A Blockchain-Based Distributed Computational Resource Trading System for Industrial Internet of Things Considering Multiple Preferences

Tonghe Wang†, Songpu Ai‡, Zhihong Tian§, Brij B. Gupta†, and Chun Shan†∗

Abstract—Computational task offloading based on edge computing can deal with the performance bottleneck faced by traditional cloud-based systems for industrial Internet of things (IIoT). To further optimize computing efficiency and resource allocation, collaborative offloading has been put forward to enable the offloading from edge devices to IIoT terminal devices. However, there still lack incentive mechanisms to encourage participants to take over the tasks from others. To counter this situation, this paper proposes a distributed computational resource trading strategy considering multiple preferences of IIoT users. Unlike most existing works, the objective of our trading strategy comprehensively considers different satisfaction degrees with task delay, energy consumption, price, and user reputation of both requesters and collaborators. Our system uses blockchain to enhance the decentralization, security, and automation. Compared with the trading method based on classical double auction matching mechanism, our trading method will have more tasks offloaded and executed, and the trading results are more friendly to collaborators with higher reputation scores.

Index Terms—blockchain, computation offloading, edge computing, industrial internet of things, resource trading.

I. INTRODUCTION

The extensive application of sensor technologies in daily objects has given birth to the Internet of things (IoT). Industrial Internet of things (IIoT), the adoption of the IoT concept in industrial scenarios, has revolutionized the industrial world with enhanced intelligence, efficiency, connectivity, and user experience [1]. As the number of IIoT devices deployed increases, the significant volume of the data acquired from the environment has brought great challenges to data transmission, processing, and storage services provided by centralized cloud centers. In many time-sensitive scenarios, such as healthcare, vehicular network, and smart grid, cloud centers may fail to respond in a timely manner and may cause serious consequences [2]. In response, the edge computing paradigm emerges as the times require. The essence of edge computing is to migrate the data storage and computing tasks that originally need to be completed by the cloud to the network edge near terminal devices, therefore improving the response speed and alleviating the bottleneck of the cloud center [3].

Computation offloading is the central topic of edge computing, where terminal devices with limited computational resources decide to transfer some or all their tasks to the edge, and edge devices also decide to transfer their tasks further to the cloud [4]. Unfortunately, edge computing still suffers from high latency caused by task queuing due to the restricted computing power of edge servers [5]. To further reduce the latency of computation, collaborative edge computing has recently been proposed to enable the task offloading between edge servers or from edge servers to nearby terminal devices with available computational resources [6]. However, participants may still lack the motivation to take over tasks from others in practical scenarios, so recent works start to introduce economic incentives to encourage collaborative offloading [7]. In practice, decisions of task offloading are nevertheless determined by multiple factors, which is seldom considered in previous works. In this paper, we model collaborative task offloading as the resource trading with multiple attributes (e.g., task delay, energy consumption, price, and user reputation) considered during the transaction matching stage. It would bring more incentives to resource requesters and offloading collaborators by satisfying more personalized trading preferences of participants.

In recent years, blockchain has been widely adopted to tackle various security issues in IIoT systems because of its advantages of decentralization, traceability, immutability, and automation [8], [9]. Blockchain stores data in blocks, which are shared among participants through peer-to-peer communication, verified by distributed consensus, and then connected into a chain in order [9]. It uses cryptographic schemes to ensure the security of data and messages [10]. More importantly, smart contracts can bring more automation to blockchain-based systems [8]. Yet most blockchain-based IIoT systems fail to give full play to the key features of blockchain as they only use blockchain as secure databases. This paper instead adopts the Blockchain-as-a-Service (BaaS) [11] design into our system. In particular, many parts, such as satisfaction score calculation, matching, and reputation update, of the system can be programmed into smart contracts that can be automatically executed once conditions are met. Moreover, we include a distributed reputation mechanism to enhance the trustworthiness of the resource trading system.
The main contributions of this paper are as follows:

1) This paper designs a distributed computational resource trading system for IIoT users, where the BaaS design is extended and included in the architecture. Unlike most related works that simply use blockchain as a secure database, this paper takes full advantage of blockchain to promote the decentralization, reliability, and automation of resource trading.

