated to a worker. The distributed computing resource interactions between P_i and workers is modeled as a single-leader multi-followers Stackelberg game. In the leader game, the MSP selects an optimal computation reward to motivate workers to execute CDC rendering tasks in the vehicular metaverse. In the follower game, workers try to obtain higher profit by adjusting their computing speed. The Stackelberg game model can be extended to multiple MSPs with two approaches. The first one is that MSPs make decisions on incentive independently and they do not affect each other as MSPs may use different applications. The second one is that MSPs can compete with each other and this forms a Nash game which can be investigated in the future work.

A. Profit Function of Workers

We consider that the CDC rendering task execution mainly contains computing the task and transmitting the computation result to MSP P_i . In the following, the profit function of workers is studied.

In order to incentivize workers to join the CDC rendering task actively, the MSP P_i gives the reward to workers that contribute to vehicular metaverse services. The reward contains two kinds, i.e., base reward $\mathcal{R}_{\text{base}}$ and competition reward \mathcal{R}_{com} . The workers who participate in the CDC rendering task can receive the reward $\mathcal{R}_{\text{base}}$. The workers whose average task execution time is no more than the average task execution time of the K -th worker can receive the reward \mathcal{R}_{com} . Similar to the analysis in [40], we assume that the task execution time of workers follows a uniform distribution, where $\frac{T_w}{T_{\text{max}}} \in (0, 1)$, and T_{max} is the maximum value of the task execution time. The normalized task execution time of workers are ranked and represented by its order statistics, which are expressed as $T_{1,N}, T_{2,N}, \dots, T_{N,N}$. $T_{K,N}$ is the K -th highest execution time among N workers. The cumulative distribution function of the normalized task execution time is $F(T) = T$. The probability density function of the normalized task execution time is $f(T) = 1$. Based on the order statistics, the probability density function of $T_{k,N}$ is given as

$$f_{(k)}(T) = N f(T) \binom{N-1}{k-1} F(T)^{k-1} (1-F(T))^{N-k}, \quad (20)$$

which is also a beta distribution $Beta(k, N-k+1)$. Hence, the expectation of $T_{K,N}$ is given as

$$\mathbb{E}(T_{K,N}) = \frac{K}{N+1}. \quad (21)$$

The workers adopt the dynamic voltage scaling technology that allows workers to adaptively adjust and control the computing speed. Each selected worker tries to obtain a higher profit. The profit function of the worker w is expressed as

$$u_w = \mathcal{R}_{\text{base}} + \mathcal{P}_w \mathcal{R}_{\text{com}} - \varepsilon \mu_w \mathbb{E}(T_w^{\text{cmp}}) - \zeta \mathbb{E}(T_w^{\text{com}-u}), \quad (22)$$

where ε is the computing cost of the worker per CPU circle, and ζ is the communication cost of the worker per unit of communication time. \mathcal{P}_w is the probability of worker w getting the reward from MSP P_i . \mathcal{P}_w is expressed as

$$\begin{aligned} \mathcal{P}_w &= 1 - e^{-\mu_w \left(\frac{\mathbb{E}(T_{K,N}) \times T_{\text{max}} - \mathbb{E}(T_{K,N}^{\text{com}-u})}{l} - a_w \right)}, \\ &= 1 - e^{-\mu_w A_w}, \end{aligned} \quad (23)$$

where $\mathbb{E}(T_{K,N}^{\text{com}-u})$ is the average communication delay of the K -th worker, and $A_w = \frac{\mathbb{E}(T_{K,N}) \times T_{\text{max}} - \mathbb{E}(T_{K,N}^{\text{com}-u})}{l} - a_w$. Here, worker w selects the optimal computing speed μ_w that maximizes u_w .

B. Utility Function of Metaverse Service Provider

To motivate workers to contribute more to the CDC rendering tasks, MSP P_i should adjust the reward \mathcal{R}_{com} to maximize

its utility. The selected workers contribute their computing resources to MSP P_i . The utility that MSP P_i can gain depends on the computing resource that workers contribute, the reputation values of workers, and the reward paid to the workers. The utility function of MSP P_i is expressed as

$$u_{P_i} = \nu \sum_{w=1}^N f(\mu_w) h(T_{i \rightarrow w}^{com}) - N\mathcal{R}_{base} - \sum_{w=1}^N \mathcal{P}_w \mathcal{R}_{com}, \quad (24)$$

where ν is a weight parameter, and $f(\mu_w) = \log(1 + \mu_w)$, which is the utility of MSP P_i gained from the workers' computation contribution. The log of $f(\cdot)$ reflects MSP P_i 's diminishing return on the computation speed of each selected worker [41]. $h(\cdot)$ is the reputation utility of workers and is expressed as [42]

$$h(T_{i \rightarrow w}^{com}) = \alpha + (1 - \alpha) \log \left(1 + \frac{(e - 1)(T_{i \rightarrow w}^{com} - T_{th}^{com})}{T_{max}^{com} - T_{th}^{com}} \right), \quad (25)$$

where α is the default reputation utility for the worker with $T_{i \rightarrow w}^{com} = T_{th}^{com}$, T_{th}^{com} is the reputation threshold required by the MSP. T_{max}^{com} is the maximum reputation value.

