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Blockchain Enabled Credible Energy Trading at the Edge of the Internet of Things

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Abstract: In order to promote the value circulation of energy resources and improve energy efficiency, credible energy sharing between Internet of Things Devices (IoTDs) came into being. However, sometimes IoTDs do not obtain the required energy in the required time period, resulting in less active participation in energy sharing. To address these challenges, this paper first proposes a credible energy transaction model based on the distributed ledger blockchain at the Edge of the Internet of Things, where the Edge Cloud Server (ECS) can collect a large number of surplus energy resources of IoTDs in a secure and credible energy sharing environment and share them with other IoTDs in urgent need of charging. Meanwhile, in order to attract IoTDs to participate in energy sharing for a long time and meet the energy demand of ECS to the maximum extent, a smart contract-based Expected Social Welfare Maximized double auction incentive mechanism of Single ECS to Multi-IoTDs (ESWM-StM) is proposed to enable dynamic and adaptive energy sharing from multiple IoTDs to a single ECS. In addition, this paper compares the proposed algorithm with the benchmark method in terms of energy-sharing cost and long-term utility. The simulation results show that the proposed incentive mechanism can enable IoTDs to provide more surplus energy per unit cost to meet the energy demand of ECSs, and can sustainably attract more energy trading participants to enhance the expected social welfare in the long term.

Keywords: Internet of Things; energy trading; double auction; blockchain; smart contract

MSC: 91B26

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1. Introduction

The growing popularity of mobile devices, such as smartphones, tablets and wearables is accelerating the rapid growth of the Internet of Things (IoT) and sparking a revolution in mobile applications [1]. Cameras and embedded sensors on IoTD support and facilitate new applications with advanced features, such as virtual reality, facial recognition and interactive online gaming. The conflict between resource-constrained devices and compute-intensive applications, on the other hand, is a roadblock in offering a good quality of experience, which may postpone the creation of a mature mobile app market [2].

Mobile Edge Computing (MEC) provides cloud computing capabilities in wireless access networks (RAN), providing a new paradigm that can free mobile devices from heavy computing workloads [3]. MEC has the potential to significantly reduce latency, avoid congestion and extend the battery life of mobile devices by offloading computational tasks from mobile devices to physical proximity to MEC servers [4,5].

However, while the utilization of cloud server computing resources can be improved through compute offloading, for traditional battery-powered devices, compute performance may be compromised because there is not enough battery power for task offloading, i.e., mobile applications will be terminated and mobile devices will be terminated. This can be achieved by using a larger battery or recharging the battery regularly. However, using a larger battery in a mobile device means increasing hardware costs, which is not desirable. Energy harvesting (EH) is a promising technology to solve these problems. By harvesting idle energy resources in the IoTDs, we can provide energy resources to the terminal equipment in need [6].

However, energy-surplus IoTDs may be hesitant to join as energy suppliers in energy trading due to concerns about battery life or privacy. At the same time, IoTDs that fail to obtain the required energy in an emergency will refuse the next energy collection task associated with them, and the traditional trading mechanism will terminate the transaction if the buyer fails to obtain the required energy within the specified time, failing to take into account that the seller can still provide energy after the specified time, which will lead to increasingly inefficient energy trading. Furthermore, traditional centralized energy trading, which relies on trusted third parties, has flaws such as single points of failure and privacy breaches. It is therefore necessary to encourage more IoTDs to share their energy resources. In addition, it is important to design a secure and decentralized energy trading system in order to protect the privacy of both parties during the trading process [7].

Recently, blockchain technology has been introduced for resource trading (e.g., transactions involving energy, data and computing resources [7,8]). Smart contracts in blockchain contracts, in particular, can operate as autonomous agents to enforce preset rules (e.g., auction process) without the need for censorship or third-party interference. We use blockchain at the Edge of the Internet of Things in this paper to propose a secure and efficient framework for energy resource transactions that can perform transaction verification without relying on trusted third parties. It provides an efficient, secure and tamper-proof resource allocation environment. In a blockchain-based energy trading framework, an ESWM-StM mechanism is proposed to long-term attract IoTDs to participate in energy sharing and meet the required ECS energy as much as possible.

The main research work of this paper is summarized:

- This paper proposes a blockchain-based energy trading framework at the Edge of the Internet of Things, enabling energy trading to be executed in a decentralized centralized, transparent and secure environment. Each ECS collects surplus energy from multiple IoTDs in order to provide it to the IoTDs that need it urgently at a given moment. Without a central authority, we adopt blockchain to enable automatic, efficient and verified transactions in the energy trading framework. More specifically, we propose smart contract-based trading mechanisms to enhance the system efficiency of automatic transactions.
- The corresponding task valuation depreciation function is proposed based on the variation of the task valuation of energy collection of ECS with the degree of urgency of energy consumption.
- We designed ESWM-StM based on smart contracts to automatically activate the transactions with the aim of enhancing the expected social welfare while maximizing the energy demand of ECS and attracting IoTDs to participate in energy sharing in the long term. We prove that the proposed The ESWM-StM mechanism is computationally efficient and is individually rational, budget balanced and truthful. Furthermore, ESWM-StM can improve the expected social welfare compared with the traditional double auction mechanism.
- Simulation results show that the incentive mechanism proposed in this paper can distribute ECS's energy collection tasks to multiple IoTDs to better meet energy demand, and compared to the baseline approach [9], the incentive mechanism in this paper can attract more users to participate and enhance the expected social welfare.

The remainder of this paper is organized as follows. Related research is presented in Section 2. The transaction framework of this paper is presented in Section 3. The system model and problem statement of this paper are presented in Section 4. The algorithm design is presented in Section 5. The performance analysis is presented in Section 6. The simulation analysis is presented in Section 7. Finally, the conclusion is summarized in Section 8.

2. Related Research

Single-level auctions for allocating resources among IoTDs have received a lot of attention [10,11]. For example, Li et al. [12] proposed an algorithm based on an iterative double auction algorithm to solve the "cold start" and "long return" problems of computational resource allocation between ECSs and IoTDs. Sun et al. [13] proposed two double auction algorithms with dynamic pricing to determine matching pairs between IoTDs and ECSs. In order to effectively allocate small clouds to meet the service demand of mobile devices and set pricing, Jin et al. [14] proposed an incentive-compatible auction mechanism for resource transactions between mobile devices (buyers) and small clouds (sellers).