2) This paper proposes a multi-preference matching (MPM) mechanism for resource trading. The matching results between requesters and collaborators comprehensively consider the satisfaction with task delay, energy consumption, price, and reputation of each participant. As far as we know, few relevant studies have taken these factors into account all at once.

3) We compare our MPM mechanism with the matching strategy based on classical double auction (DA) matching mechanism [12]. We perform simulation experiments to show the advantages of MPM against DA.

The rest of this paper is arranged as follows: Section II briefly reviews related works; Section III introduces system architecture and the workflow of blockchain-based resource trading; Section IV explains MPM mechanism in detail; Section V conducts simulation experiments and performs numerical analysis by comparing MPM mechanism with the DA-based matching mechanism; Section VI concludes this paper.

II. RELATED WORKS

To explain the motivations of our work, we provide a brief summary of the related works on blockchain-based IIoT and collaborative offloading in this section.

A. Blockchain-Based IIoT

As one of the core technologies of the Industry 4.0 concept, IIoT faces a series of challenges [13]–[15]. Among them, security issues, such as data security, user privacy, and service trustworthiness, are the major concerns of IIoT-related studies [16]–[18]. Recent works have shown that blockchain can not only provide desirable security features for IIoT systems, but also improve system performance through its decentralization and automation. For example, the IIoT data sharing system in [19] involves a blockchain layer to validate, sort, and store data trading records in a distributed, secure, and reliable way. By integrating federated learning into blockchain, the data sharing system of [20] can effectively protect user privacy. Unfortunately, many related works simply use blockchain to provide security for data storage, and the advantages of blockchain are not fully exploited [9]. How to combine the features of blockchain more closely with IIoT scenarios deserves further exploration.

B. Collaborative Offloading

Due to the large number of IIoT terminal devices and the massive data generated along, traditional cloud-based IIoT systems can no longer meet the high requirements for data storage, network stability, and computing speed [3]. Recently, the edge computing paradigm has been extensively applied into IIoT systems [21]. To mitigate the task queuing issue in edge servers, some works recommend collaborative offloading of computation tasks to allow terminal users with additional computational resources to take over the tasks of edge servers [6], [22].

However, the promotion of collaborative offloading in practice has also encountered some obstacles, because users lack incentive mechanisms to complete the computing tasks unloaded by others [23], [24]. As a result, some studies include economic measures and transform collaborative offloading into computational resource trading problem. In [6], the intelligence and selfishness of terminal users are taken into account when making trading decisions. The offloading strategy tries to maximize social welfare by considering the cooperation between edge devices and terminal users as resource trading. Similarly, [25] also studies social welfare maximization in computation offloading and proposes a set of online-offline auction mechanisms. In fact, in addition to economic factors, many other factors, such as response time, energy consumption, and reputation, may also affect the results of computing task allocation. Therefore, the comprehensive consideration of various factors in the computational resource trading is more in line with practical requirements.

III. SYSTEM ARCHITECTURE AND COMPUTATIONAL RESOURCE TRADING WORKFLOW

The IIoT system considered in this paper is based on the classical three-layered architecture of edge computing and further extends the BaaS design described in [11]. As shown by Fig. 1, this architecture consists of four major components:

Informal: The terminal layer is made up by IIoT terminal devices embedded with sensors for data perception. We assume that all IIoT terminals are lightweight in the sense that their computing capabilities are rather limited compared to that of edge servers.

Edge: The edge layer contains edge servers deployed near terminals. These servers have some computational resources so that they can take over the tasks offloaded from terminals. However, for economic concerns, edge servers usually have less computational resources compared to that of cloud
servers. Although the transmission time between terminals and edge servers can be largely reduced, the latency caused by task queuing in edge servers cannot be neglected.

Cloud: The cloud layer has cloud servers with powerful computational capabilities, which is far away from edge servers. It is generally assumed that the cloud can process any number of tasks at the same time, but with significant transmission latency.

