Reliable Coded Distributed Computing for Metaverse Services: Coalition Formation and Incentive Mechanism Design

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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 with each other 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 graphic and audio rendering from metaverse service providers cannot be processed efficiently on a single resource-limited mobile and Internet of Things (IoT) device. Alternatively, such devices can adopt the collaborative computing paradigm based on Coded Distributed Computing (CDC) to support metaverse services. Therefore, this paper introduces a reliable collaborative CDC framework for metaverse. In the framework, idle resources from mobile devices, acting as CDC workers, are aggregated to handle intensive computation tasks in the metaverse. A coalition can be formed among reliable workers based on a reputation metric which is maintained in a double blockchains database. The framework also considers an incentive to attract reliable workers to participate and process computation tasks of metaverse services. Moreover, the framework is designed with a hierarchical structure composed of coalition formation and Stackelberg games in the lower and upper levels to determine stable coalitions and rewards for reliable workers, respectively. The simulation results illustrate that the proposed framework is resistant to malicious workers. Compared with the random worker selection scheme, the proposed coalition formation and Stackelberg game can improve the utilities of both metaverse service providers and CDC workers.

Index Terms—Metaverse, Reliable coded distributed computing, Blockchain, Coalition game, Incentive mechanism, Stackelberg game.

I. INTRODUCTION

The concurrent development of emerging technologies, such as real-time rendering technologies, digital twin, artificial intelligence, 6G communications and blockchain, has promoted the proliferation of the metaverse [1]. The metaverse was first created in the science fiction named Snow Crash [2], which is a three-dimensional (3D) virtual space parallel to the physical world. Then, the success of the famous film Ready Player One brings the concept of metaverse back to the cutting-edge discussions [3]. As a result, more and more leading companies, especially Facebook, are striving to bring the metaverse to life. To provide immersive experiences for people in the metaverse, real-time rendering technologies (e.g., Virtual Reality (VR), Augmented Reality (AR), and spatial sounding rendering) are considered to be the main interaction interfaces [4]. For the medium graphic and audio rendering services in the metaverse, the providers may not have dedicated computing resources. Besides, the intensive computation from medium metaverse services is usually unbearable for resource-limited mobile or IoT devices [1]. In such conditions, the distributed collaborative computing could be adopted to solve computing-intensive tasks in the metaverse [5].

For the distributed computing of metaverse services, multiple devices work in parallel to collaboratively complete a large-scale computing task. One of the main challenges of the distributed computing system for metaverse services is the straggler effects. The stragglers refer to the devices whose computing speed is significantly slower than average due to their weak computing capability or poor communication link, thus causing large latency and bad immersive experience for 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 effects of stragglers and provide fault-tolerance by aggregating the extra computing resources from devices [6]. CDC introduces computing redundancy to the metaverse by code techniques, and metaverse service providers only need to wait for a subset of workers to return their final results of graphic and voice rendering tasks. However, there are two critical problems that need to be addressed: i) The devices may be unwilling to participate in metaverse services without a reasonable incentive mechanism; ii) Some devices may even misbehave to damage metaverse service providers’ benefits, thus resulting in bad user experience. How to select reliable devices and incentivize them to participate in metaverse services are still challenging.

In this paper, we first introduce reputation as a metric to evaluate the reliability of workers in CDC to support metaverse services, and a stable coalition is formed based on reputation values. Moreover, we apply a hierarchical structure
composed of coalition formation and Stackelberg game to design an efficient incentive mechanism for reliable CDC in the metaverse. To achieve secure reputation management and worker participation records, a double blockchains framework is designed. The main contributions of this paper are summarized as follows.

1) We are the first to propose a reliable and efficient distributed collaborative computing framework for the metaverse based on CDC and double blockchains, which can support the immersive user experiences in the metaverse.

2) We adopt the reputation metric to form coalitions, as the reputation metric is the abstraction and aggregation of multiple factors that affect the quality of coalitions. Besides, the coalition formation is based on the estimate of future reward from the history records in the double blockchains.

3) We propose a hierarchical game-theoretic approach to investigate the reliable and sustainable CDC scheme in the metaverse. In the lower level, the coalition game is innovatively combined with the reputation metric to choose reliable CDC workers for Metaverse Service Providers (MSPs). In the upper level, the Stackelberg game is formulated to stimulate the reliable CDC workers to participate in metaverse services.

4) We carry out experiments on the Fisco Bcos platform to show that the double blockchains is more efficient than the single blockchain in transaction processing. Besides, the numerical results show that the proposed hierarchical game-theoretic scheme is resistant to the malicious workers. Both the MSP and CDC workers can obtain higher utility with the proposed scheme than that of the random worker selection scheme.

The remainder of this paper is organized as follows. Related works are presented in Section II. The preliminary of the proposed CDC scheme for the metaverse is 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. Section VII concludes this paper.

II. RELATED WORKS

A. CDC Applications to Metaverse Services

Some works study the metaverse services that require graphic or audio rendering. In [7], the authors propose an efficient deep reinforcement learning-based incentive mechanism for VR services in the metaverse. In order to realize the audio/visual and virtual/reality congruence in metaverse services, the authors in [8] design the 6-degree-of-freedom interactive audio engines based on objects. In [9], the authors introduce the advertising strategy and covert communication technique to the wireless edge metaverse services to protect users’ privacy. In [10], the authors propose a resource allocation scheme to support the sync between the metaverse and real world.

The research on CDC to rendering services mainly focuses on mitigating the straggler effects and minimizing the communication cost. Coding techniques have become the popular method to solve the above issues. In [11], the authors explore the use 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 extend the problem of distributed matrix multiplication in [11] to heterogeneous environments, and propose a coding framework for speeding up distributed matrix multiplication in heterogeneous clusters with straggling servers. In [13], the authors consider that the performance of wireless distributed computing networks is straggled by not only local computation but also wireless transmission. In [14], a coded computing framework for federated learning is proposed, which uses structured coding redundancy to mitigate the straggler effect 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 focus on designing platforms’ incentive mechanisms for encouraging workers’ participation in the coded machine learning. However, the reliable CDC incentive mechanism for the metaverse has not been studied.

B. Collaborative Blockchains

There are some studies investigating collaborative blockchains. In [17], the authors propose a collaborative blockchain for the space-air-ground integrated network (SAGIN). Multiple parallel blockchains are used to manage different segments of SAGIN efficiently. The collaborative blockchain technology based on the relay chain realizes the interactions between different blockchains. In [18], the authors propose SynergyChain, a multichain data sharing and data access control framework. The authors consider that a single blockchain system can realize data sharing between multiple institutions but cannot guarantee the security of some sensitive data for the institution. Since all full nodes have a blockchain ledger, and every transaction on the blockchain can be accessed, the privacy of data from multiple institutions will not be preserved. In [19], the authors use the multi-edge chain structure to decrease the single blockchain’s burden due to the massive computing-as-a-service (CaaS) scheduling data and computing result storage. A single cloudlet chain and multi-edge chain structure are adopted. Multiple blockchains might meet the requirements of decentralized metaverse. However, there is no research focusing on the blockchain assisted distributed computing for the metaverse.