C. Stackelberg Game-Based Incentive Mechanism

The interactions between the MSP and workers is formulated as a single-leader multi-followers Stackelberg game. In the leader game, the MSP sets the optimal computation reward to motivate workers to execute CDC rendering tasks. In the follower game, the coalition of workers adjust the computation speed to maximize their profits. The strategy optimization problems for the MSP and workers are formulated as follows.

- 1) Workers' computing speed strategies in Stage II: In Stage II, based on the reward strategy of the MSP, worker w ($w \in \mathbb{W}_{sel}$) determines its computation speed μ_w to maximize the profit that is given as

$$u_w(\mu_w; \mathcal{R}_{com}) = \mathcal{R}_{base} + \mathcal{P}_w(\mu_w) \mathcal{R}_{com} - \varepsilon \mu_w \mathbb{E}(T_w^{cmp}) - \zeta \mathbb{E}(T^{com-u}). \quad (26)$$

The set of workers' computing speed is $\boldsymbol{\mu} = \{\mu_1, \dots, \mu_w, \dots, \mu_N\}$, which are used to derive the computation delay of workers based on (7). The worker subgame problem is expressed as follows.

Problem 1 (Worker w Subgame):

$$\begin{aligned} & \underset{\mu_w}{\text{maximize}} && u_{w, w \in \mathbb{W}_{sel}}(\mu_w; \mathcal{R}_{com}) \\ & \text{subject to} && \underline{\mu} \leq \mu_w \leq \bar{\mu}, \end{aligned} \quad (27)$$

where $\underline{\mu}$ is the minimum computation speed, and $\bar{\mu}$ is the maximum computation speed.

- 2) MSP's reward strategy in Stage I: In Stage I, according to workers' computation speed strategies $\boldsymbol{\mu}$, the MSP determines the reward strategy to maximize its utility that is expressed as

$$u_{P_i}(\mathcal{R}_{com}; \boldsymbol{\mu}) = \nu \sum_{w=1}^N f(\mu_w) h(T_{i \rightarrow w}^{com}) - N\mathcal{R}_{base}$$

$$- \sum_{w=1}^N \mathcal{P}_w \mathcal{R}_{com}. \quad (28)$$

The MSP subgame problem is expressed as follows.

Problem 2 (MSP P_i Subgame):

$$\begin{aligned} & \underset{\mathcal{R}_{com}}{\text{maximize}} && u_{P_i}(\mathcal{R}_{com}; \boldsymbol{\mu}) \\ & \text{subject to} && \underline{\mathcal{R}}_{com} \leq \mathcal{R}_{com} \leq \bar{\mathcal{R}}_{com}, \end{aligned} \quad (29)$$

where $\underline{\mathcal{R}}_{com}$ is the minimum computation reward, $\bar{\mathcal{R}}_{com}$ is the maximum computation reward.

The Stackelberg game is formulated by combining Problem 1 and Problem 2, and the goal of the Stackelberg game is to find the Nash equilibrium solution.

D. Game Equilibrium Analysis

The Stackelberg equilibrium makes sure that the utility of the MSP is maximized considering that the workers make computing strategies based on the best response. This means that the computing speed strategy of each worker maximize its profit given the strategies of the other workers and the computing reward given by the MSP. The Stackelberg equilibrium is expressed as follows.

Definition 6: We denote $\boldsymbol{\mu}^*$ and \mathcal{R}_{com}^* as the optimal computation speed of all the selected workers and optimal computation reward given by the MSP, respectively. Then, the strategy $(\boldsymbol{\mu}^*, \mathcal{R}_{com}^*)$ is the Stackelberg equilibrium if we have

$$u_{P_i}(\mathcal{R}_{com}^*; \boldsymbol{\mu}^*) \geq u_{P_i}(\mathcal{R}_{com}; \boldsymbol{\mu}^*), \quad (30)$$

$$u_w(\boldsymbol{\mu}_w^*; \boldsymbol{\mu}_{-w}^*, \mathcal{R}_{com}^*) \geq u_w(\mu_w; \boldsymbol{\mu}_{-w}^*, \mathcal{R}_{com}^*), \forall w \in \mathbb{W}_{sel}. \quad (31)$$

The backward induction is adopted to analyze the Stackelberg game.

1) *Workers' Optimal Strategies as Equilibrium in Stage II:* Based on the reward strategy \mathcal{R}_{com} given by the MSP, the workers determine the optimal computation speed strategy for profit maximization in Stage II.

Theorem 2: The sub-game perfect equilibrium in the workers' subgame is unique.