BaaS: BaaS is fundamental to achieve distributed computational resource trading for collaborative offloading. Once a transaction data block gets validated through distributed consensus, it will be stored into the distributed ledger, i.e., the chain of blocks that stores all previous transaction records. The use of smart contracts enables the automation of the entire trading workflow. A referable instance of BaaS component is proposed in [25], in which BaaS is designed to undertake energy supply-demand matching in the grid.

In our system, task offloading can take place between two terminals, two edge servers, and between a terminal and a server. The participants with tasks to be offloaded are called requesters, and the participants with extra computational resources are called collaborators. During computational resource trading, collaborators can reveal the information of the resources they are willing to offer, and requesters with computational tasks can then choose the collaborators to which they will offload tasks with payments.

The distributed resource trading works as follows:

Step 1: Collaborator $j$ with surplus computational resources publishes its service information including:

- $C_j$: size of the cache offered;
- $f_j$: CPU frequency offered;
- $r_j$: transmission rate offered;
- $\epsilon_j$: maximum acceptable energy consumption per CPU cycle;
- $op_j$: offering price, i.e., (the lowest) price of task execution offered per CPU cycle;
- $R_j^C$: collaborator reputation score.

Meanwhile, requester $i$ with computational tasks to offload submits their offloading requirement information including:

- $s_i$: size of tasks;
- $Q_i$: CPU cycles required by tasks;
- $\tau_i$: maximum tolerable delay of tasks;
- $bp_i$: bidding price, i.e., (the highest) acceptable price of task execution per CPU cycle;
- $R_i^R$: requester reputation score.

In order to prevent some requester from maliciously forcing down the price and some collaborator from maliciously forcing up the price, we require that bidding price $bp_i$ and offering price $op_j$ should fall in $[p_{min}, p_{max}]$, where $p_{min}$ and $p_{max}$ are the lowest price and the highest price allowed by the resource trading system. All the requirements and services whose prices are out of the range will be forcibly removed.

Step 2: The service of collaborator $j$ and the requirement of requester $i$ is stored in blockchain.

Step 3: The smart contract of MPM, a matching mechanism considering multiple preferences, is triggered, and corresponding pre-matching results will be returned to their requesters for confirmation. We will provide more details about the MPM mechanism in Section IV.

Step 4: Once confirmed, each pre-transaction result will generate a transaction contract with the trading price calculated and will be stored in blockchain. Then, requesters make the payment according to their confirmed transactions.

Step 5: On the execution time, transaction contracts will be triggered automatically, and the corresponding task offloading will take place. The reputation scores of both the requester and the collaborator will be updated according to the execution results. Note that the submitter of an unmatched requirement can choose to either execute the tasks locally or offload the tasks further to the cloud, while the submitter of an unmatched service can choose to keep the service and wait for another round of matching.

Reputation scores of requesters and collaborators, $R_i^R$ and $R_j^C$, are defined to evaluate and regulate the behavior of requesters and collaborators. We will provide more details about our reputation system in Section IV-E.

IV. MULTI-PREFERENCE MATCHING MECHANISM

The core of our resource trading system is the MPM mechanism. Unlike existing works, the MPM mechanism aims to maximizing the overall satisfaction of both requesters and collaborators considering their respective preferences.

Suppose there are $m$ requesters and $n$ collaborators in a matching round. For the sake of simplicity, we assume that no participant is both a collaborator and a requester at the same time. Moreover, we assume that each requester submits one requirement, and each collaborator submits one service. These assumptions can be easily removed by assigning unique identifiers to different services and requirements.

We use matrix $X = \{x_{ij}\}_{m \times n}$ to represent the result of one round of matching, where $x_{ij} \in [0, 1]$ represents the proportion of the tasks in requirement $i$ to be offloaded to collaborator $j$. The MPM mechanism to decide $X$ works as follows:

Step 1: Fetch the information of the services of collaborators and the requirements of requesters. Filter out the offering prices and bidding prices that exceed the allowed ranges. If $bp_i \notin [p_{min}, p_{max}]$, then set $x_{ij} = 0$ for all $j \in \{1, 2, \ldots, n\}$. Likewise, if $op_j \notin [p_{min}, p_{max}]$, then set $x_{ij} = 0$ for all $i \in \{1, 2, \ldots, m\}$.