However, the reality is that IoTDs may not be able to deliver the required resources within the specified time, and the task valuation may change over time. Additionally, the majority of existing research has concentrated on developing offline bilateral auction mechanisms and supporting a single type of task and fixed auction service models. Accordingly, the literature [15] proposes an expected social welfare maximized mechanism (ESWM), which aims to enhance expected social welfare by attracting and retaining more participants over a long time. The literature [16] takes into account an actual crowdsourcing application with an on-demand service strategy. In particular, the online single-tender single-task, online single-tender multi-task, and online multi-tender multi-task models are made to accommodate various task and bidding requirements.

None of the above efforts consider the security of resource allocation and lack a fully reliable ledger for transactions. To address trust and security challenges, blockchain technology is combined with various single-level resource allocation protocols. He et al. [17] designed a blockchain-based real incentive mechanism to meet the various needs of users in a dynamic distributed P2P environment. Kang et al. [18] proposed a localized P2P energy distribution model for the local purchase and sale of energy among plug-in hybrid electric vehicles. Yao et al. [19] used blockchain to create a decentralized self-organizing transaction platform for industrial IoTDs and modeled the interaction as a Stackelberg game. The literature [20] proposed a consortium blockchain-based secure energy trading scheme for demand response management between EVs and the SPs in a V2G environment. In this scheme, a double auction mechanism has been used between EVs and the SPs to maximize social welfare. In order to solve the problem that the cumbersome issuing process of renewable energy certificate (REC) and inflexible pricing mechanisms consume a lot of manpower and material resources, Gao et al. [21] propose a hybrid REC trading system based on Consortium Blockchain. The literature [22] proposes the use of blockchain technology to create a decentralized transactive energy platform for peer-to-peer energy trading without authorized third-party agents. The literature [23] employs a McAfee-priced double auction mechanism and assigns the scores based on the preference of factors such as price, locality, and the type of energy generation, in addition to the quantity of energy being traded. Yang et al. [24] prove that blockchain technology is also effective in securing distributed control systems against the false data injection attack. With the aim of improving participants' profits and reducing the impacts on the grid, the literature [25] study a peer-to-peer (P2P) energy trading system among prosumers using a double auction-based game theoretic approach, where the buyer adjusts the amount of energy to buy according to varying electricity price in order to maximize benefit, the auctioneer controls the game, and the seller does not participate in the game but finally achieves the maximum social welfare. Hou et al. [26] design a privacy-preserving energy trading mechanism by using blockchain and zero-knowledge proofs. The literature [27] develops a platform—VirtElect based on a double auction market to support the matching interaction between prosumers.

However, few papers have focused on the security and efficiency of continuous energy collection at the Edge of the Internet of Things enabled by blockchain. It is the focus of this paper due to the complex relationship between the supply and demand of different ECSs and IoTDs energy and the difficulty of design. The comparison of the proposed scheme with the existing proposals is as shown in Table 1.

Table 1. Comparison of our scheme with the existing proposals.

Papers	Architectures	Game or Auction	Trading Resources	Security of Transactions	Quantitative Relationship between Trading Parties	Utilities for Maximization	Considered QoS
[12]	ECA	Iterative double auction	Computing resource	Yes	one to more	Social welfare	Efficiency of computing, Participants' privacies
[15]	None	Double auction	None	None	one to one	Expected social welfare	Long-term attraction
[18]	ECA	Iterative double auction	Electricity	Yes	one to more	Social welfare	Security and privacy
[19]	CBA	Stackelberg game	Computing resource	Yes	more to more	Individual utility	The power and computation
[20]	ECA	Double auction	Energy	Yes	one to more	Social welfare	Security and privacy
[22]	CBA	Double auction	Energy	Yes	one to one	Social welfare	Preferences and needs of the peers, Efficiency of the system
[23]	CBA	Double auction	Energy	Yes	one to one	Social welfare	Energy costs, Empowers consumers
[25]	CBA	Double auction, Stackelberg game	Energy	Yes	one to one	Social welfare	Security and privacy
[26]	CBA	Double auction	Energy	Yes	one to one	Social welfare	Security and privacy
This paper	ECA	Double auction	Energy	Yes	one to more	Expected social welfare	Long-term attraction, Variation of the task valuation, Energy costs

ECA = edge-cloud-based architecture, CBA = collaboration-based architecture.

3. Transaction Framework

Figure 1 shows the framework for trading energy resources between IoTDs and ECSs based on smart contract blockchain. Transaction information is stored in a blockchain network in ECSs located in a base station or edge cloud. We will describe the entities and the key operations for the framework in the following subsections.

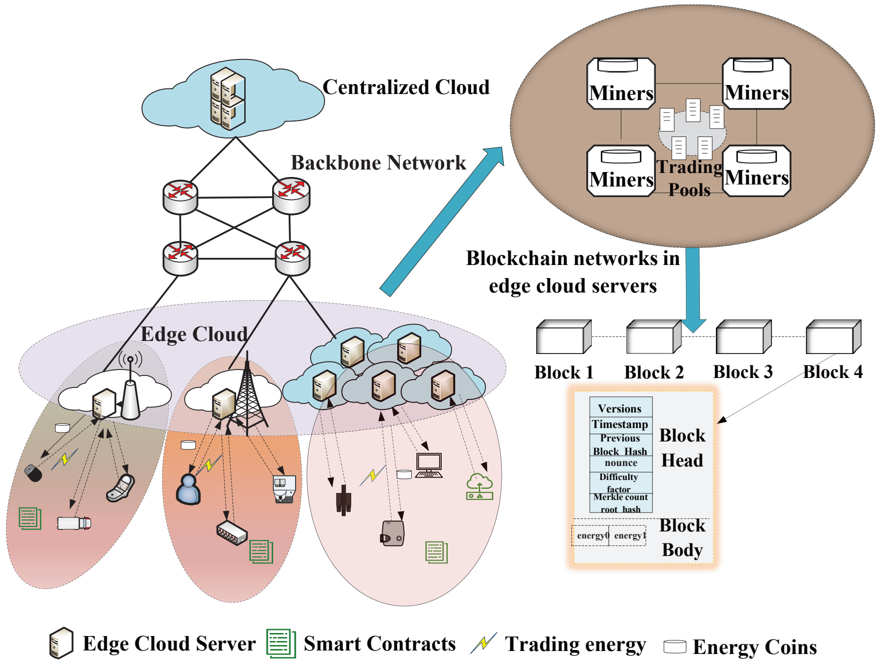

Figure 1. Blockchain-based energy trading framework at the Edge of the Internet of Things.