III. PRELIMINARY

A. System Model

The system model of CDC to support metaverse services is shown in Fig. 1. The metaverse mainly includes the virtual world, the physical world, and the interaction layer that bridges the virtual and physical world. The immersive user experience is an important part in the interaction layer. To achieve the immersive user experiences, key technologies (e.g., graphic
and spatial sound rendering) are adopted, which may bring intensive matrix computation tasks to related IoT devices. Those devices can choose to render rendering tasks by collaborating with other IoT devices. In the metaverse, IoT devices that distribute the large-scale matrix computation tasks (e.g., projection and shadow mapping in graphic rendering [20]) are called MSPs. The devices that execute the computation tasks of metaverse services are called workers. In order to realize the reliable distributed computing, the MSP first selects workers based on reputation values, and then allocates the computation tasks to workers based on the CDC technology. Blockchain is used to realize the decentralized CDC in the metaverse. In the blockchain layer, double blockchains are adopted to manage reputation values and record worker participation. A single blockchain may bring intolerable delay by sequentially validating transactions, and the complete replica of the entire chain stored in each full node could consume numerous storage resources in large-scale distributed computing networks. In the proposed system model, the reputation chain and resource chain are designed. In the reputation chain, the direct reputation opinions and reputation interactions are recorded to realize the decentralized reputation management. In the resource chain, the resource interactions and workers’ information, including register information, logout information are recorded. The reputation chain and resource chain perform automatically cross-chain information exchange through smart contract. Supported by double blockchains, the CDC process in the metaverse can be realized in a decentralized way.

As shown in Fig. 2, the whole CDC process in the metaverse mainly includes the worker selection phase and CDC rendering task execution phase. In the worker selection phase, the MSPs select workers based on workers’ reputation values recorded on the reputation chain. In the CDC task execution phase, MSPs distribute the rendering tasks to the selected workers based on the CDC technology. The workers process the computation tasks and transmit the final results to MSPs. Then MSPs update workers’ reputation values and record the updated values on the reputation chain. All the resource interactions between MSPs and workers are recorded on the resource chain. The details about the steps of the CDC process are given as follows.

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

Step 2: In order to obtain the reputation opinions of online workers that are willing to help the MSP with metaverse services, the resource chain needs to request the compositive reputation opinions of online workers from the reputation chain through smart contract. The online worker set is denoted as $\mathbb{W} = \{1, 2, \ldots, w, \ldots, W\}$.

Step 3: The reputation chain needs to return the compositive reputation opinions of workers computed based on the subjective logical model, which combines the MSP’s direct reputation with the latest indirect reputation opinions from other MSPs. Miners in the reputation chain are responsible for the computing of workers’ reputation opinions. The set of miners is expressed as $\mathbb{M} = \{1, 2, \ldots, m, \ldots, M\}$. Each miner selects several workers and computes workers’ compositive reputation opinions. The number of workers selected by the miner $m$ is denoted as $|W_m|$, and $|W_m| = W/M$. The workers whose compositive reputation opinions are lower than $T_{th}^{com}$ are discarded by miners, and the discarded worker set is denoted as $W_{dis}$. $T_{th}^{com}$ is set based on MSPs’ service requirements. The set of workers selected by miner $m$ is denoted as $W_m = \{W_{m,1}, W_{m,2}, \ldots, W_{m,|W_m|}\}$, and $(\cup_{m=1}^M W_m) \cup W_{dis} = \mathbb{W}$.

Step 4: Miners in the reputation chain form coalitions to increase their chance to be selected. This is due to the fact that multiple reliable workers evaluated by their reputation can offer larger computational resources to the MSP. The reputation chain will return the worker coalition with the highest coalition utility.

Step 5: The reputation chain transmits the compositive reputation opinions of selected workers to the resource chain through smart contract.
**Step 6:** The resource chain returns the selected workers’ information, including the location information and reputation opinions, to the MSP.

**Step 7:** The MSP allocates the rendering tasks to the selected workers based on Stackelberg game. The MSP acts as the leader to give the reward strategy, and workers act as followers to adjust computing speed strategy. Without loss of generality, we consider matrix-vector multiplication computation task, e.g., gradient descent algorithms and deep learning exist in metaverse services [16]. The Maximum Distance Separable (MDS) code is adopted to alleviate the straggler effects in the distributed computing [6]. The MSP $P_i$ has a matrix-vector multiplication computation task $y_i = A_i x_i$ ($A_i \in \mathbb{R}^{n_r \times n_c}$). The MSP $P_i$ first divides the matrix $A_i$ into $K$ equal-sized submatrices in $\mathbb{R}^{\frac{n_r}{K} \times n_c}$. Then, by applying an $(N, K)$ MDS code, the MSP gets $N$ encoded submatrices with unchanged size $\frac{n_r}{K} \times n_c$. Each submatrix is allocated to a worker. The MSP $P_i$ can reconstruct the final result when receiving the results from any $K(K < N)$ workers, which can mitigate straggler effects.

**Step 8:** The resource interactions between the MSP and workers are recorded on the resource chain. Then, the workers can receive the deserved reward from the MSP.

**Step 9:** After finishing the CDC rendering tasks, the MSP updates the local reputation opinions of workers on the reputation chain.

**B. Hierarchical Game-theoretic Approach**

The outline of this paper is shown in Fig. 3. Double blockchains are utilized to achieve the decentralized management for CDC in the metaverse. In order to realize reliable and sustainable CDC in the metaverse, we adopt a hierarchical game-theoretic approach. In the lower level, the coalition game is formulated to selected reliable workers. In the upper level, the Stackelberg game is designed to incentivize workers to contribute computing resources to CDC rendering tasks. The coalition-Stackelberg game makes the proposed framework suitable for reliable CDC in the metaverse. The description of the hierarchical game-theoretic approach is expressed as follows:

1) **Lower level:** In the lower level, the coalition formation game is adopted to investigate the cooperation among miners that contribute to the computing of workers’ compositive rep-

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**Fig. 2:** Worker selection and CDC rendering task execution phase.

**Fig. 3:** Hierarchical game-theoretic approach for double blockchains assisted CDC.
utation values in the reputation chain. The miners select online workers and compute online workers’ compositive reputation values based on reputation opinions stored on the reputation chain. Then the miners form coalitions by maximizing the coalition utility that includes the sum of online worker’s compositive reputation values and cost. In order to be selected to execute the CDC tasks, each miner prefers to form coalitions with other miners to get higher total reputation values. Besides, considering the coalition formation cost, the grand coalition may not be stable. Due to the fact that the high communication overhead deters all the miners to participate and act as a coalition. The coalition with the highest coalition utility will be selected to execute CDC rendering tasks.

2) Upper level: In the upper level, the Stackelberg game is used to incentivize workers selected in the lower level 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 lower and upper levels: In the lower level, the miners who compute online workers’ compositive reputation values form coalitions. The coalition with the highest coalition utility will be selected by the reputation chain and execute the CDC rendering tasks published by the MSP. Specifically, without forming coalitions, the MSP may not be able to distinguish which workers are reliable, which may degrade the utility of the MSP. In order to motivate selected workers to contribute their computing resource to the CDC rendering tasks and guarantee the utility of the MSP, the Stackelberg game is used in the upper level. The MSP gives reward strategy, and the selected coalitions of workers, which are formed in the lower level, contribute their computing resource to maximize their utilities. Besides, in order to increase probabilities to be selected in the next round of coalition formation game, the workers should also consider their local reputation values when adjusting the computing resource strategy. The hierarchical game theoretic approach ensures that the CDC rendering tasks can be executed by reliable workers and maximize the MSP’s utility. Meanwhile, the selected reliable workers are incentivized to contribute their computing resources to the CDC rendering tasks generating from metaverse services.