Step 2: Calculate the service preference score (SPS) of each collaborator service for requester $i \in \{1, 2, \ldots, m\}$, and calculate the requirement preference score (RPS) of each requester requirement for each collaborator $j \in \{1, 2, \ldots, n\}$, with respect to different preferences. We will provide more details about the calculation of these two scores later on in Section IV-A and IV-B.

Step 3: Calculate the average requester satisfaction (ARS) for requester $i$ and the average collaborator satisfaction (ACS) for collaborator $j$. The calculation will be introduced in Section IV-C.

Step 4: Model the matching as an optimization problem and find the solution. This step will be further explained in Section IV-D.

Step 5: Requesters and collaborators decide to either to accept or reject the matching results. Since the MPM mechanism
tries to maximize the overall satisfaction of all participants, it might be possible that some individuals are not willing to compromise their interests. In this case, they can choose not to accept the transaction based on their own rejection rules.

In the next, we will describe how the scores mentioned above are calculated. Like many related works, we ignore the energy consumption and the time delay for collaborators to transfer the computation results back to requesters as the data sizes of the outcomes are usually very small in practice [27]. Moreover, to make our notation more compact, we define the following characteristic function:

\[
\mathbb{I}[X] = \begin{cases} 
1 & \text{if } X \text{ is true;} \\
0 & \text{otherwise.}
\end{cases}
\] (1)

A. Service Preference Score Calculation

First, let \(SPS(x_{ij})\) be the SPS of service \(j\) for requester \(i\). It evaluates \(i\)'s comprehensive satisfaction with \(j\) considering \(i\)'s preference in task delay, offering price, and collaborator reputation, which can be calculated by:

\[
SPS(x_{ij}) = \left( \sum_{k=1}^{3} \phi_i \cdot sps_{i,j,k} \right) \cdot \mathbb{I}[x_{ij} \neq 0],
\] (2)

where \(\phi_i (k = 1, 2, 3)\) are significance factors, and \(sps_{i,j,k} \in [0, 1] \) \(k = 1, 2, 3\) will be explained in the next.

1) Task Delay: Task delay is the main factor that influence the quality of service (QoS) of requesters, which composes transmission delay and computation delay:

\[
t_{ij} = \frac{x_{ij}s_{i}}{r_{ij}} + \frac{x_{ij}Q_{i}}{f_{j}}.
\] (3)

Then \(sps_{i,j,1}\), the task delay SPS of service \(j\) for requester \(i\), is calculated by:

\[
sps_{i,j,1} = \left( 1 - \frac{t_{ij}}{\tau_{i}} \right) \cdot \mathbb{I}[t_{ij} \leq \tau_{i}].
\] (4)

The shorter the task delay is, the better the QoS of the service is, and the higher \(sps_{i,j,1}\) will be.

2) Offering Price: The offering price SPS of service \(j\) for requester \(i\), denoted by \(sps_{i,j,2}\), is calculated by:

\[
sps_{i,j,2} = exp_{i,j} - bp_{i} \cdot \mathbb{I}[exp_{i,j} \leq bp_{i}].
\] (5)

The closer \(op_{j}\) and \(bp_{i}\) are, the more satisfied the requester will be with the matching result.

3) Collaborator Reputation: Collaborator reputation score \(R_{c}\) reflects the credibility of service \(j\) and directly serves as \(sps_{i,j,3}\) in MPM mechanism:

\[
sps_{i,j,3} = R_{c}.
\] (6)

B. Requirement Preference Score Calculation

Then, let \(RPS(x_{ij})\) be the RPS of requirement \(i\) for collaborator \(j\). It evaluates \(j\)'s comprehensive satisfaction with \(i\) considering \(j\)'s preference in energy consumption, bidding price, and requester reputation, which can be calculated by:

\[
RPS(x_{ij}) = \left( \sum_{l=1}^{3} \psi_{l} \cdot rps_{j,i,l} \right) \cdot \mathbb{I}[x_{ij} \neq 0],
\] (7)

where \(\psi_{l} \) \(l = 1, 2, 3\) are significance factors, and \(rps_{j,i,l} \) \(l = 1, 2, 3\) will be explained in the next.