3.1. The Entities for the Framework

- ECS: There are two types of ECS: energy collectors and blockchain nodes. As shown in Figure 1, the energy collector is the ECS that conducts energy transactions with the IoTDs. It is in charge of collecting idle energy resources and utilizing a mechanism to ensure that the entire energy trading framework operates properly and efficiently. The blockchain node is responsible for providing a secure and trusted environment for energy transactions between the ECS and the IoTDs through smart contracts that record the detailed auction process. Furthermore, in our framework, only the blockchain node can be a trusted authority, which generates keys for each gaming player by using asymmetric encryption algorithms.
- IoTD: Different IoTDs provide idle energy resources to ECS that are closer to them. Depending on the amount of energy required by ECS, IoTDs dynamically share energy with ECS on a one-to-one or multi-to-one basis.

3.2. The Key Operations for the Framework

According to [28], We used blockchain technology to ensure the security of the transaction framework. The operation of the blockchian enabled energy trading system can be summarized as follows:

- System initialization: Each player joins the framework and receives their own dedicated address and public and private key in the blockchain system. Then, they will be given a set number of resource coins, which are the virtual digital currency used in the blockchain system.
- Resource allocation and payment: Each transaction has its own smart contract for automatically recording player allocations and payments, thus ensuring player security. Details of the smart contract design can be found in Section 5.
- Detail transaction and block generation: Any operations in the smart contract will be broadcast to the blockchain network as transactions. After that, each blockchain node adds transactions to its transaction pool. A blockchain node may have the opportunity to construct some transactions into a new block over time using a consensus mechanism such as Proof-of-Work or Proof-of-Stake.

- Public auditing: After a successful block construction, it is broadcasted to the blockchain network and audited by all blockchain nodes to determine whether the transactions in the block are correct or not. A correct block will be added to the blockchain's tail.

4. System Model and Problem Statement

The energy collection system model proposed in this paper assumes that there are M ECSs and N IoTDs, ECSs as the buyer of the auction, is denoted by $\mathbf{G} = \{g_1, g_2, \ldots g_M\}$ and IoTDs as the seller, is denoted by $\mathbf{V} = \{v_1, v_2, \ldots v_N\}$. ECSs collect shared energy from the IoTDs with the goal of minimizing communication overhead and latency during the auction with the IoTDs. The system model implements auctions and handles some other conflicts based on smart contracts, and determines the subset of winning buyers and sellers that will eventually trade. The communication between ECSs and IoTDs is either a 4G or 5G network. The model can derive which energy providers will benefit from the auction, in which the IoTDs participate in the auction process and receive a reward if they have excess battery energy. Although each IoTD has a certain amount of surplus energy for trading, the energy sharing of a single IoTD usually cannot meet the requirements of ECS, and this model solves the problem by multiple IoTDs participating in energy sharing together.

The model denotes the energy collection time period by $T = [W_S, W_E]$ and divides it into discrete time periods $t_i \in T$ of equal size, such that the energy collection time period is denoted as $T = \{t_1, t_2, \ldots t_n\}$, and the model focuses on one of these time periods for inference verification. It considers the decrease in the task valuation of energy collection of ECS over time and the punctuality of the IoTDs to complete the ECS's energy collection task. The symbols used in this paper and their corresponding meanings are listed in Table 2.

The process of establishing utility functions for ECS, IoTD and virtual smart contract-based crowdsourcing platforms will be described next, respectively.

(1) ECS:

In a crowdsourcing platform, ECSs act as buyers in a double auction, with each ECS g_j submitting its own bidding information $\theta_j^g = (T_j, t_j^d, t_j^{ex}, w_j^{\max}, \alpha_j)$ to the platform, Here, T_j, t_j^d, and t_j^{ex} represent the tasks issued by ECS, the moment when the task valuation starts to depreciate after the energy collection time period, and the moment when the task valuation is zero, respectively. The maximum task valuation is $w_j^{\max}$ and α_j is the depreciation rate of the task valuation after the energy collection time period is exceeded. Every ECS is rational and selfish, and will only engage in the auction process if the value of T_j is higher than the value of q_j charged for it.

Considering the charging schedule of all IoTDs in a given time period, the Euclidean distance between ECS g_j and IoTD v_i is denoted as d_{ij}. Xie et al. [29] argued that the wireless energy transfer efficiency μ_{ij} decreases as the distance d_{ij} increases, $\mu_{ij} = -0.0958d_{ij}^2 - 0.0377d_{ij} + 1$, where $0 \leq \mu_{ij} \leq 1$. If we assume that the output power of the seller v_i is P_o, the buyer g_j receives power denoted as:

$$P_{ij} = \mu_{ij} P_o \tag{1}$$

In this paper, using the binary variable x_{ij} to indicate whether a buyer and seller transaction has occurred and t as the length of a given time period, the total amount of energy received by ECS g_j from IoTDs can be expressed as:

$$e_j = \sum_{i \in \mathbf{V}_s} P_{ij} \cdot t \cdot x_{ij},\ 1 \leq j \leq N \tag{2}$$

where $\mathbf{V}_s$ denotes the set of winning IoTDs.

Table 2. System Parameters.

Parameters	Meaning
g_j	A j-th ECS
$\mathbf{G}$	A set of ECSs
θ_j^g	A bidding information submitted by g_j
$\lvert T_j \rvert$	The energy required for g_j
$\lvert T_{ij} \rvert$	The amount of energy g_j gets from v_i
$w_j^{\max}$	The variation of the task valuation of energy collection of g_j
t_j^d	The moment when the task valuation starts to depreciate
t_j^{ex}	The moment when the task valuation is zero
α_j	Depreciation rate of the task valuation after the deadline
v_i	A i-th IoTD
$\mathbf{V}$	A set of IoTDs
c_i	cost per unit of energy provided by v_i
λ_i	The punctuality level of v_i in providing the required energy
K	Maximum number of task requests
$\mathbf{G}_s$	The winning ECSs
$\mathbf{V}_s$	The winning IoTDs
q_j	The temporary fee for g_j
p_i	The temporary payment for v_i
μ_{ij}	The efficiency of the energy transfer between g_j and v_i
d_{ij}	The transmission distance between g_j and v_i
P_o	Output power of v_i
P_{ij}	Receiving power of g_j
e_j	Total energy received by g_j
t_{sub}	The moment v_i completed the energy collection task
E_i	Remaining energy of v_i

According to [15], the time-varying function of the ECS's task valuation is proposed with the degree of urgency of energy consumption:

$$w_j(t) = \begin{cases} w_j^{\max}, & \text{if } 0 \le t \le t_j^d \\ \max\left\{0, w_j^{\max} - \frac{\tau}{|T_j| - e_j}\left(t - t_j^d\right)^2\right\}, & \text{otherwise.} \end{cases} \tag{3}$$

The quadratic function of time t is used to represent a depreciation method, where the task valuation $w_j(t)$ remains constant until the deadline t_j^d. After the energy collection time period, $w_j(t)$ starts to decrease as shown in the above equation, and the rate of decrease depends on $\frac{\tau}{|T_j| - e_j}$, τ is a constant, and $|T_j|$ is the energy required by ECS g_j.