Proof: We give the first-order and second-order derivatives of the profit function of workers $u_w(\cdot)$ with respect to worker's strategy μ_w . The first-order derivative of $u_w(\cdot)$ is shown as

$$\frac{\partial u_w}{\partial \mu_w} = \mathcal{R}_{com} A_w e^{-\mu_w A_w} - \varepsilon l a_w e^{a_w \mu_w}. \quad (32)$$

The second derivative of $u_w(\cdot)$ is shown as

$$\frac{\partial^2 u_w}{\partial \mu_w^2} = - (A_w^2 e^{-\mu_w A_w} \mathcal{R}_{com} + \varepsilon l a_w^2 e^{a_w \mu_w}) < 0. \quad (33)$$

As the second-order derivative of $u_w(\cdot)$ is negative, so the profit function $u_w(\cdot)$ is strictly concave with respect to worker's computing speed strategy μ_w . Besides, based on the first-order derivative condition, there is

$$\frac{\partial u_w}{\partial \mu_w} = \mathcal{R}_{com} A_w e^{-\mu_w A_w} - \varepsilon l a_w e^{a_w \mu_w} = 0. \quad (34)$$

Then, the best response function of the worker w , i.e., μ_w^* , is shown as

$$\mu_w^* = \frac{1}{a_w + A_w} \log \left[\frac{\mathcal{R}_{com} A_w}{\varepsilon l a_w} \right]. \quad (35)$$

Algorithm 2: Bisection-based algorithm to find Stackelberg equilibrium.

Input: Minimum computation reward $\underline{\mathcal{R}}_{com}$, maximum computation reward $\overline{\mathcal{R}}_{com}$, error Ξ ;
Output: Optimal reward strategy of the MSP \mathcal{R}_{com}^* and optimal computing speed of workers μ^* ;
1: MSP find the optimal reward strategy based on the following steps;
2: **while** $\partial u_{P_i}/\partial \underline{\mathcal{R}}_{com} \times \partial u_{P_i}/\partial \overline{\mathcal{R}}_{com} < 0$ **do**
3: $\mathcal{R}_{com} = 0.5 \times (\underline{\mathcal{R}}_{com} + \overline{\mathcal{R}}_{com})$;
4: **if** $\partial u_{P_i}/\partial \underline{\mathcal{R}}_{com} \times \partial u_{P_i}/\partial \overline{\mathcal{R}}_{com} < 0$ **then**
5: $\overline{\mathcal{R}}_{com} = \mathcal{R}_{com}$;
6: **else**
7: $\underline{\mathcal{R}}_{com} = \mathcal{R}_{com}$;
8: **end if**
9: **if** $|\overline{\mathcal{R}}_{com} - \underline{\mathcal{R}}_{com}| < \Xi$ **then**
10: **break**;
11: **end if**
12: **end while**
13: $\mathcal{R}_{com}^* = 0.5 \times (\overline{\mathcal{R}}_{com} + \underline{\mathcal{R}}_{com})$;
14: Each worker w decides its computing speed strategy μ_w based on (35);
15: Return: Optimal reward strategy of the MSP \mathcal{R}_{com}^* and optimal computing speed of workers μ^* .

TABLE I
PARAMETER SETTINGS

Parameter	Value
Number of workers W and miners M	100, 20
Weight of positive and negative events σ_1, σ_2	0.6, 0.4
Packet size s^u	400B
Bandwidth assigned to workers B	10MHz
Pathloss exponent	3
Log-normal shadowing standard deviation	3dB
Variance of the Gaussian noise $\tilde{\sigma}^2$	-30dBm
Maximum transmitting power of workers p	5w
Feedback period of mobile devices T_c	0.1ms
Threshold of reputation value T_{th}^{com}	0.6
Workers' computation cost per CPU circle ε	0.1
Workers' communication cost per unit time ζ	10
Default parameters ν	10
Maximum relative speed between MSP and workers	15m/s

$E_w A_w = \frac{A_w}{a_w + A_w} = \frac{1}{\frac{a_w}{A_w} + 1} < 1$, the second-order derivative of

the MSP's utility function always satisfies $\frac{\partial^2 u_{P_i}}{\partial \mathcal{R}_{com}^2} < 0$, which indicates that u_{P_i} is a concave function. Thus, the MSP has a unique optimal solution that can be efficiently obtained by bisection method [44]. Based on the optimal strategy of the MSP, the workers' optimal strategies can be obtained. Then, the Stackelberg equilibrium can be obtained in the proposed model. The MSP can achieve optimal utility and workers can obtain optimal profit, and neither of them would alter their strategies to gain higher benefits.

We design Algorithm 2 to obtain the unique Stackelberg equilibrium for the proposed game. In algorithm 2, the MSP first searches the optimal reward strategy, and the complexity is $O(\log_2(\overline{\mathcal{R}}_{com} - \underline{\mathcal{R}}_{com}))$. Then, each worker needs to decide its optimal computing speed strategy, the complexity is $O(N)$. So the algorithm complexity is $O(N) + O(\log_2(\overline{\mathcal{R}}_{com} - \underline{\mathcal{R}}_{com}))$. Stackelberg equilibrium is utilized to prove the stability of the Stackelberg game. The definition of Stackelberg equilibrium is given in Definition 6. For the follower subgame, the optimal computing strategy of CDC workers is calculated by closed-form expressions, so the computing strategy μ^* is always optimal and the condition $u_w(\mu_w^*; \mu_{-w}^*, R_{com}^*) \geq u_w(\mu_w; \mu_{-w}^*, R_{com}^*)$ always holds. For the leader subgame, the bisection algorithm is employed to obtain the reward solution of the MSP, which is optimal and always satisfies $u_{P_i}(R_{com}^*; \mu^*) \geq u_{P_i}(R_{com}; \mu^*)$. Hence, the proposed Stackelberg game is stable [45].