1) Energy Consumption in Collaborator: Compared to task delay, collaborators care more about their energy consumption when taking over the tasks from requesters. The energy consumption in collaborator \(i\) is mainly caused by receiving the data of the offloaded tasks and executing them, which can be calculated by:

\[
E_{ji} = \epsilon_{j}^{com} \frac{x_{ij}s_{i}}{r_{j}} + \epsilon_{j}^{exe} \frac{x_{ij}Q_{i}}{f_{j}},
\] (8)

where \(\epsilon_{j}^{com}\) and \(\epsilon_{j}^{exe}\) are the energy consumption of communication and task execution per second. Considering \(\epsilon_{j}\), the maximum energy consumption of the tasks offloaded to collaborator \(j\), the RPS of requirement \(i\) for collaborator \(j\), denoted by \(rps_{j,i,1}\), is calculated by:

\[
\begin{align*}
\text{rps}_{j,i,1} & = \left( 1 - \frac{E_{ji}}{\epsilon_{j}} \right) \cdot \mathbb{I}[E_{ji} \leq \epsilon_{j}].
\end{align*}
\] (9)

We can see that \(\text{rps}_{j,i,1}\) decreases as \(E_{ji}\) increases.

2) Bidding Price: The bidding price RPS of requirement \(i\) for collaborator \(j\), denoted by \(rps_{j,i,2}\), is calculated by:

\[
\begin{align*}
\text{rps}_{j,i,2} & = e^{-\frac{op_{j}}{bp_{i}}} \cdot \mathbb{I}[op_{j} \geq bp_{i}].
\end{align*}
\] (10)

The larger \(bp_{i}\) is, the higher the requester is willing to pay, and the more the collaborator can benefit.

3) Requester Reputation: Similarly, requester reputation reflects the credibility of requirement, which is directly regarded as \(rps_{j,i,3}\):

\[
\text{rps}_{j,i,3} = R_{i}.
\] (11)

C. Average Requester/Collaborator Satisfaction Score Calculation

The requester and collaborator average satisfaction scores, denoted by \(ARS(X)\) and \(ACS(X)\) respectively, evaluate the overall satisfaction degree of all requesters and collaborators with matching result \(X\). The two scores are calculated by:

\[
\begin{align*}
\text{ARS}(X) & = \frac{1}{m} \sum_{i=1}^{m} \sum_{j=1}^{n} SPS(x_{ij})x_{ij}, \\
\text{ACS}(X) & = \frac{1}{n} \sum_{i=1}^{n} \sum_{j=1}^{m} RPS(x_{ij})x_{ij}.
\end{align*}
\] (12) (13)

By requiring \(\sum_{k=1}^{3} \psi_{k} = \sum_{l=1}^{3} \psi_{l} = 1\), \(ARS(X)\) and \(ACS(X)\) are also in the range of \([0, 1]\).

D. Modeling and Solving the Optimization Problem

The objective of the MPM mechanism is to find the optimal \(X = X^{*}\) that maximize \(J(X)\), the overall satisfaction of all participants:

\[
\max_{X \in [0,1]^{m \times n}} J(X)
\] (14)

s.t.

\[
\begin{align*}
\sum_{j=1}^{m} x_{ij} & \leq 1, \quad i = 1, 2, \ldots, m, \\
\sum_{i=1}^{m} s_{i}x_{ij} & \leq C_{j}, \quad j = 1, 2, \ldots, n, \\
0 & \leq x_{ij} \leq 1, \\
i = 1, 2, \ldots, m, \quad j = 1, 2, \ldots, n,
\end{align*}
\] (15) (16) (17)
where
\[ J(X) = w_1 ARS(X) + w_2 ACS(X), \]  
(18)

and \( w_1 \) and \( w_2 \) are the weights that indicate the significance of requesters and collaborators. Constraint (15) means that the total tasks offloaded by requester \( i \) cannot exceed what is submitted in requirement \( i \), and constraint (16) means that the total size of the tasks offloaded to collaborator \( j \) cannot exceed the cache size offered by service \( j \).

Since \( SP(x_{ij}) \) is a linear function to \( x_{ij} \) because of the calculation of \( t_{ij} \) by (3), the optimization problem represented by (14) is a quadratic programming problem.