IV. WORKER SELECTION BASED ON REPUTATION MODEL AND COALITION GAME

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 data between MSPs and workers. Subjective logic is a popular tool to model the reliability of entities in the metaverse, as it quantifies belief, disbelief and uncertainty [21]–[23]. By using the subjective logic model, both direct and indirect reputations from other MSPs are combined to derive the compositive reputation values of workers. The second problem is how to select reliable workers based on the reputation values of workers in a distributed way. Miners in the reputation chain are responsible for the calculation of workers’ reputation values. Once the reputation chain obtains the online workers’ information from the resource chain, each miner in \( M = \{1, 2, \ldots, m, \ldots, M\} \) selects several workers from \( W = \{1, 2, \ldots, w, \ldots, W\} \) to compute the reputation opinions. The miners in the reputation chain store all workers’ direct reputation opinions. The miners can compute the selected workers’ compositive reputation opinions based on the stored direct reputation opinions and subjective logic model. The workers whose compositive reputation opinions are lower than the reputation threshold \( T_{th}^{com} \) are discarded by miners. Then, miners in the reputation chain form coalitions to increase their chance to be selected by the MSP. The reputation chain returns reputation values of workers in the coalition with the highest coalition utility. In this section, we first introduce the subjective logic model, then the miner coalition formation game is formulated.

A. Reputation Model Based on Subjective Logic Model

1) Local opinions for subjective logic: The MSPs’ direct reputation opinions to all workers are recorded on the reputation chain. The MSP \( P_i \) sends a transaction to the resource chain to recruit workers. Then the resource chain sends data access requests about the online workers’ reputation value to the reputation chain through smart contract. Miners in the reputation chain need to compute the selected workers’ compositive reputation opinions by combining the direct reputation opinions updated by the MSP \( P_i \), and those updated by other MSPs on the reputation chain. The 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.

Considering the MSP \( P_i \) and worker \( w \), the local opinion of the MSP \( P_i \) to \( w \) in the subjective logic can be expressed as a vector \( b_{i \rightarrow w}^{local} = \{b_{i \rightarrow w}^{local}, d_{i \rightarrow w}^{local}, u_{i \rightarrow w}^{local}\} \), 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 \( b_{i \rightarrow w} + d_{i \rightarrow w} + u_{i \rightarrow w} = 1 \). Similar to the subjective logic models in [24], \( b_{i \rightarrow w}^{local}, d_{i \rightarrow w}^{local}, u_{i \rightarrow w}^{local} \) are represented as follows

\[
\begin{align*}
    b_{i \rightarrow w}^{local} &= \frac{\sigma_1 p_{i \rightarrow w} + \sigma_2 q_{i \rightarrow w} + 2}{\sigma_1 p_{i \rightarrow w} + \sigma_2 q_{i \rightarrow w} + 2}, \\
    d_{i \rightarrow w}^{local} &= \frac{\sigma_1 p_{i \rightarrow w} + \sigma_2 q_{i \rightarrow w} + 2}{\sigma_1 p_{i \rightarrow w} + \sigma_2 q_{i \rightarrow w} + 2}, \\
    u_{i \rightarrow w}^{local} &= \frac{\sigma_1 p_{i \rightarrow w} + \sigma_2 q_{i \rightarrow w} + 2}{\sigma_1 p_{i \rightarrow w} + \sigma_2 q_{i \rightarrow w} + 2},
\end{align*}
\]

where \( p_{i \rightarrow w} \) and \( q_{i \rightarrow w} \) are the number of positive and negative interaction events between the 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 returns the effective computation results that is beneficial to the graph resolution or audio playback resolution. \( \sigma_1 \) is the weight of positive interaction events, \( \sigma_2 \) is the weight of negative interaction events, and \( 0 < \sigma_2 < \sigma_1 < 1 \). The local reputation value \( T_{i \rightarrow w}^{local} \) is expressed as

\[
T_{i \rightarrow w}^{local} = b_{i \rightarrow w}^{local} + \gamma u_{i \rightarrow w}^{local} \tag{2}
\]

where \( \gamma \in [0, 1] \) is the effective coefficient of uncertainty on the reputation of the worker \( w \).
2) Recommended opinions: Apart from the MSP $P_i$'s local reputation opinions, the miners also need to search for selected workers' direct reputation opinions updated by other MSPs on the reputation chain to obtain the recommended reputation opinions. Suppose that the miner $m$ gets a number of $R$ recommended opinions about $w$ on the reputation chain. $R$ is also the number of recommenders. For each recommender $r \in R$, the weight factor $\omega_r$ is expressed as

$$\omega_r = \frac{b_{l \rightarrow r} \times \left(b_{local}^{local} + d_{local}^{local}\right)}{\sum_{r \in R} b_{l \rightarrow r} \times \left(b_{local}^{local} + d_{local}^{local}\right)},$$  

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

$$b_{l \rightarrow r} = \frac{|\Gamma (P_l) \cap \Gamma (r)|}{|\Gamma (P_l) \cup \Gamma (r)|}.$$  

The overall recommended reputation opinion for the $w$ is denoted as $R_{w}^{rec} = \{b_{rec}^{local}, d_{rec}^{local}, u_{rec}^{local}\}$. $b_{rec}^{local}, d_{rec}^{local}$ and $u_{rec}^{local}$ are represented as follows

$$\begin{cases}
    b_{rec}^{local} = \sum_{r \in R} \omega_r b_{local}^{local}, \\
    d_{rec}^{local} = \sum_{r \in R} \omega_r d_{local}^{local}, \\
    u_{rec}^{local} = \sum_{r \in R} \omega_r u_{local}^{local}.
\end{cases}$$

3) Combining local opinions with recommend opinions:

Based on the local opinion and recommended opinions from other MSPs. The miner $m$ can obtain the final compositive reputation opinion of the MSP $P_l$ to the worker $w$. The compositive reputation opinion of the MSP $P_l$ to the worker $w$ is represented as $R_{w}^{com} = \{b_{com}^{local}, d_{com}^{local}, u_{com}^{local}\}$, and $b_{com}^{local}, d_{com}^{local}$, $u_{com}^{local}$ are expressed as follows:

$$\begin{cases}
    b_{com}^{local} = b_{local}^{com} + b_{local}^{rec} + \frac{b_{local}^{com}b_{local}^{rec}}{b_{local}^{com} + b_{local}^{rec}}, \\
    d_{com}^{local} = d_{local}^{com} + d_{local}^{rec} + \frac{d_{local}^{com}d_{local}^{rec}}{d_{local}^{com} + d_{local}^{rec}}, \\
    u_{com}^{local} = u_{local}^{com} + u_{local}^{rec} + \frac{u_{local}^{com}u_{local}^{rec}}{u_{local}^{com} + u_{local}^{rec}}.
\end{cases}$$

The compositive reputation value of the MSP $P_l$ to the worker $w$ is expressed as

$$T_{w}^{com} = b_{com}^{local} + u_{com}^{local}.$$  

B. Coalition Formation Game Formulations

In the proposed model, miners in the reputation chain cooperate to select reliable workers for 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 might 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 formulated as a coalition formation game with transferable utility (TU), which means that the value or the utility of a coalition can randomly be divided between the coalition's players. The game is modeled as $G = \{M, u\}$, where $M$ is the set of miners, $u$ is the utility function. The reputation chain returns the compositive reputation opinions of the workers in the coalition with the highest utility. The definitions for the coalition formation game are given as follows.