For convenience, $\frac{\tau}{|T_j| - e_j}$ is denoted by α_j. When the ECS collects close to the required energy in the specified charging time period, α_j is larger and the task valuation decreases faster, and if the energy collected in the specified charging time period is small, α_j is smaller and the task valuation decreases slower.

In this paper, we use $q_j^{'}$ to denote the price that the auction platform should charge ECS g_j after the task devaluation, then the utility of ECS g_j can be expressed as the following equation:

$$u_j^g = \begin{cases} w_j\left(t_*^{sub}\right) - q_j', & \text{if } g_j \in \mathbf{G}_s \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

where t_*^{sub} represents the moment when the IoTD completes its energy collection task and $\mathbf{G}_s$ represents the set of winning ECSs.

(2) IoTD:

The IoTD acts as a seller in the auction process, and each ECS matches multiple winning IoTDs to provide the required amount of energy. Similarly, the IoTD submits its own bidding information $\theta_i^v = (c_i)$ to the platform, which indicates the minimum payoff that IoTD v_i wishes to receive for providing a unit of energy. v_i is also rationally selfish and decides to provide the corresponding amount of energy only when the following equation is satisfied:

$$p_i' \geq \sum_{g_j \in \mathbf{G}_s} c_i \left|T_{ij}\right| \tag{5}$$

where p_i' is the price paid adjusted to take into account the punctuality of the IoTD supply, and $\left|T_{ij}\right|$ is the amount of energy received by ECS g_j from IoTD v_i.

According to [15], consider the problem of whether the IoTD can provide the energy required by the edge server within a specified time, modeling this stochastic behavior as a probability density function, using the following truncated normal distribution:

$$f_i\left(t; \mu_i, \sigma_i, t_*^d, t_*^{ex}\right) = \begin{cases} \dfrac{\frac{1}{\sigma_i}\phi\left(\frac{t-\mu_i t_*^d}{\sigma_i}\right)}{\Phi\left(\frac{t_*^{ex}-\mu_i t_*^d}{\sigma_i}\right) - \Phi\left(\frac{-\mu_i t_*^d}{\sigma_i}\right)}, & 0 \leq t \leq t_*^{ex} \\ 0, & \text{otherwise} \end{cases} \tag{6}$$

$$\phi(\zeta) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{1}{2}\zeta^2\right) \tag{7}$$

where t_*^d and t_*^{ex} represent the task deadline and the time when the task valuation is zero, respectively, (7) and $\Phi(\cdot)$ are the probability density function and cumulative density function of the standard normal distribution, respectively, and $\mu_i t_*^d$ is the mean value of the truncated normal distribution, indicating that the probability of v_i submitting a task at this moment is higher. In order to quantify the punctuality of the IoTD's completion of the energy collection task, the punctuality coefficient λ_i, which is equal to $1/\mu_i$, is introduced, in which case the IoTD submits the bidding information becomes $\theta_i^v = (c_i, \lambda_i)$.

We express the utility of IoTD v_i as follows:

$$u_i^v = \begin{cases} p_i' - \sum\limits_{g_j \in \mathbf{G}_s} c_i \left|T_{ij}\right|, & \text{if } v_i \in \mathbf{V}_s \\ 0 & \text{otherwise} \end{cases} \tag{8}$$

(3) Crowdsourcing Platform:

Since this paper uses smart contracts to automatically execute the auction mechanism, there is no need for a third party to perform the auction process, but for the sake of analysis, the existence of a virtual smart contract-based crowdsourcing platform is assumed. The crowdsourcing platform acts as the auctioneer, which is responsible for selecting the winners of both sides of the auction and matching each winning ECS with multiple IoTDs to satisfy their required energy as much as possible. Define the platform utility as follows:

$$u_0 = \sum_{g_j \in \mathbf{G}_s} q'_j - \sum_{v_i \in \mathbf{V}_s} p'_i \tag{9}$$

In order to express the degree of excellence of crowdsourcing services, social welfare is generally used to quantify it and is applied to the present model by the following formula:

$$\sum_{g_j \in \mathbf{G}_s} w_j^{\max} - \sum_{v_i \in \mathbf{V}_s} \sum_{g_j \in \mathbf{G}_s} c_i |T_{ij}| \tag{10}$$

However, when the IoTD provides the promised energy during the time period beyond the specified peak, the task valuation is zero in the binary task model, but in the model proposed in this paper, it is still possible to provide energy to the ECS without this time period, but with a devaluation. Considering the stochastic nature of the energy provided by the IoTD, combined with [15], an expected social welfare (ESW) is used to judge the excellence of the crowdsourcing service, defined as follows:

$$ESW = \sum_{g_j \in \mathbf{G}_s} \sum_{v_i \in \mathbf{V}_s} \mathbf{E}_i \left(\frac{w_j(t)}{\sum\limits_{v_i \in \mathbf{V}_s} l_{ji}} \right) - \sum_{v_i \in \mathbf{V}_s} \sum_{g_j \in \mathbf{G}_s} c_i |T_{ij}| \tag{11}$$

where $\sum\limits_{v_i \in \mathbf{V}_s} l_{ji}$ is the number of IoTDs matched with ECS g_j and $\mathbf{E}_i \left(\frac{w_j(t)}{\sum\limits_{v_i \in \mathbf{V}_s} l_{ji}} \right)$ is the expected valuation when task T_j is assigned to IoTD v_i.

Assuming that the cost per unit of energy is constant, the function $\mathbf{E}_i(x(t))$ is defined as follows:

$$\begin{aligned} &\mathbf{E}_i(x(t)) = \int_0^{t_j^d} w_j^{\max} f(t; \mu_i; \sigma_i; t_j^d; t_j^{ex}) dt \\ &+ \int_{t_j^d}^{t_j^{ex}} w_j(t) f(t; \mu_i; \sigma_i; t_j^d; t_j^{ex}) dt \end{aligned} \tag{12}$$

The above equation is divided into two parts, the first part is the expected value before the cut-off date and the second part is the expected value after the cut-off date.