VI. PERFORMANCE ANALYSIS

In this section, we give the numerical results of the coalition game-based worker selection and stackelberg game-based incentive mechanism for reliable CDC in the vehicular metaverse. The parameter values are given in Table I [14] [27].

A. Numerical Results for Reliable Worker Selection

For the reputation calculation scheme, we consider an unreliable worker that performs well to all MSPs to increase its reputation value to 0.8 at first, and keeps such reputation value for a certain period of time. Then, the unreliable worker keeps performing well to several specific MSPs, but misbehaves to other MSPs

We denote $E_w = \frac{1}{a_w + A_w}$ and $F_w = \frac{A_w}{\varepsilon l a_w}$. The sub-game perfect equilibrium of the workers' subgame is unique [43].

$$u_{P_i}(\mathcal{R}_{com}; \mu) = U(\mu_1^*, \dots, \mu_w^*, \dots, \mu_N^*) - N \mathcal{R}_{base} - \sum_{w=1}^N \left[1 - (F_w \mathcal{R}_{com})^{-E_w A_w} \right] \mathcal{R}_{com}. \quad (36)$$

$$\frac{\partial u_{P_i}}{\partial \mathcal{R}_{com}} = \frac{\partial U(\mu_1^*, \dots, \mu_w^*, \dots, \mu_N^*)}{\partial \mathcal{R}_{com}} - \sum_{w=1}^N \left[1 + (E_w A_w - 1) (F_w \mathcal{R}_{com})^{-E_w A_w} \right]. \quad (37)$$

$$\frac{\partial^2 u_{P_i}}{\partial \mathcal{R}_{com}^2} = \frac{\partial^2 U(\mu_1^*, \dots, \mu_w^*, \dots, \mu_N^*)}{\partial \mathcal{R}_{com}^2} - \sum_{w=1}^N \left[-E_w A_w F_w (E_w A_w - 1) (F_w \mathcal{R}_{com})^{-E_w A_w - 1} \right]. \quad (38)$$

2) *MSP's Optimal Reward Strategy in Stage I:* Based on the optimal computing speed strategies of workers, the MSP acts as the leader to optimize its utility in Stage I.

Theorem 3: The uniqueness of the proposed Stackelberg game's equilibrium can be guaranteed.

Proof: The utility function of the MSP can be transformed into (36), and $U(\mu_1^*, \mu_2^*, \dots, \mu_w^*, \dots, \mu_N^*) = \nu \sum_{w=1}^N f(\mu_w^*) h(T_{i \rightarrow w}^{com})$. The first-order derivative of the MSP's utility function is shown in (37). The second-order derivative of the MSP's utility function is shown in (38). As $\frac{\partial^2 U(\cdot)}{\partial \mathcal{R}_{com}^2} < 0$, when $E_w A_w < 1$, there is $\frac{\partial^2 u_{P_i}}{\partial \mathcal{R}_{com}^2} < 0$. Because

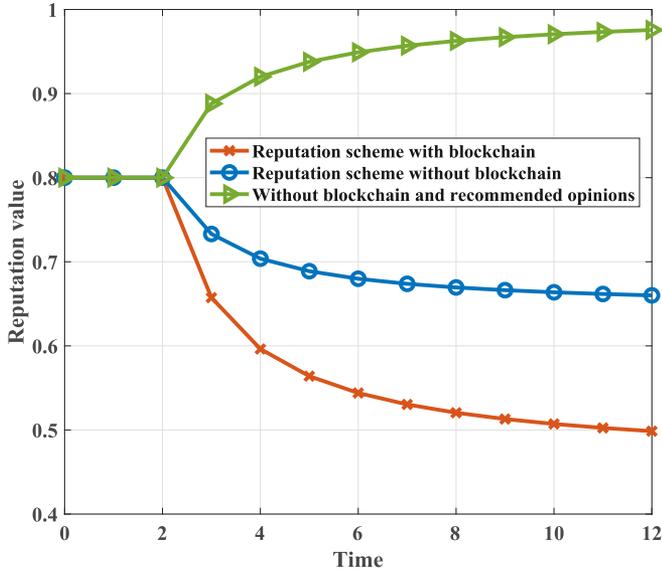


Fig. 4. Reputation values variation of an unreliable worker.

with the probability of 90%. The proposed blockchain-enabled reputation scheme is compared with the reputation scheme without blockchain, and the reputation scheme without blockchain and recommended opinions. For the reputation scheme without blockchain, such as the reputation scheme in [46], workers’ reputation values are all stored in centralized platforms in which unreliable workers’ negative interaction behaviors are manipulated into positive interaction behaviors with the probability of 25%. For the reputation scheme without blockchain and recommended opinions, workers’ reputation values only depend on MSPs’ local reputation opinions. Fig. 4 shows the reputation values variation of an unreliable worker over time, and the unit of time is minute. From Fig. 4, when the unreliable worker begins to misbehave, the reputation value significantly decreases with the proposed blockchain-enabled reputation scheme. For the reputation scheme without blockchain, the reputation value decreases more slowly than that of the reputation scheme with blockchain. As the centralized platform manipulate the unreliable workers’ negative interactions into positive interactions, which increases the unreliable worker’s reputation value. For the reputation scheme without the blockchain and recommended opinions, the reputation value of unreliable worker still increases. Because the unreliable worker may only act honestly for a specific MSP and act maliciously for other MSPs, and the specific MSP computes the unreliable worker’s reputation value based on the local observation that does not contain the misbehavior of the unreliable worker.