**Definition 1:** A coalition of miners is denoted by $G_l \in M$, and $l$ is the index of the coalition.

**Definition 2:** A group of coalitions in $M$ is a set of mutually disjoint coalitions of $M$, and is represented as $\Pi = \{G_1, G_2, ..., G_l, ..., G_L\}$, where $G_l \cap G_i = \phi$ for $l \neq i$, $L$ is the number of miner coalitions. If the group spans all the players in $M$, that is $\bigcup_{l=1}^{L} G_l = M$. The group is called a coalition structure or a partition of $M$.

The miners prefer to form the worker coalitions with maximum possible reputation values, because the work coalition with the higher total reputation values has a higher possibility to be selected by the reputation chain. The probability that the coalition $G_l$ is selected by the reputation chain is expressed as

$$Pr (G_l) = \frac{\sum_{m \in G_l} |W_m| \cdot T_{w}^{com}}{\sum_{w=1}^{W} T_{w}^{com}}.$$  

As the number of miners in the coalition increases, the communication cost between miners also increases, because forming a miner coalition requires negotiation and information exchange that can incur the cost and reduce the gains from forming the coalition. The coalition utility of the coalition $G_l$ is expressed as

$$u (G_l) = Pr (G_l) \sum_{m \in G_l} |W_m| \cdot T_{w}^{com} - \rho \cdot C (G_l),$$

where $C (G_l)$ is the communication cost of the coalition $G_l$, $\rho$ is the cost to compute the compositive reputation value of each worker. As the number of miners in the coalition increases, the average reputation values that the coalition can bring to the reputation chain increase. Meanwhile, the coalition cost including communication and computation cost also increase.

For the coalition $G_l$, the communication cost $C (G_l)$ should reflect the negotiation and information exchange overhead, which are determined by the number of miners in the coalition $G_l$. The communication cost $C (G_l)$ should satisfy the following requirements. Firstly, the communication cost $C (G_l)$ should
The rules of merge and split are shown as follows [34]. The communication cost $C(G_l)$ is expressed as

$$C(G_l) = \begin{cases} \log (1 - \frac{(|M_l| - o)^2}{M_l^2}), & \text{if } |M_l| \geq 2 \\ 0, & \text{otherwise} \end{cases} \quad (10)$$

where $o$ is used to avoid an infinite value of $C(G_l)$ when $|M_l| = M$, and $o = 0.1$ [31].

By applying the transferable utility property, the utility of the coalition can be divided between the coalition miners arbitrarily. Next, we use the equal fair allocation rule. The utility of the miner $m$ is given by

$$u_m(G_l) = \frac{\sum_{i \in w \in A} T_{com} \sum_{m \in G_{l}} |W_m| T_{com} - u(G_l)}{\sum_{m \in G_l} |W_m| T_{com} - u(G_l)}. \quad (11)$$

The utility function of each miner does not correspond to the physical quantity (e.g., resources or reward) that the miner can get from a coalition, the motivation behind this assumption is to highlight the importance of the workers’ compositive reputation value for the coalition formation. Each miner is able to leave its current coalition and join another coalition based on the received utility. Here, we give the definition of the preference order.

**Definition 3:** A preference operator $\succ$ is defined to compare two collections $\Pi_1 = \{G_1, \ldots, G_l\}$ and $\Pi_2 = \{G_1', \ldots, G_l'\}$ that are partitions of the same subset $A \subseteq M$ (i.e., same players in $\Pi_1$ and $\Pi_2$). Then, $\Pi_1 \succ \Pi_2$ implies that the way $\Pi_1$ partitions $A$ is preferred to the way $\Pi_2$ partitions $A$ [33].

Various orders can be used as preference orders. The Pareto order and coalition order are adopted to compare relations. The Pareto order means that the collection $\Pi_1$ is preferred over the collection $\Pi_2$ only if at least one player can improve its utility without decreasing other players’ utilities when the coalition structure change from $\Pi_2$ to $\Pi_1$. The utility of the miner $m$ in the collection $\Pi_1 = \{G_1, \ldots, G_l\}$ and $\Pi_2 = \{G_1', \ldots, G_l'\}$ are denoted as $u_m(\Pi_1)$ and $u_m(\Pi_2)$, respectively. With the Pareto order, $\Pi_1 \succ \Pi_2$, if and only if

$$u_m(\Pi_1) \geq u_m(\Pi_2) \quad \forall m \in \Pi_1, \Pi_2, \quad (12)$$

with at least one strict inequality ($\succ$) for a player $m$. The coalition order compares the collection $\Pi_1$ and $\Pi_2$ by using the utility of coalitions inside the collections. With the coalition order, $\Pi_1 \succ \Pi_2$, if $\sum_{l=1}^{L} u(G_l') > \sum_{l=1}^{L'} u(G_l)$.

Based on the preference order, a coalition formation algorithm using the simple rules of merge and split is proposed. The coalition formation process usually takes many rounds, and all the coalitions should be involved in each round, so that their utilities are ensured to increase or remain stable. The rules of merge and split are shown as follows [34].

1) **Merge Rule:** For any set of coalitions $\{G_1, \ldots, G_l, \ldots, G_L\}$, where $\{\cup_{l=1}^{L} G_l\} \succ \{G_1, \ldots, G_l, \ldots, G_L\}$, then merge $\{G_1, \ldots, G_l, \ldots, G_L\}$ into $\{\cup_{l=1}^{L} G_l\}$, which is denoted as $\{G_1, \ldots, G_l, \ldots, G_L\} \rightarrow \{\cup_{l=1}^{L} G_l\}$.

2) **Split Rule:** For any coalitions $\cup_{l=1}^{L} G_l$, where $\{G_1, \ldots, G_l, \ldots, G_L\} \succ \{\cup_{l=1}^{L} G_l\}$, then split $\{\cup_{l=1}^{L} G_l\}$ into $\{G_1, \ldots, G_l, \ldots, G_L\}$, which is denoted as $\{\cup_{l=1}^{L} G_l\} \rightarrow \{G_1, \ldots, G_l, \ldots, G_L\}$.

The coalitions will merge or split if merging and splitting can yield a preferred collection based on the preference 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. By using the coalition order, a coalition will merge or split only if the coalition utility is higher than the original coalition utility. Based on the merge and split rule, a stable coalition structure can be obtained, as any algorithm constructed based on merge and split rules always converges [29]. The coalition formation algorithm for miners is given as follows.

---

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

**Input:** Set of miners $M = \{1, 2, \ldots, m, \ldots, M\}$. Workers selected by miners $W_m = \{W_{m,1}, W_{m,2}, \ldots, W_{m,|W_m|}\}$, $1 \leq m \leq M$;

**Output:** The coalition with the highest coalition utility;

1: Initialization: The partition of miners, where all the miners are disjoint is selected as the initial state. Each miner selects several workers and computes selected workers’ compositive reputation value;

2: Merge mechanism: The Coalition $G_l$ tries to merge with $G_{l'}$ based on the merge rule;

3: Split mechanism: The Coalition $G_l$ tries to split with $G_{l'}$ based on the split rule;

4: Until: Merge and split iteration terminates;

5: Return: The coalition with the highest coalition utility.

Next, we use the defection function $D_{hp}$ to analyze the stability of the final coalition partition.