In the energy trading system of this paper, the objective is to find the optimal ECS-IoTD matching pair that enhances the expected social welfare, and the matching matrix is shown below:

$$\mathbf{L} = \begin{bmatrix} l_{11} & l_{12} & \cdots & l_{1|V|} \\ l_{21} & l_{22} & \cdots & l_{2|V|} \\ \vdots & \vdots & \vdots & \vdots \\ l_{|G|1} & l_{|G|2} & \cdots & l_{|G||V|} \end{bmatrix} \tag{13}$$

The ECS and IoTD are matched only when the value in the matrix is 1, otherwise, it is 0. The expected social welfare maximization problem formulated in this paper is as follows:

$$\mathbf{L}^* = \underset{L}{\operatorname{argmax}} \sum_{g_j \in \mathbf{G}_s} \sum_{v_i \in \mathbf{V}_s} \left(\mathbf{E}_i \left(\frac{w_j(t)}{\sum\limits_{g_j \in \mathbf{G}_s} l_{ji}} \right) - c_i |T_{ji}| \right) l_{ji} \tag{14}$$

Subject to

$$l_{ji} \in \{0, 1\}, \forall l_{ji} \in \mathbf{L} \tag{15}$$

$$\sum_{g_j \in \mathbf{G}_s} \sum_{v_i \in \mathbf{V}_s} l_{ji} \leq K \tag{16}$$

$$\sum_{v_i \in \mathbf{V}_s} l_{ji}|T_{ji}| \leq |T_j|, \forall g_j \in \mathbf{G}_s \quad (17)$$

$$\sum_{g_j \in \mathbf{G}} l_{ji}|T_{ji}| \leq E_i, \forall v_i \in \mathbf{V} \quad (18)$$

The above objective function (14) is a combinatorial optimization problem, and Equations (15) to (18) are constraints on the optimization problem. Equation (15) is used to indicate whether the two sides of the auction are paired. Equation (16) shows the upper limit of the number of task requests, and K indicates the maximum number of task requests. Equation (17) indicates that the sum of all IoTDs energy supplies matched by an ECS is as close as possible to the energy it needs. Equation (18) indicates that the sum of the energy supplied by the IoTDs to the ECS cannot exceed its remaining energy, and E_i indicates the remaining energy of the IoTD v_i.

5. Algorithm Design

5.1. Ideal Economic Properties

In designing an incentive mechanism, the following four desirable economic attributes need to be satisfied: (1) individual rationality, (2) budget balance, (3) computational efficiency, and (4) truthfulness. It is assumed that the auction algorithm does not satisfy individual rationality, which leads to a negative utility for both sides of the auction; does not satisfy budget balance, which leads to a negative utility for the auction platform; does not satisfy truthfulness, which leads to both sides of the auction submitting untrue bidding information to gain greater profit; and does not satisfy computational efficiency, which leads to poor real-time transactions and additional overhead. We describe them as follows:

- Personal rationality: incentives are personally rational if the auction parties have non-negative utility in reporting their true valuations and costs.
- Budget balanced: The incentive is said to be budget balanced if the fee charged by the platform to ECSs at the end of the auction process is not less than the fee paid to IoTDs.
- Computational efficiency: An incentive is said to be computationally efficient if it runs in polynomial time and is computationally effective.
- Truthfulness: An incentive is said to be truthful if neither party to the auction can obtain a higher utility by altering their bidding information.

5.2. Specific Steps of Algorithm Design

In order to apply the proposed double auction model to the blockchain framework in Section 3, we implemented it in the form of a smart contract, the details of which are given in the following algorithm.

The expected social welfare maximized mechanism proposed in this paper consists of three specific parts: winner selection, matching algorithm, and price allocation strategy.

5.2.1. Winner Selection

Winner selection: After ECSs and IoTDs have submitted their bidding information, the auction platform determines the winning subset of both parties and sets the subset capacity of both parties as K and $3K$, respectively, considering the relative relationship between the number of ECS and IoTD in the real situation. The selection process includes Algorithms 1 and 2.

In Algorithm 1, the winner selection is based on selecting those ECSs with high initial task valuations and slow task valuations decrease after the deadline. The quantification process is embodied in the third row, where the larger one is selected as the winner in order according to the defined selection criterion $\frac{1}{\alpha_j^\beta}\frac{w_j^0}{|T_j|}$. β is an adjustable parameter to determine the priority between the task valuation and depreciation rate of the task valuation in the winner selection process, and the loop ends when the number of members of the winner subset reaches $K+1$. The ratio $\frac{1}{\alpha_{K+1}^{\beta}}\frac{w_{K+1}^{0}}{|T_{K+1}|}$ of the $K+1$th ECS is set as a threshold and it is excluded from the ECS winner subset.

Algorithm 1 ECS Winner Algorithm

Input: $\mathbf{G}$, K, β
Output: $\mathbf{G}_s$, g_{th}
$\mathbf{G}_s \leftarrow \emptyset$;
while $|\mathbf{G}_s| \neq K+1$ **do**
  $g^* \leftarrow \arg\max_{g_j \in \mathbf{G}} \frac{1}{\alpha_j^{\beta}}\frac{w_j^0}{|T_j|}$;
  $\mathbf{G}_s \leftarrow \mathbf{G}_s \cup \{g^*\}$, $\mathbf{G} \leftarrow \mathbf{G} \backslash \{g^*\}$;
  if $|\mathbf{G}| = 0$ **then**
    break;
  end if
end while

Similarly, in Algorithm 2, unlike Algorithms 1 and 2 sequentially selects the winner with the smaller ratio $\frac{c_i}{\lambda_i^{\beta}}$ and sets the ratio $\frac{c_{3K+1}}{\lambda_{3K+1}^{\beta}}$ of the $3K+1$th IoTD as a threshold value to exclude it from the subset of IoTDs winners.