E. Distributed Requester/Collaborator Reputation

As mentioned before, requester reputation \( R^i \) and collaborator reputation \( R^j \) evaluate the credibility of requester \( i \) and collaborator \( j \) respectively. Implementing a distributed reputation system can promote the collaborative regulation of the resource trading stage. In this paper, we adopt a similar idea of [28] in the design of the distributed reputation mechanism.

The design of blockchain-based distributed reputation mechanism of this paper is shown in Fig. [2]. Two blockchains are maintained, one for requester reputation and the other for collaborator reputation. These reputation scores can be queried by any participant in the system. Reputation rules are smart contracts that specifies the methods for reputation updates and the conditions under which these updates are triggered. All requesters and collaborators make the decision on the addition, deletion, and modification of reputation rules together by running consensus.

1) Reputation-Based Trading Price: Traditional double auction method usually set the final trading price as the bidding price submitted by the buyer. In order to enhance the fairness, we adopt the reputation-based \( \alpha \)-double auction [28], which calculates the trading price as follows:
\[ t_{p_{ij}} = \alpha \cdot b_{pi} + (1 - \alpha) \cdot op_j, \]  
(19)

where \( \alpha = \frac{R^i_i}{R^i_i + R^j_j} \). The resulting trading price will be closer to the price given by the party with the lower reputation, which is more beneficial to the party with the higher reputation.

2) Reputation Rules: Reputation rules are the core of the distributed reputation mechanism. To reduce the system complexity, here we adopt the following simple rules:

- A new participant is assigned with an initial reputation score of 0.6.
- On a successful resource transaction, the reputation scores of both the requester and collaborator increase by 0.01.
- For every failed resource transaction: if requester \( i \) fails to pay the trading price, then \( R^i_i \) is decreased by 0.1; if collaborator \( j \) fails to provide the claimed service, then \( R^j_j \) is decreased by 0.1.
- The final reputation scores should be restricted in \([0, 1]\).

These reputation rules are implemented as smart contracts. Once the current trading period is over, these rules will automatically trigger reputation updates once predefined conditions are satisfied.

V. Evaluation

This section evaluates our system through simulation. In the evaluation, we mainly compare our MPM mechanism with the classical DA matching mechanism [12].

A. Simulation Setup

All simulation programs are written by Python 3.8 (64 bit) and are executed on a computer with Intel® Core™ i7-6500U CPU at 2.50GHz and 12GB. The optimization problem (14) is solved via GEKKO Python library.

The ranges of parameters in the simulation are shown by Table I and all parameters are selected in their ranges uniformly at random. We set \( m = n \), and the ratio of the numbers of edge servers and IIoT terminals is set by \( 1 / 30 \). In addition, by repeated adjustment and verification, we choose \( w_1 = w_2 = 0.5 \), \( \phi_1 = \phi_3 = \psi_1 = \psi_3 = 0.36 \), and \( \phi_2 = \psi_2 = 0.28 \).

B. Double Auction

DA is a simple matching mechanism and is very popular in the market design of various fields. Specifically, DA sorts the requirement list according to the ascending order of bidding
prices and the service list according to the descending order of offering prices \[12\]. It then traverses each list from the top and finds a match when it encounters an offering price in the service list that is lower than the bidding price at the current location of the requirement list. The trading price of this match will be the bidding price provided by the requester. For each group of requirements and services generated, we execute MPM and DA respectively and compare their performance indices under the same conditions. We use solid lines to represent MPM and dashed lines to represent DA in all the figures that follows.

C. Satisfaction Scores

Fig. 3 compares the ARS, ACS, and objective values of MPM and DA mechanisms. We can see that there are significant gaps between the two methods in these scores; the values of \[ARS(X), ACS(X), \text{ and } J(X)\] of MPM are much higher than that of DA. In particular, the objective value \[J(X)\] of MPM is more than twice of that of DA.