**Definition 4:** A partition $\Pi = \{G_1, G_2, \ldots, G_l, \ldots, G_L\}$ is a stable partition if no coalition $G_l$ has an incentive to change the current partition $\Pi$ by joining another coalition $G_{l'}$, where $G_l \cap G_{l'} = \emptyset$, for $l \neq l'$, or splitting into smaller disjoint coalitions [28].

**Definition 5:** A partition of coalitions $\Pi = \{G_1, G_2, \ldots, G_l, \ldots, G_L\}$ is $D_{hp}$-stable if it satisfies the following two conditions:

1) For $l \in \{1, \ldots, L\}$ and each partition $\{R_1, \ldots, R_p\}$ of coalition $G_l$, we have $\{R_1, \ldots, R_p\} \not\succ G_l$;

2) For $S \in \{1, \ldots, L\}$, we have $\bigcup_{l \in S} G_l \succ \{G_l \mid l \in S\}$, where $\not\succ$ is the opposite rule of $\succ$.

**Theorem 1:** The coalition partition under the proposed scheme is $D_{hp}$-stable.

**Proof:** We first consider the condition 1. $\Pi = \{G_1, G_2, \ldots, G_l, \ldots, G_L\}$ is the final partition obtained from the merge-and-split algorithm. If for $l \in \{1, \ldots, L\}$ and any partition $\{R_1, \ldots, R_p\}$ of $G_l$, there is $\{R_1, \ldots, R_p\} \not\succ G_l$, then the partition $G_l$ will split, which is in contradiction with the fact that $\Pi$ is a final partition resulted from the merge-and-split
iteration. For condition 2, we consider the situation in the same final coalition set \( \Pi = \{G_1, G_2, \ldots, G_t, \ldots, G_L\} \). If for each \( S \in \{1, \ldots, L\} \), there satisfies \( \bigcup_{t \in S} G_t \neq \{G_t \mid t \in S\} \), then the partition \( \Pi \) can be modified through the merge rule, which is also in contradiction with the fact that \( \Pi \) is a final stable partition. So the coalition partition under the proposed scheme is \( D_{hp} \)-stable.

V. STACKELBERG GAME-BASED INCENTIVE MECHANISM FOR CDC RENDERING TASKS

After the worker selection phase, the MSP \( P_i \) gets the information of workers in the selected coalition \( G_i \). The MSP \( P_i \) selects \( N \) workers from the coalition \( G_i \) based on selected workers’ reputation opinions. The set of selected workers is denoted as \( \mathbb{W}_\text{sel} = \{1, 2, \ldots, w, \ldots, N\} \). In the CDC rendering task execution phase, the MSP \( P_i \) divides the matrix \( A_i \) into \( K \) equal-sized submatrices \( \mathbb{R}^{\frac{n_f}{K} \times n_e} \), then the MSP \( P_i \) gets \( N \) encoded submatrices with unchanged size \( \frac{n_f}{K} \times n_e \) by applying an \((N, K)\) MDS code. Each submatrix is allocated to a worker. The distributed computing resource interactions between the MSP \( P_i \) and workers is modeled as a one-leader multiple-followers Stackelberg game. In the leader subgame, the MSP selects the optimal computation reward to motivate workers to execute CDC rendering tasks. In the follower subgame, the MSP tries to obtain higher utility and keep good reputation opinions by adjusting their computing speed.

A. Utility Function of Workers

We consider that the CDC rendering task execution mainly contains computing the task and transmitting the computation result to the MSP \( P_i \). In the following, we study the utility function of workers.

1) Communication model of workers: In the metaverse, the communication between the MSP \( P_i \) and workers takes place over wireless links that fluctuate in quality. The communication quality is necessary for the user immersive experience. We consider that the wireless link between the MSP \( P_i \) and worker is modeled as a tuple \((\eta, p)\), where \( \eta \) is the achievable data rate (in bits per second per Hz), \( p \) is the link erasure probability [14]. The uplink communication delay is given as

\[
T^{\text{com}-u} = Q^u \frac{s^u N}{\eta B}, \tag{13}
\]

where \( Q^u \) is the number of transmissions required for successful uplink communications. \( s^u \) is the packet size of computation results. \( B/N \) is the bandwidth assigned to each worker. \( Q^u \) is distributed IID according to the distribution as follows

\[
P(Q^u = x) = p^{x-1}(1 - p). \tag{14}
\]

The average uplink communication delay of the worker is expressed as

\[
E(T^{\text{com}-u}) = \frac{s^u N}{(1 - p) \eta B}. \tag{15}
\]

2) Computation model of workers: The computation time of each worker can be modeled as a 2-parameter shifted exponential distribution [11] [12]. For the worker \( w \), the cumulative distribution function of the time \( T^{\text{cmp}}_w \), that the worker \( w \) finishes the computation task is expressed as

\[
\Pr(T^{\text{cmp}}_w \leq t) = 1 - e^{-\mu_w(\frac{t}{a} - a)}, \forall t \geq a, \tag{16}
\]

where \( \mu_w \) is the average computation speed of the worker \( w \), \( a \) is the start-up time to begin the computation, \( l \) is the amount of computation task allocated to each worker. The probability density function of the above distribution is expressed as

\[
f(t) = \frac{\mu_w}{t} e^{-\mu_w(\frac{t}{a} - a)}. \tag{17}
\]

The average computation time for the worker \( w \) is expressed as

\[
E(T^{\text{cmp}}_w) = \int_0^{+\infty} t \frac{\mu_w}{t} e^{-\mu_w(\frac{t}{a} - a)} dt = \frac{a e^{a \mu_w}}{\mu_w}. \tag{18}
\]

The average task execution time of the worker \( w \) is expressed as

\[
E(T_w) = E(T^{\text{com}-u}) + E(T^{\text{cmp}}_w). \tag{19}
\]

3) Utility function of workers: In order to incentivize workers to join the CDC rendering task actively, the MSP \( P_i \) gives the reward to workers who contribute to the metaverse services. The reward is classified into two kinds, i.e., base reward \( R_{\text{base}} \) and competition reward \( R_{\text{cmp}} \). The workers who participate in the CDC rendering task can receive the reward \( R_{\text{base}} \). The workers whose average task execution time is less than or equal to the average task execution time of the \( K \)-th worker can receive the reward \( R_{\text{cmp}} \). Similar to the analysis in [35], we assume that the task execution time of workers follows a uniform distribution, where \( T_{\text{max}} = \frac{T_{\text{max}}}{T_{\text{max}} \in (0, 1)} \), and \( T_{\text{max}} \) is the maximum value of the task execution time. The normalized task execution time of workers is ranked and represented by its order statistics, which are expressed as \( T_{1, N}, T_{2, N}, \ldots, T_{N, N}, T_{K, N} \). The \( K \)-th highest execution time among \( N \) workers. The cumulative distribution function of the normalized task execution time is \( F(T) = T \), and 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 expressed as

\[
f_{(k)}(T) = Nf(T) \left( \frac{N - 1}{k - 1} \right) F(T)^{k-1}(1 - F(T))^{N-k}, \tag{20}
\]

which is also a beta distribution \( \text{Beta}(k, N - k + 1) \). So the average value of \( T_{K, N} \) is expressed as

\[
E(T_{K, N}) = \frac{K}{N + 1}. \tag{21}
\]

The workers adopt the dynamic voltage scaling technique, which allows workers to adaptively control the computing speed by scheduling CPU-cycle frequency [36]. Each worker
tries to obtain a higher utility and keeps a good reputation value. The profit function of the worker $w$ is expressed as

$$u_{\text{pro},w} = R_{\text{base}} + P_w R_{\text{com}} - \xi \mu_w E\left( T^{\text{com}}_w \right) - \zeta E\left( T^{\text{com}} - w \right),$$

(22)

where $\xi$ is the computation cost of the worker per CPU circle, and $\zeta$ is the communication cost of the worker per unit of communication time. $P_w$ is the probability of the worker getting the reward from the MSP $P_i$. $P_w$ is expressed as

$$P_w = 1 - e^{-\mu_w \left( \frac{I_{(K,N)} \times T_{\text{max}} - \frac{E(T^{\text{com}}_w)}{I_{(K,N)}} - a}{\gamma} \right)},$$

(23)

where $E\left( T^{\text{com}}_w \right)$ is average uplink communication delay of the $K$-th worker, and $A = \frac{E(T^{\text{com}}_w)}{I_{(K,N)}} - a$.