Algorithm 2 IoTD Winner Algorithm

Input: $\mathbf{V}$, K, β
Output: $\mathbf{V}_s$, v_{th}
$\mathbf{V}_s \leftarrow \emptyset$;
while $|\mathbf{V}_s| \neq 3K+1$ **do**
  $v^* \leftarrow \arg\min_{v_i \in \mathbf{V}} \frac{c_i}{\lambda_i^{\beta}}$;
  $\mathbf{V}_s \leftarrow \mathbf{V}_s \cup \{v^*\}$, $\mathbf{V} \leftarrow \mathbf{V} \backslash \{v^*\}$;
  if $|\mathbf{V}| = 0$ **then**
    break;
  end if
end while

5.2.2. Matching Algorithm

The matching process is mainly embodied in Algorithm 3, which aims to satisfy the ECS demand energy to the maximum extent. Firstly, ECSs are sorted in descending order according to $\frac{1}{\alpha_j^{\beta}}\frac{w_j^0}{|T_j|}$ size and IoTDs are sorted in ascending order according to $\frac{c_i}{\lambda_i^{\beta}}$. The thresholds obtained in Algorithms 1 and 2 are set to their respective revenue and expense prices and stored in $\mathbf{Q}$ and $\mathbf{P}$. Then, each ECS is sequentially matched with multiple IoTD agents in order until its required energy is satisfied, while the matched pairs are added to the Match tuple and the corresponding ECSs and IoTDs in the winning subset of both sides of the auction are removed.

Algorithm 3 Dynamic Matching Algorithms to meet electricity demand

Input: $\mathbf{V}_s$, $\mathbf{G}_s$, v_{th}, g_{th}, β
Output: **Match**, $\mathbf{Q}$, $\mathbf{P}$

Sort ECS by $\frac{1}{\alpha_j^{\beta}} \frac{w_j^0}{|T_j|}$ size in descending order;
Sort IoTD by $\frac{c_i}{\lambda_i^{\beta}}$ size in ascending order;
Initialize the values in $\mathbf{Q}$, $\mathbf{P}$ with the thresholds obtained from the winning subsets of both sides of the auction;
Match $\leftarrow \emptyset$;
if $\sum_{p_i \in \mathbf{P}} p_i > \sum_{q_j \in \mathbf{Q}} q_j$ **then**
  $\mathbf{G}_s \leftarrow \emptyset, \mathbf{V}_s \leftarrow \emptyset, \mathbf{Q} \leftarrow \emptyset, \mathbf{P} \leftarrow \emptyset$;
  return **Match**, $\mathbf{Q}$, $\mathbf{P}$;
end if
while $\sum_{v_i \in \mathbf{V}_s} E_i \neq 0 \&\& \sum_{g_j \in \mathbf{G}_s} |T_j| > \sum_{g_j \in \mathbf{G}_s} \sum_{v_i \in \mathbf{V}_s} |T_{ij}|$ **do**
  for $g_j \in \mathbf{G}_s$ **do**
    if $|T_j| <= \sum_{v_i \in \mathbf{V}_s} |T_{ij}|$ **then**
      $\mathbf{G}_s \leftarrow \mathbf{G}_s \backslash g_j$;
    end if
    while $\sum_{v_i \in \mathbf{V}_s} E_i \neq 0$ **do**
      for $v_i \in \mathbf{V}_s$ **do**
        if $E_i >= 0$ **then**
          $match_j \cup \{g_j, v_i\}$, $\mathbf{V}_s \leftarrow \mathbf{V}_s \backslash v_i$;
          $E_i = E_i - |T_{ij}|$;
        end if
      end for
    end while
  end for
end while

5.2.3. Price Allocation Strategy

Since the task valuation decreases after the energy collection time period, the previous pricing strategy will be unrealistic. The respective revenue and expense prices are adjusted accordingly according to the ratio between the task valuation and the original task valuation at the moment when the IoTDs complete the energy collection task, and the revenue and expense price matrices **Q**, **P** are updated. As shown in Algorithm 4:

Algorithm 4 Pricing Optimization Algorithm

Input: **Match**, $\mathbf{Q}$, $\mathbf{P}$
Output: $\mathbf{Q}'$, $\mathbf{P}'$

Initialize $\mathbf{Q}'$, $\mathbf{P}'$ to $\emptyset$;
while The matching tuple has not yet been updated with the prices of income and expenses of both agents **do**
  Calculate the task submission time of v_i, denoted by the variable t_i^{sub};
  $q_j' \leftarrow \frac{w_j(t_i^{sub})}{w_j^0} q_j, \mathbf{Q}' \leftarrow \mathbf{Q}' \cup \{q_j'\}$;
  $p_i' \leftarrow \frac{w_j(t_i^{sub})}{w_j^0} p_i, \mathbf{P}' \leftarrow \mathbf{P}' \cup \{p_i'\}$;
end while
return $\mathbf{Q}'$, $\mathbf{P}'$;

The overall algorithm flow of the ESWM-StM proposed in this paper is organized as Algorithm 5. follows:

Algorithm 5 ESWM-StM

1: Obtain the winning subsets $\mathbf{G}_s$, $\mathbf{V}_s$ with thresholds g_{th}, v_{th} according to Algorithms 1 and 2;
2: According to Algorithm 3 to obtain the matching tuple **Match** with the initial income and expenditure price matrix $\mathbf{Q}$, $\mathbf{P}$;
3: The final optimized revenue and expense price matrix $\mathbf{Q}^{'}$, $\mathbf{P}^{'}$ is obtained according to Algorithm 4.

6. Performance Analysis

6.1. Individual Rationality

The first thing to prove is that the ESWM-StM incentive mechanism proposed in this paper is individually rational for both ECS and IoTD parties, i.e., to show that the utility of each agent is non-negative at the end of the auction.

For the ECS to be analyzed, for $g_j \in \mathbf{G}_s$, its temporary payment cost is calculated as $g_j = \left(\alpha_j^{\beta} w_{th}^{\max} |T_j|\right) / \left(\alpha_{th}^{\beta} |T_{th}|\right) \leq w_j^{\max}$. Bringing it into Equation (4), the utility of the winning ECS can be obtained, which can be seen to be non-negative. For the task submission after, i.e., in the price pricing step, the auction platform uses the task valuation $w_j(t_i^{sub})$ at the moment of completion based on the shared completion time of each IoTD energy to determine the final price $q_j^{'}$ paid by each ECS. Then, the utility of each ECS is shown in Equation (19).

$$u_j^g = w_j\left(t_i^{sub}\right) - q_j' = w_j\left(t_i^{sub}\right)\left(1 - \frac{q_j}{w_j^{\max}}\right) \tag{19}$$

Because $w_j\left(t_i^{sub}\right)$ is non-negative and $q_j \leq w_j^{\max}$, the utility of ECS is non-negative, ensuring the individual rationality of all ECSs.