To further analyze these differences, we extract the scores of SPS and RPS that rank the top 10\% and the bottom 10\% from each group of data. We can see from the two graphs in Fig. 4 that the high scores of SPS and RPS of MPM are slightly higher than that of DA. Moreover, the low scores of SPS and RPS of MPM fall between 0.2 and 0.3, but the low scores of DA remain at 0. It indicates that more than 10\% requirements and services cannot find a match through DA, which is much higher than the proportion of unmatched requirements and services of by following MPM.

A similar conclusion can be drawn in Fig. 5 which visualize an example of the matching result \[X\] of both mechanisms when \(m = n = 30\). In Fig. 5a, the color difference of the blocks is not very obvious, but the distribution is quite uniform. It is because that matrix \(X\) of MPM does not have many zero entries, but all nonzero entries are relatively small. In other words, most requirements will be matched, but each matching collaborator receives a fairly small portion of these tasks. On the other hand, Fig. 5b has several dark-colored blocks, saying that matrix \(X\) of DA has only a small number of nonzero entries. It suggests that the number of matches DA generates is much smaller, but some of the matched collaborator may need to undertake a large proportion of the tasks.

D. Task Completion of Requesters

Here we observe the completion of the requesters’ tasks. Fig. 6 compares the total sizes of the tasks executed of both mechanisms. It shows that the total size of the tasks completed by using MPM is about 2.8 times of that of DA. On the other hand, compared with DA, Fig. 7 exhibits a reduction of more than 50\% times in the maximum task delay of MPM. The huge gaps in Fig. 6 and 7 are caused by MPM’s more equal distribution of tasks among collaborators. This is also supported by the example in Fig. 5.

E. Resource Consumption of Collaborators

Next, we evaluate the resource consumption of collaborators. Fig. 8 compares the consumption of total CPU cycles, cache sizes, and energy of collaborators between two mechanisms. By calculation, we find that compared with DA, MPM increases the consumption of these three resources by 105\%, 108\%, and 115\% respectively. This significant increase in resource consumption of collaborators is because more tasks can be executed by adopting the matching results of MPM.
Fig. 6. Comparison of total sizes of tasks executed.

Fig. 7. Comparison of maximum task delays.

**F. Reputation and Trade Price**

Fig. 9 compares the average trade prices of two matching mechanisms. The trade prices of MPM is about 37.67% lower than that of DA on average. This drop is because that MPM adopts $\alpha$-double auction in (19) where the reputation scores of both collaborator and requester are taking into account while calculating the trade price.

We then look into the relationship between requester/collaborator reputation and average cost/income. Fig. 10 looks into the matching results of the case of $m = n = 300$. In Fig. 10b, we plot the scatter chart of average cost versus requester reputation and then draw the corresponding linear fitting line. The slope of the linear fitting line, denoted by $corr$, is the correlation coefficient between average cost and requester reputation. Since the $corr$ of DA is negative but has a greater absolute value, it indicates that the DA mechanism is more friendly to requesters with higher reputation scores. Similarly, Fig. 10a shows that the $corr$ of MPM is positive and has a slightly greater absolute value, it indicates that the MPM mechanism is more friendly to collaborators with higher reputation scores. This also indirectly proves that our resource trading system with MPM can better incentivize the participation of collaborators through the distributed reputation system.

**VI. CONCLUSION**

In this paper, we design a distributed computational resource trading system for IIoT systems. The trading adopts a multi-preference matching mechanism that can well encourage the participation of collaborators with higher reputation scores. With the help of blockchain, the decentralization of resource trading is achieved, the security, traceability, and immutability of transaction records are guaranteed, and the automation of distributed matching and reputation mechanisms is enabled. It is worth noting that the reputation mechanism in our system is simplified for illustrative purposes. A practical reputation system can be more comprehensive and complicated. How to design a reasonable reputation mechanism for IIoT systems in a distributed way is a direction worthy of further study. In addition, computational workload prediction can help to bring more intelligence to collaborative computation task offload-
Therefore, combining our resource trading strategy with computational workload prediction will be another direction of our future work.

Fig. 10. Comparisons of average costs of requesters and average incomes of collaborators.

(a) Average Cost vs. Requester Reputation

(b) Average Income vs. Collaborator Reputation

Fig. 10. Comparisons of average costs of requesters and average incomes of collaborators.

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