The change of workers’ average computing speed will affect the workers’ local reputation opinions. For the worker $w$, the interactions between the MSP $P_i$ and worker $w$ is considered as a positive interaction event. By contrast, the interaction event between the MSP $P_i$ and worker $w$ is considered as an negative interaction event. Then the MSP’s updated local reputation values to the worker $w$ can be computed and expressed as

$$T_{i \rightarrow w}^{\text{local,new}} = P_w \left( \frac{\sigma_1 \left( p_{i \rightarrow w} + 1 \right) + 2 \gamma}{\sigma_1 \left( p_{i \rightarrow w} + 1 \right) + \sigma_2 \left( q_{i \rightarrow w} + 1 \right) + 2} \right) + \left( 1 - P_w \right) \left( \frac{\sigma_1 \left( p_{i \rightarrow w} + 1 \right) + 2 \gamma}{\sigma_1 \left( p_{i \rightarrow w} + 1 \right) + \sigma_2 \left( q_{i \rightarrow w} + 1 \right) + 2} \right)\right) = P_w B_w + \left( 1 - P_w \right) C_w,$$

(24)

where $B_w = \frac{\sigma_1 \left( p_{i \rightarrow w} + 1 \right) + 2 \gamma}{\sigma_1 \left( p_{i \rightarrow w} + 1 \right) + \sigma_2 \left( q_{i \rightarrow w} + 1 \right) + 2}$, and $B_w - C_w > 0$. The worker $w$ needs to maximize the profit $u_{\text{pro},w}$ and updated local reputation opinion $T_{i \rightarrow w}^{\text{local,new}}$. The utility function of the worker $w$ is expressed as

$$u_w = \xi u_{\text{pro},w} + \beta T_{i \rightarrow w}^{\text{local,new}}.$$

(25)

Here, the worker $w$ selects the optimal computing speed $\mu_w$ that maximizes $u_w$, $\xi$ and $\beta$ are default parameter to ensure that $u_w$ and $T_{i \rightarrow w}^{\text{local,new}}$ are in the same range.

B. Utility Function of Metaverse Service Provider

To motivate workers to contribute more to the CDC rendering tasks, the MSP $P_i$ should adjust the reward $R_{\text{com}}$ to maximize the utility. The selected workers contribute their computing resources to the MSP $P_i$. The utility the MSP $P_i$ can gain depends on the computing resource that workers contribute, the reputation values of workers, and the expense pay for workers. The utility function of the MSP $P_i$ is expressed as

$$u_{P_i} = \nu \sum_{w=1}^{N} f(\mu_w) h\left( T^{\text{com}}_{i \rightarrow w} \right) - N R_{\text{base}} - \sum_{w=1}^{N} P_w R_{\text{com}},$$

(26)

where $\nu$ is a system parameter, and $f(\mu_w) = \log\left(1 + \mu_w\right)$, which is the utility of the MSP $P_i$ gained from the workers’ computation contribution. The log of $f(\bullet)$ reflects the MSP $P_i$’s diminishing return on the computation speed of each selected worker $\{\mu_1, \ldots, \mu_N\}$. $h(\bullet)$ is the reputation function of workers and is defined as

$$h\left( T^{\text{com}}_{i \rightarrow w} \right) = \left\{ \begin{array}{ll}
\alpha + (1 - \alpha) \ln(1 + \zeta), & \text{if } T^{\text{com}}_{i \rightarrow w} \leq T^{\text{com}}_{\text{th}} \\
\alpha e^{(T^{\text{com}}_{i \rightarrow w} - T^{\text{com}}_{\text{th}})/(T^{\text{com}}_{\text{max}} - T^{\text{com}}_{\text{th}})}, & \text{if } T^{\text{com}}_{\text{min}} \leq T^{\text{com}}_{i \rightarrow w} \leq T^{\text{com}}_{\text{th}} \max,
\end{array} \right.$$

(27)

where $\alpha$ is the default value, $\zeta$ is expressed as $\zeta = \frac{\left( e - 1 \right) \left( T^{\text{com}}_{i \rightarrow w} - T^{\text{com}}_{\text{th}} \right) / \left( T^{\text{com}}_{\text{max}} - T^{\text{com}}_{\text{th}} \right)}{T^{\text{com}}_{\text{th}}}$. $T^{\text{com}}_{\text{th}}$ is the reputation threshold required by the MSP. $T^{\text{com}}_{\text{max}}$ is the maximum reputation value. The function $h(\bullet)$ means that when the reputation value of a worker is lower than the reputation threshold, $h(\bullet)$ will decrease sharply. On the contrary, $h(\bullet)$ will increase significantly.

C. Stackelberg Game Formulation

The interactions between the MSP and workers can be modeled as a one-leader multiple-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 utilities. The optimization problems for the leader and followers are formulated as follows.

1) Worker’s strategies in Stage II: In Stage II, given the reward strategy of the MSP, the worker $w(\mu \in \mathbb{W}_w)$ determines its computation speed $\mu_w$ to maximize the utility that is given as

$$u_w(\mu_w; \mu_w, R_{\text{com}}) = \xi u_{\text{pro},w}(\mu_w) + \beta T_{i \rightarrow w}^{\text{local,new}}(\mu_w),$$

(28)

where $\mu = \{\mu_1, \ldots, \mu_N\}$ is the set of workers’ strategies. $\mu_w$ denotes the workers’ strategies that expect the worker $w$. The worker subgame problem can be expressed as follows.

Problem 1 (Worker $w$ Subgame):

maximize $u_w(\mu_w; \mu_w, R_{\text{com}})$

subject to $\mu \leq \mu_w \leq \bar{\mu}_w$.

(29)

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

2) MSP’s strategy in Stage I: In Stage I, based on workers’ computation speed strategies $\mu = \{\mu_1, \ldots, \mu_N\}$, the MSP determines the reward strategy to maximize its utility that is expressed as

$$u_{P_i}(R_{\text{com}}; \mu) = \nu \sum_{w=1}^{N} f(\mu_w) h\left( T^{\text{com}}_{i \rightarrow w} \right) - N R_{\text{base}} - \sum_{w=1}^{N} P_w R_{\text{com}},$$

(30)

The MSP subgame problem can be expressed as follows.

Problem 2 (MSP $P_i$ Subgame):

maximize $u_{P_i}(R_{\text{com}}; \mu)$

subject to $R_{\text{com}} \leq R_{\text{com}} \leq \bar{R}_{\text{com}}$,

(31)

where $\bar{R}_{\text{com}}$ is the minimum computation reward, $\bar{R}_{\text{com}}$ is the maximum computation reward.
Problem 1 and problem 2 together form the Stackelberg game, and the goal of the game is to find the game equilibrium solution.