For each IoTD $v_i \in \mathbf{V}_s$ to be analyzed, assuming that an IoTD submits its true cost value, the initial price paid to it is calculated as $p_i = \sum_{g_j \in \mathbf{G}_s} (c_{th}|T_{ij}|\lambda_i^{\beta})/\lambda_{th}^{\beta} \geq c_i$, brought into Equation (8), and the utility of each IoTD is non-negative until the task is submitted, the utility after the pricing optimization algorithm can be expressed by the following equation:

$$u_i^v = \sum_{g_j \in \mathbf{G}_s} \frac{w_j\left(t_i^{sub}\right)}{w_j^{\max}} \left(p_i - \frac{w_j^{\max}}{w_j\left(t_i^{sub}\right)} c_i |T_{ij}|\right) \tag{20}$$

The above equation shows that the utility of the IoTD is non-negative only before the task deadline when $t_i^{sub} \leq t_j^d$, $p_i - \sum_{g_j \in \mathbf{G}_s} c_i|T_{ij}| \geq 0$, but there is no guarantee that $p_i - \frac{w_j^{\max}}{w_j\left(t_i^{sub}\right)} c_i|T_{ij}|$ in the above equation is non-negative if the task deadline is exceeded, so there is an additional incentive for the IoTDs to provide the appropriate amount of energy at the specified time.

6.2. Budget Balance

In the proposed Algorithm 3, before performing the matching step, it first determines whether the budget balance condition $\sum_{p_i \in \mathbf{P}} p_i \leq \sum_{q_j \in \mathbf{Q}} q_j$ is satisfied, and if this condition is not satisfied, it terminates the auction and returns with the winning subset and the initial revenue and expense price allocation matrix set to null, so that the platform utility is always non-negative in the proposed ESWM-StM algorithm.

6.3. Computational Efficiency

In the ESWM-StM algorithm proposed in this paper, the worst-case time complexity of the winner selection process, matching process, and pricing process are $O(\max(M, N)K)$, $O(MN)$, and $O(K)$, respectively. Therefore, the time complexity upper bound of the ESWM-StM algorithm proposed in this paper is $O(MN)$, which can be computed within polynomial time with high computational efficiency.

6.4. Truthfulness

In proving the authenticity of the incentive mechanism in this paper, Myerson's theorem [9] is used. As long as the two conditions of monotonicity and critical value are satisfied, the incentive mechanism designed in this paper has truthfulness. For ECS (IoTD), if bid $c_i(w_j^{\max})$ is the winner of the auction, bid $c_i' \leq c_i(w_j'^{\max} \geq w_j^{\max})$ will also win the auction so that the monotonicity of the incentive is satisfied. In the scenario of this paper, the critical value is the maximum and minimum value required by both the seller and the buyer, and the bids c_i, $w_j^{\max}$ are the critical values. Given that this paper uses a double auction format, the veracity of the mechanism is verified by proving the veracity of both sides of the auction separately.

For ECS g_j, which wins the auction by bidding $w_j^{\max}$, there must be a threshold ECS g_{th} that satisfies the relation $w_j^{\max}/(\alpha_j^{\beta}|T_j|) \geq w_{th}^{\max}/(\alpha_{th}^{\beta}|T_{th}|)$. Suppose an ECS bid $w_j'^{\max}$ is higher than $w_j^{\max}$, then $w_j'^{\max}/(\alpha_j^{\beta}|T_j|) \geq w_j^{\max}/(\alpha_j^{\beta}|T_j|) \geq w_{th}^{\max}/(\alpha_{th}^{\beta}|T_{th}|)$, and thus satisfies monotonicity; for the threshold, if g_j bids less than $w_{th}^{\max}$, then $w_j^{\max}/(\alpha_j^{\beta}|T_j|) < w_{th}^{\max}/(\alpha_{th}^{\beta}|T_{th}|)$, it will be eliminated from the winning subset $\mathbf{G}_s$, and thus the ECS has a threshold value.

For IoTD v_i to win the auction, there must be a threshold IoTD c_{th} that satisfies the relation $c_i/\lambda_i^{\beta} \leq c_{th}/\lambda_{th}^{\beta}$. Assuming an IoTD $c_i' \leq c_i$, then $c_i'/\lambda_i^{\beta} \leq c_i/\lambda_i^{\beta} \leq c_{th}/\lambda_{th}^{\beta}$, thus satisfying monotonicity; similarly for the threshold, if c_i'' of v_i is greater than c_{th}, then $c_i''/\lambda_i^{\beta} > c_{th}/\lambda_{th}^{\beta}$, thus the IoTD has a threshold value.

In summary, the incentive mechanism designed in this paper possesses authenticity.

7. Simulation Analysis

In this section, we first provide the simulation model and description of the model. Next, a description of all algorithms and their complexity is provided. Then the experimental parameters required to perform the simulation experiments are briefly described. Finally, we provide the evaluation results and the necessary explanations.

7.1. Simulation Model

In this subsection, we show the simulation model and a detailed description of the proposed trading mechanism. First, we design two main functions of the smart contract in this phase as follows:

(1) An "upload" function that enables ECSs and IoTDs to upload messages to smart contracts.
(2) A "double auction" function that enables the ECSs to purchase the IoTDs' energy.

We now introduce the smart contract-based double auction design in detail. As shown in Figure 2, the IoTDs and ECSs are sellers and buyers, respectively, and the smart contract can work as an auctioneer to establish the automatic transactions between the IoTDs and ECSs via the proposed double auction mechanism.

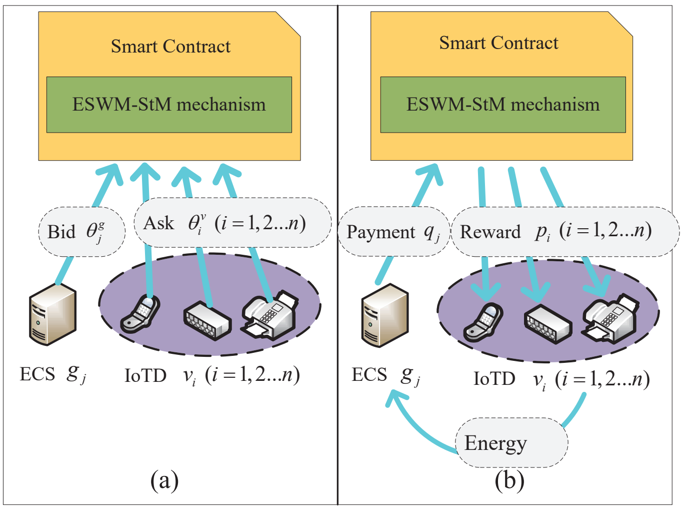

Figure 2. Double auction mechanism based on smart contract.