Next, we analyze the coalition formation game. We set the number of positive and negative interaction events as $[0, 120]$, and $[0, 40]$, respectively. Then compositive reputation values of workers are calculated by miners based on the subjective logical model. Fig. 5 shows the average reputation value of the selected workers as a function of the misbehavior ratio. Misbehavior ratio is the percentage of workers with negative interactions toward MSPs to the total number of workers. From Fig. 5, compared

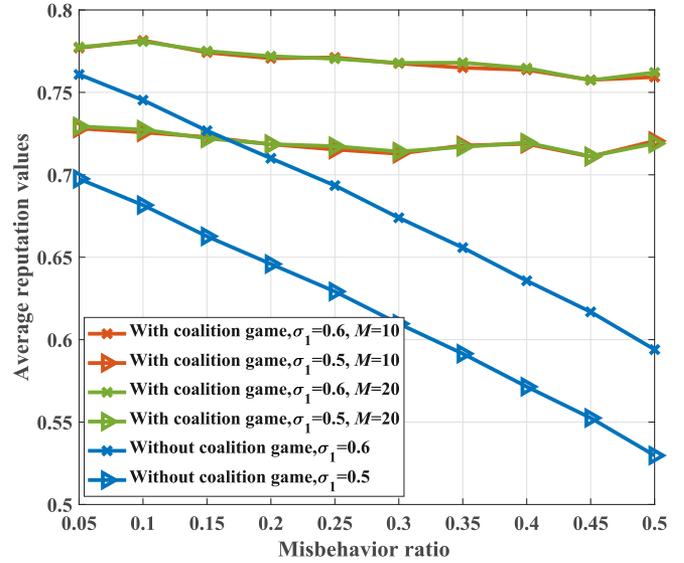


Fig. 5. Average reputation values as function of misbehavior ratio.

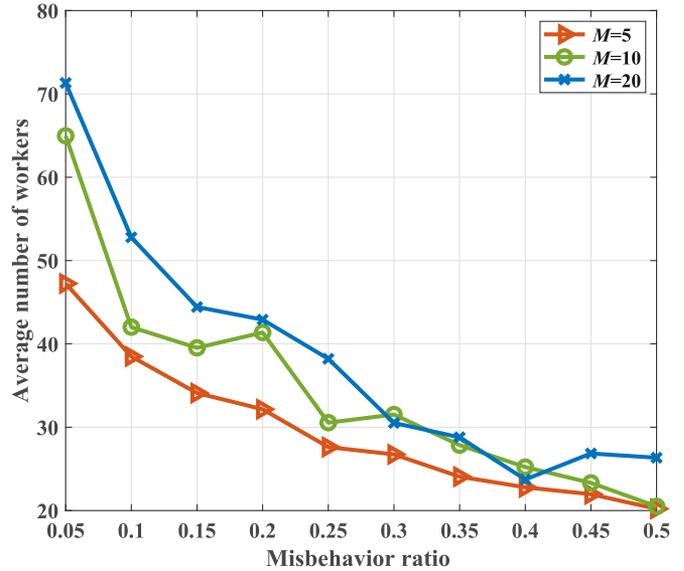


Fig. 6. Number of selected workers as function of misbehavior ratio.

with the scheme without coalition game, the selected workers’ average reputation value of the proposed scheme decreases slightly with the growth of misbehavior ratio. The misbehavior ratio has little effect on the average reputation value of workers in the selected worker coalition, as the coalition game-based method helps to exclude the workers with low reputation values. When the weight of positive event σ_1 is fixed, the number of miners joining in the reputation calculation does not affect the average reputation values of selected workers. When the misbehavior ratio is fixed, the selected workers’ average reputation value increases with the increase of σ_1 . Fig. 6 shows the number of selected workers as a function of misbehavior ratio. From Fig. 6, the number of selected workers decreases with the rise of misbehavior ratio. When the misbehavior ratio is fixed, the number of selected workers increases with the growth

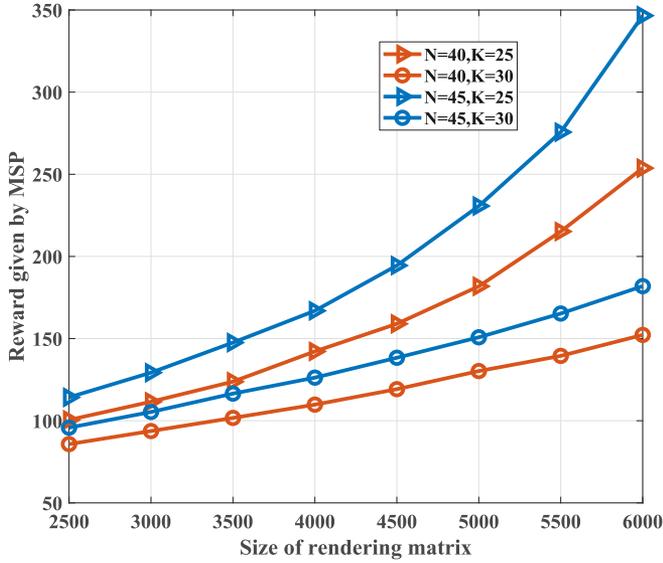


Fig. 7. Reward strategy of MSP as function of size of rendering matrix.