D. Game Equilibrium Analysis

The Stackelberg equilibrium ensures that the utility of the MSP is maximized considering that the workers contribute their computation resource to metaverse services based on the best response. This means that the computation resources from the workers maximize their utilities. In the proposed scheme, the Stackelberg equilibrium can be expressed as follows.

Definition 6: Let \( \mu^* \) and \( R^*_{\text{com}} \) denote the optimal computation speed of all the selected workers and optimal computation reward given by the MSP, respectively. Then, the strategy \( (\mu^*, R^*_{\text{com}}) \) is the Stackelberg equilibrium if the following conditions are satisfied:

\[
u P_1(R^*_{\text{com}}; \mu^*) \geq \nu P_1(R_{\text{com}}; \mu), \quad (32)
\]

\[
u w(\mu^*; \mu^*_{\text{w}}, R^*_{\text{com}}) \geq \nu w(\mu^*_{\text{w}}; \mu^*_{\text{w}}, R^*_{\text{com}}), \quad \forall \mu^* \in \mathbb{W}_{\text{sel}}. \quad (33)
\]

The backward induction is adopted to analyze the Stackelberg game.

1) Workers’ optimal strategies as equilibrium in Stage II

After observing the reward strategy \( R_{\text{com}} \) given by the MSP, the workers determine the optimal computation speed strategy for utility maximization in stage II.

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

Proof: Based on the utility function of workers, we give the first-order and second-order derivatives with respect to worker’s strategy \( \mu_{\text{w}} \). The first-order derivative of \( u_w(\bullet) \) is shown as

\[
\frac{\partial u_w}{\partial \mu_{\text{w}}} = \xi (R_{\text{com}} A e^{-\mu_{\text{w}} A} - \varepsilon l a e^{\mu_{\text{w}}}) + \beta A e^{-\mu_{\text{w}} A} (B_w - C_w). \quad (34)
\]

The second derivative of \( u_w(\bullet) \) is shown as

\[
\frac{\partial^2 u_w}{\partial \mu_{\text{w}}^2} = -\xi (A^2 e^{-\mu_{\text{w}} A} R_{\text{com}} + \varepsilon l a^2 e^{\mu_{\text{w}}}) - \beta A^2 e^{-\mu_{\text{w}} A} (B_w - C_w) < 0. \quad (35)
\]

As the second-order derivative of \( u_w(\bullet) \) is negative, so the utility function \( u_w(\bullet) \) is strictly concave with respect to \( \mu_{\text{w}} \). Besides, based on the first-order derivative condition, there is

\[
\frac{\partial u_w}{\partial \mu_{\text{w}}} = \xi (R_{\text{com}} A e^{-\mu_{\text{w}} A} - \varepsilon l a e^{\mu_{\text{w}}}) + \beta A e^{-\mu_{\text{w}} A} (B_w - C_w) = 0. \quad (36)
\]

Then, the best response of the worker \( w \), i.e., \( \mu^*_{\text{w}} \), is shown as

\[
\mu^*_{\text{w}} = \frac{1}{\eta + A} \log \left[ \frac{\xi R_{\text{com}} + \beta A (B_w - C_w)}{E \xi l a} \right]. \quad (37)
\]

where \( E = \frac{1}{\eta + A}, F = \frac{A}{\eta + A} \) and \( G_w = \frac{\beta A (B_w - C_w)}{\xi l a} \). Thus, the sub-game perfect equilibrium in the workers’ subgame is unique [41].

2) Optimal reward strategy of the MSP

Given the optimal strategies of workers in Stage II, the MSP acts as the leader to optimize its utility in Stage I.

Theorem 3: The uniqueness of the Stackelberg equilibrium can be guaranteed.

Proof: The utility function of the MSP is shown in (38), and

\[
U(\mu^1, \mu^2, ..., \mu^N) = \psi \sum_{w=1}^{N} \phi (\mu^*_{\text{w}}) h(T^*{\text{com}}). \quad (39)
\]

The first-order derivative of the MSP’s utility function is shown in (39). The second-order derivative of the MSP’s utility function is shown in (40). As \( \frac{\partial^2 U(\bullet)}{\partial \mu_{\text{com}}^2} < 0 \), when \( R_{\text{com}} > \frac{2G \xi}{\eta A}, \) there is \( \frac{\partial^2 U(\bullet)}{\partial \mu_{\text{com}}^2} < 0 \). Because \( E A = \frac{A}{\eta + A} = \frac{1}{\frac{1}{\eta + A} + 1} < 1 \), so \( \frac{2G \xi}{\eta A} < 0 \). As \( R_{\text{com}} > 0 \), so the second-order derivative of the MSP’s utility function always satisfies \( \frac{\partial^2 U(\bullet)}{\partial \mu_{\text{com}}^2} < 0 \), which indicates \( u_{P_1} \) is a concave function. So the MSP has a unique optimal solution that can be efficiently obtained by bisection method [42]. Based on the optimal strategy of the MSP, the workers’ optimal strategies can be obtained. Then, the Stackelberg equilibrium can be achieved in the proposed model. Both the MSP and workers can get the optimal utility, and neither of them would change its strategy to gain higher benefits.

VI. PERFORMANCE EVALUATION

In this section, the performance of the double blockchains is compared with the single blockchain based on Fisco Bcos blockchain and Hyperledger caliper. Then, the numerical results about the blockchain-enabled reputation scheme and hierarchical game-theoretic scheme for reliable CDC in the metaverse are presented and analyzed. The default parameters are shown in Table I [14].

| Parameter | Value |
|-----------|-------|
| Number of workers \( W \) | \( W = 100 \) |
| Number of miners \( M \) | \( M = 20 \) |
| Weight of positive and negative events \( \sigma_1, \sigma_2 \) | \( \sigma_1 = 0.6, \sigma_2 = 0.4 \) |
| Packet size \( s^w \) | \( s^w = 400B \) |
| Start-up time to begin the computation | \( a = 5 \times 10^{-4}s \) |
| Bandwidth assigned to the worker \( B \) | \( B = 100kB/s \) |
| Link erasure probability \( \beta \) | \( p = 0.1 \) |
| Achievable data rate \( \eta \) | \( \eta = 13000bit/s/Hz \) |
| Threshold of reputation value \( T^*_{\text{com}} \) | \( T^*_{\text{com}} = 0.6 \) |
| Workers’ computation cost per CPU circle \( \varepsilon \) | \( \varepsilon = 0.1 \) |
| workers’ communication cost per unit time | \( \xi = 10 \) |
| default parameters \( \xi, \beta \) | \( \xi = 10, \beta = 30 \) |
| default parameters \( \psi \) | \( v = 10 \) |
| Base reward \( R_{\text{base}} \) | \( R_{\text{base}} = 10 \) |

A. Implementation of the Blockchain System

The blockchain system is built on the Fisco Bcos blockchain through a physical computer with 2.3GHz, Intel i7 CPU, 8GB, and the Ubuntu 18.04 operating system. This system includes single blockchain and double blockchains. The single blockchain has four nodes, and the double blockchains has two blockchains, each of which has four nodes. The double blockchains process transactions in parallel. In the Fisco Bcos blockchain, Practical Byzantine Fault Tolerance consensus algorithm is adopted. The performance of the single blockchain and double blockchains, including the transaction throughput and average transaction latency, is tested based on Hyperledger Caliper. Hyperledger Caliper is a blockchain...
\[ u_{P_i} (\mathcal{R}_{com}; \mu) = U (\mu_1^*, \mu_2^*, \ldots, \mu_w^*, \ldots, \mu_N^*) - N R_{base} - \sum_{w=1}^{N} \left[ 1 - (F_w \mathcal{R}_{com} + G_w)^{-E_w A_w} \right] \mathcal{R}_{com} \]  \hspace{1cm} (38)

\[ \frac{\partial u_{P_i}}{\partial \mathcal{R}_{com}} = \frac{\partial U (\bullet)}{\partial \mathcal{R}_{com}} - \sum_{w=1}^{N} \left\{ 1 - (F \mathcal{R}_{com} + G_w)^{-E A} + \mathcal{R}_{com} \left[ E AF (F \mathcal{R}_{com} + G_w)^{-E A - 1} \right] \right\} \]  \hspace{1cm} (39)

\[ \frac{\partial^2 u_{P_i}}{\partial \mathcal{R}_{com}^2} = \frac{\partial^2 U (\bullet)}{\partial \mathcal{R}_{com}^2} - \sum_{w=1}^{N} \left\{ 2 E AF (F \mathcal{R}_{com} + G_w)^{-E A - 1} - \mathcal{R}_{com} \left[ E AF^2 (E A + 1) (F \mathcal{R}_{com} + G_w)^{-E A - 2} \right] \right\} \]  \hspace{1cm} (40)

The throughput is defined as the rate at which valid transactions are committed by the blockchain system under test during unit time. The average latency is defined as the average time taken for a transaction’s effect to be usable across the network. The average latency contains the time from the point that it is submitted by the transaction node to the point that the result is widely available in the network [43].

Fig. 4 shows the throughput as a function of the number of transactions considering the single blockchain and double blockchains. As shown in Fig. 4, the throughput of the double blockchains is approximately twice of that of the single blockchain. Fig. 5 shows the average latency as a function of the number of transactions. From Fig. 5, the average latency increases slightly with the increase of the number of transactions. Besides, the average latency of the double blockchains is lower than that of the single blockchain. We can get conclusion that the double blockchains can solve transactions more efficiently than that of the single blockchain.

B. Numerical Results for the Reputation Calculation Scheme

In this section, the reputation values of workers are simulated and analyzed. Especially, we consider an unreliable worker, which performs well to all MSPs to increase its reputation value to 0.8 at first, and keeps that reputation value for a while. Then, the unreliable worker keeps performing well to several specific MSPs, but misbehaves to other MSPs 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, workers’ reputation values are all stored in the centralized cloud platform, who might manipulates unreliable workers’ reputation values into good reputation opinions 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. 6 shows the reputation variation of an unreliable worker. As can be seen from Fig. 6, 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 the reputation scheme with blockchain. As the centralized platform manipulates the unreliable workers’ negative interactions into positive interactions, which increases the unreliable worker’s reputation...
value. For the reputation scheme without blockchain and recommended opinions, the reputation value of the unreliable worker still increases, as the MSPs who served well by the unreliable worker compute the reputation value only based on local reputation opinions.

C. Numerical Analysis for CDC Incentive Scheme

In this section, some numerical results about the coalition game-based worker selection and Stackelberg game-based incentive mechanism are given and analyzed.

Fig. 7 shows the selected workers’ average reputation value as a function of misbehavior ratio considering Pareto order and coalition order. Misbehavior ratio $m_r$ is the percentage of workers that are misbehaving to the total number of workers. As shown in Fig. 7, when $\sigma_1$ is fixed, the selected workers’ average reputation value decreases slightly with the increase of misbehavior ratio. The misbehavior ratio does not have much effect on the average reputation value of workers in the selected worker coalition, as the coalition game-based worker selection method helps exclude the workers with low reputation values. When the misbehavior ratio is fixed, the selected workers’ average reputation value increases with the increase of $\sigma_1$. Besides, there is no significant difference between the Pareto order and coalition order for the selected workers’ average reputation values.

Fig. 8 and Fig. 9 show the effects of the total amount of rendering task on the reward given by the MSP and utility of the MSP, respectively. As shown in Fig. 8, the reward given by
the MSP increases with the amount of rendering task. When $K$ is fixed, a higher value of $N$ results in higher reward given by the MSP. When $N$ is fixed, the reward decreases with the growth of $K$. As the increase of $K$ means that the MSP needs to award more workers, which makes the reward reduced. As can be seen from Fig. 9, the utility of the MSP increases slightly with the amount of rendering task to a maximum point at first. Then the utility of the MSP decreases slightly with the amount of computation task. 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 get higher utility with the CDC scheme, as the MSP obtains the final result when receiving the computation results from $K$ workers, and $K < N$.

Fig. 10 and Fig. 11 show the effects of the total amount of rendering task on the selected workers’ average computation speed and average utility, respectively. As shown in Fig. 10, the average computation speed of workers increases with the amount of rendering task. When $K$ is fixed, a higher value of $N$ results in higher average computation speed, as the workers need to increase their speed to 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. As shown in Fig. 11, the average utility of selected workers declines with the increase of the amount of rendering task. 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 amount of rendering task is less than 3200, a lower value of $K$ results in higher average utility of workers. When the amount of rendering task is more than 3200, a higher value of $K$ results in higher average utility of workers.

Then, we compare the proposed scheme with the random worker selection scheme considering different values of misbehavior ratio. In the random worker selection scheme, the MSP selects workers randomly. Fig. 12 shows the utility of the MSP as a function of $N$ considering different schemes. As shown in Fig. 12, the utility of MSP increases with $N$ in all schemes. The misbehavior of workers almost has no effect on the utility of the MSP with the proposed scheme, as the proposed scheme has excluded the workers with low reputation values before executing CDC tasks. For the random worker selection scheme, the misbehavior of workers makes the utility of the MSP decreased. When $m_r = 0.2$, the utility of the MSP has been maximally increased by 24% compared with the random worker selection scheme. Fig. 13 shows the average utility of selected workers as a function of $N$ considering different schemes. From Fig. 13, the average utility of workers increases with the increase of $N$ in all schemes. As the proposed scheme excludes the malicious workers, the misbehavior of workers almost has no effect on the average utility of selected workers. For the random worker selection scheme, the misbehavior of workers makes the average utility of selected workers decreased. When $m_r = 0.2$, the average utility of workers has been maximally increased by 57% compared with the random worker selection scheme.

VII. CONCLUSION

In this paper, a distributed computing framework is proposed for the metaverse services based on CDC and double blockchains. Each blockchain provides one kind of service for CDC in the metaverse. In order to quantify workers’ reliability, the subjective logical model is used to compute the reputation values of IoT devices. A hierarchical game-theoretic approach is proposed, the coalition formation game is formulated in the lower level to select reliable workers, and the Stackelberg game is designed in the upper level to incentivize workers to join the CDC rendering tasks. Finally, the performance of the double blockchains is tested based on Fisco Bcos blockchain and Hyperledger Caliper. The hierarchical game-based reliable worker incentive mechanism is simulated and analyzed. Simulation results show that the proposed scheme is resistant to the malicious workers. When the misbehavior ratio is 0.2, the utility of the MSP has been maximally increased by 24%, and the average utility of workers has been maximally increased by 57% compared with the random worker selection scheme. In future works, specific consensus mechanisms of blockchain for the metaverse might be studied.

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