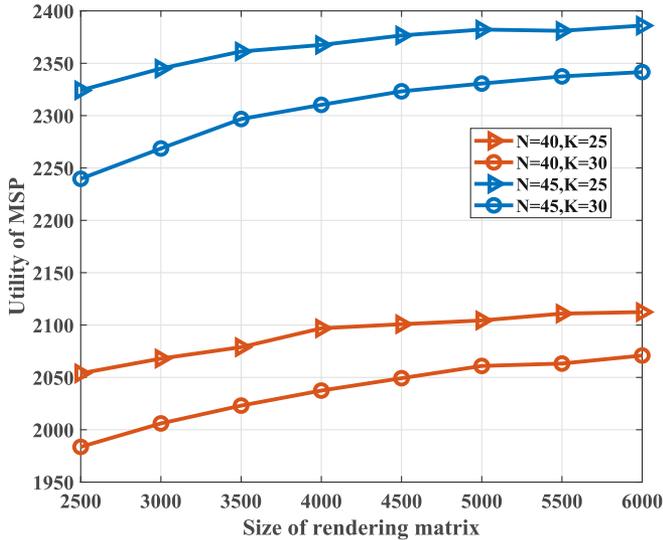


Fig. 8. Utility of MSP as function of size of rendering matrix.

of the number of miners. As more miners can calculate more workers' reputation values, which is beneficial to the reliable worker selection.

B. Numerical Analysis for CDC Incentive Scheme

In this section, according to the reliable worker selection results obtained from coalition formation game, we analyze the numerical results of Stackelberg game-based CDC incentive mechanism in the vehicular metaverse. We assume that the strat-up time of workers follows the normal distribution. Fig. 7 and Fig. 8 show the effects of the size of rendering matrix on the reward given by the MSP and utility of the MSP, respectively. From Fig. 7, the reward given by the MSP increases with the size of rendering matrix. When the number of returned results K is fixed, a higher value of N results in higher reward given by the MSP. When N is fixed, the reward decreases with the

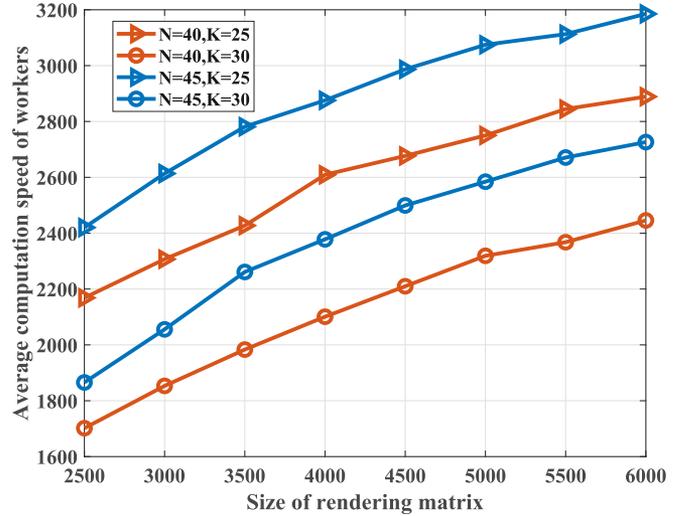


Fig. 9. Average computation speed of workers as function of size of rendering matrix.

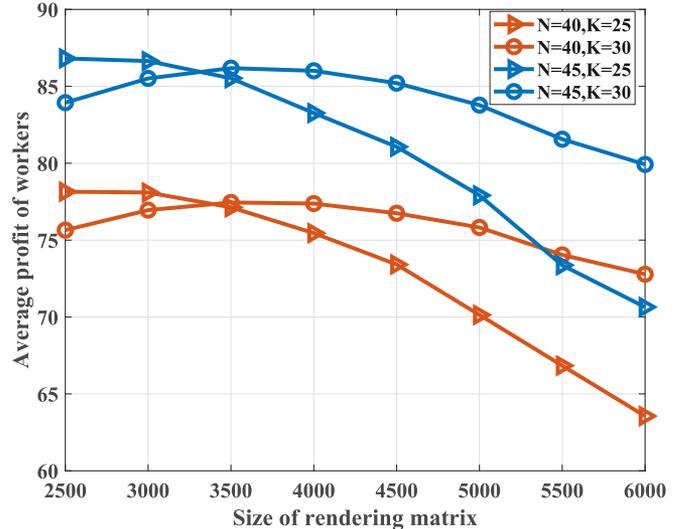


Fig. 10. Average profit of workers as function of size of rendering matrix.

growth of K . As the increase of K means that the MSP needs to reward more workers, which makes the reward reduced. From Fig. 8, the utility of the MSP increases slightly with the size of rendering matrix. A higher value of N results in higher utility for the MSP, which means that more workers' participation is beneficial to the MSP. However, a higher value of K makes the utility of the MSP reduced. This indicates that the MSP can achieve higher utility with the CDC scheme, as the MSP obtains the final computing result when receiving the computing results from K workers, and $K < N$.

Figs. 9 and 10 show the effects of the size of rendering matrix on the selected workers' average computation speed and average profit, respectively. From Fig. 9, the average computation speed of workers increases with the size of rendering matrix. When K is fixed, a higher value of N results in higher average computation speed, as the workers need to increase their speed to

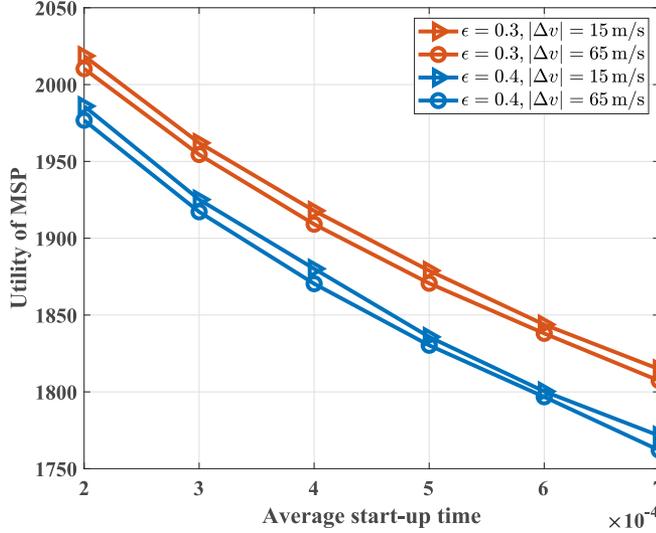


Fig. 11. Utility of MSP as function of the average start-up time.

obtain the competition reward. When N is fixed, a higher value of K results in lower average computation speed. This is because the increase of K reduces the competitiveness among workers. From Fig. 10, with the growth of the size of rendering matrix, the average profit of selected workers first increases to a peak point and then decreases. This indicates that when workers face many rendering tasks with different sizes, workers can choose to execute tasks that can maximize their profits. When K is fixed, the increase of N makes the workers' average utility increased. This is mainly because the MSP gives more reward when N increases. When the size of rendering matrix is less than 3300 for $N = 45$ and 3500 for $N = 40$, a lower value of K results in higher average profit of workers. Otherwise, a higher value of K results in higher average profit of workers.

Fig. 11 shows the utility of the MSP as a function of the workers' average start-up time considering different values of computing cost ϵ and relative vehicle speed $|\Delta v|$ between workers and the MSP. As shown in Fig. 11, the utility of the MSP decreases linearly with the increase of the workers' average start-up time. Besides, when the average start-up time is fixed, the utility of the MSP decreases with the increase of ϵ and $|\Delta v|$. Fig. 12 shows the average profit of workers as a function of the workers' average start-up time considering different values of ϵ and $|\Delta v|$. From Fig. 12, with the increase of the average start-up time, the average profit of workers first increases to a peak point and then decreases. The workers can select a suitable start-up time to execute the computing tasks from the MSP. When the average start-up time is fixed, the average profit of workers decreases with the growth of ϵ , and increases with the growth of $|\Delta v|$. From the above analysis, we obtain that the relative vehicle speed between workers and the MSP degrades the utility of MSP.

Then, we compare the proposed scheme with the baseline schemes, i.e., the pre-defined worker selection scheme and best-effort worker selection scheme. In the pre-defined worker selection scheme, we pre-select a fixed number of workers based on certain criteria, such as their similarity [47]. In the best-effort

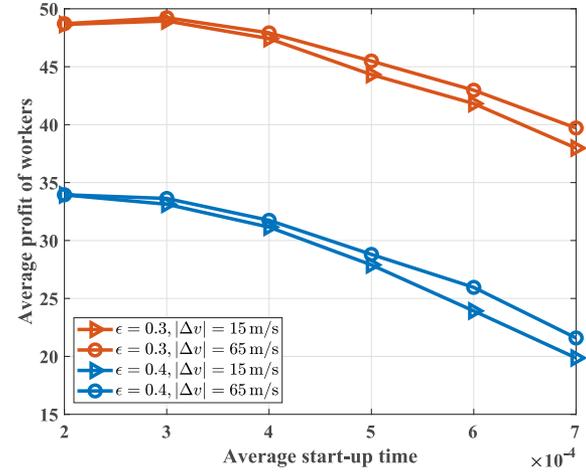


Fig. 12. Average profit of workers as function of the average start-up time.

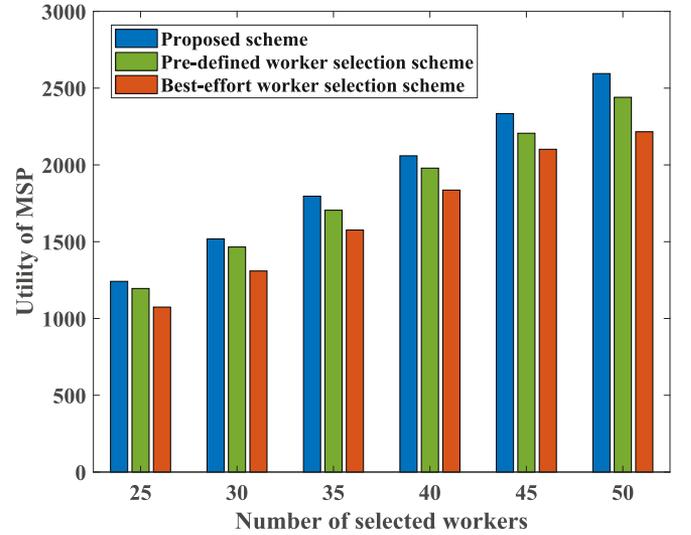


Fig. 13. Utility of MSP as function of number of selected workers.

worker selection scheme that is similar to [48], any workers available will be allowed to join the CDC process. The difference of computation complexity between the proposed scheme and baseline schemes mainly depends on the coalition formation game. From the complexity analysis of the miner coalition formation game in Section IV, the complexity of the coalition formation process is affordable. As the number of miners is not very large for the blockchain system, the complexity of the proposed scheme is further reduced. When the reputation values of workers is lower than the reputation threshold T_{th}^{com} , the reputation utility of the worker is expressed as $h(T_{i \rightarrow w}^{com}) = \alpha e^{(T_{i \rightarrow w}^{com} - T_{th}^{com})}$ [42]. Fig. 13 shows the utility of the MSP as a function of the number of selected workers N under different schemes. From Fig. 13, the utility of the MSP increases with N under all schemes. The utility of the MSP under the proposed reliable CDC scheme is higher than those under the pre-defined worker selection scheme and best-effort worker selection scheme. The utility of the MSP has been increased by 17% compared with the best-effort worker selection scheme. Fig. 14 shows the average

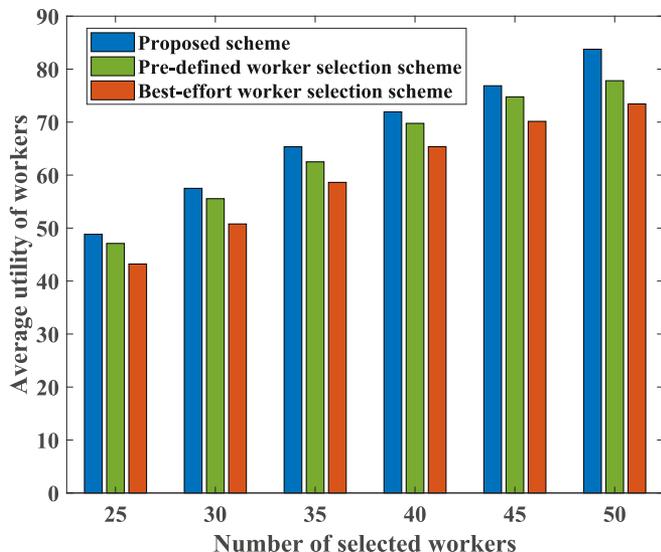


Fig. 14. Average profit of workers as function of number of selected workers.

profit of the selected workers as a function of N under different schemes. From Fig. 14, the average profit of workers increases with the increase of N under all schemes. The average profit of workers under the proposed reliable CDC scheme is higher than those under the pre-defined worker selection scheme and best-effort worker selection scheme. The average profit of workers has been increased by 14% compared with the best-effort worker selection scheme. From Figs. 13 and 14, we conclude that the proposed reliable CDC scheme enables both MSP and workers to obtain higher benefits than the pre-defined worker selection scheme and best-effort worker selection scheme. The reason is that blockchain helps the MSP select reliable CDC workers, including the decentralized management and computing of workers' reputation values. Then, the MSP can motivate reliable CDC workers to contribute to CDC rendering tasks based on the Stackelberg game. Although the complexity of the proposed scheme is slightly higher than that of baseline schemes, the positive interactions between the MSP and CDC workers can maximize both players' payoffs.

VII. CONCLUSION

In this paper, a distributed computing framework is proposed for the vehicular metaverse based on CDC and blockchain. The subjective logical model is used to compute the reputation values of vehicles. A hierarchical game-theoretic CDC framework is proposed for the vehicular metaverse, the coalition formation game is combined with the reputation metric in the upper layer to select reliable workers, and the Stackelberg game is designed in the lower layer to incentivize workers to join the CDC rendering tasks. Finally, the proposed CDC reliable worker incentive mechanism is simulated and analyzed. Simulation results indicate that the proposed reliable CDC scheme is resistant to malicious workers and is suitable for the decentralized CDC in the vehicular metaverse. The utility of the MSP has been increased by 17%, and the average profit of workers has been

increased by 14% compared with the best-effort worker selection scheme. In future works, the performance of wireless metaverse services might be studied.

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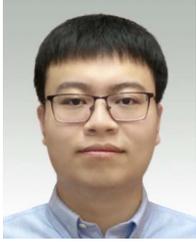
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