First, as shown in Figure 2a, Each ECS g_j and IoTD v_i sends its bidding information θ_j^g and θ_i^v to the smart contract separately to call the "upload" function.

Second, the smart contract validates the bidding information from both sides of the transaction and broadcasts them to the blockchain network.

Last, as shown in Figure 2b, the smart contract calls the "double auction" function to determine the set of winning parties and the correspondence between the ECS and the multiple IoTDs that provide the energy needed for the ECS, and finally determine the payments and rewards for the parties.

7.2. Algorithm Complexity Analysis

In the ESWM-StM algorithm proposed in this paper, the worst-case time complexity of the winner selection process, matching process, and pricing process are $O(\max(M, N)K)$, $O(MN)$, and $O(K)$, respectively. Because $K \leq M\&\&K \leq N$, the time complexity of the proposed algorithm is upper bounded as $O(MN)$. Therefore, the complexity of the algorithm grows at a square rate as the number of trading parties increases; however, overall, the proposed trading mechanism seems to be computationally efficient.

7.3. Experiment Setting

To verify the effectiveness of the incentive mechanism in this paper, it is compared with a baseline approach [9] that does not consider the β parameter in selecting the winning subset of both sides of the auction and an ESWM mechanism [15] with a single ECS and a single IoTD. In the model parameter settings in this paper, $w_j^{\max}$, $|T_j|$, t_j^d and t_j^{ex} of ECS are uniformly distributed over (0, 100] and [1, 10], (0, 100] and $[t_j^d, 1.5t_j^d]$, respectively. For IoTD, c_i and μ_i are uniformly distributed on (0, 10] and (0, 1.5], respectively. All simulation results for the following performance metrics are averaged over 200 runs. α_j is uniformly distributed on (0, 100], the number of ECS and IoTD is set to 1000 and 2000, and the β factor is set to 0.5. The system runs on a PC with AMD Ryzen 7 6800H with Radeon Graphics of 3.20 GHz and 32 GB RAM (Lenovo, China).

7.4. Results and Discussion

Figure 3 gives a comparison of the total cost of the baseline method and the ESWM mechanism for the four matching methods of one-to-one (OTO) and one-to-many (OTM), respectively. OTO represents an IoTD providing energy to an ECS, and OTM represents multiple IoTDs providing energy to an ECS. It can be seen from Figure 3 that their total costs increase as the number of ECSs increases. For the same baseline method or ESWM mechanism, the total cost of OTM is larger compared to OTM. This is because the OTM matching approach also causes an increase in the number of IoTD participating in energy sharing, resulting in an increase in the total cost. For the OTO matching method, the total cost of the ESWM mechanism is higher than that of the baseline method, but for the OTM matching method, the total cost of the ESWM mechanism is lower than that of the baseline method. Because the coefficients are introduced in the ESWM mechanism to control the weight size of task valuation and task valuation depreciation rate as well as the IoTD cost and quorum coefficients, it has a significant optimization effect on the winner selection process and cost reduction, and as the number of matched to IoTDs increases, the IoTDs with smaller cost per unit of energy can be selected to co-energy the ECS, and the total cost is smaller.

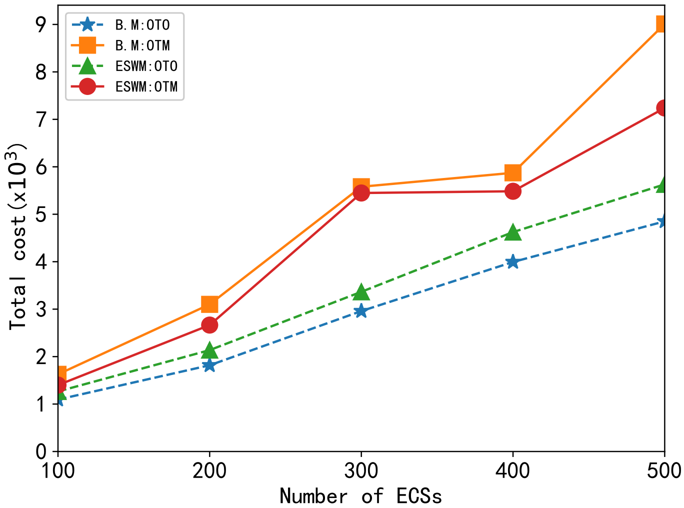

Figure 3. Comparison of total costs under different incentive mechanisms.

Figure 4 gives the amount of energy that can be supplied per unit cost of IoTD for the same incentive mechanism OTO and OTM matching approach. It can be seen from the figure that the energy generated per unit cost is higher in the OTM matching method than in the OTO matching method. This is because in the OTO matching method, if the energy demanded by ECS is much higher than that of IoTD, one IoTD is not enough to provide the energy required during the peak period. For the OTM matching method, more IoTDs can be matched to provide energy at the same cost, so more energy can be provided per unit cost than the OTO method, which promotes energy sharing.

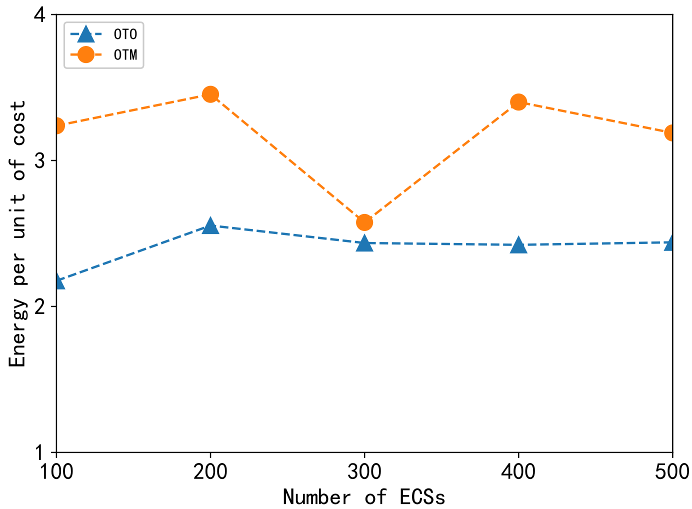

Figure 4. Energy produced per unit cost with different incentives.

Figure 5 gives the comparison between the total energy required by ECS and the energy provided by all IoTDs under the OTO and OTM matching methods of the ESWM mechanism. It can be seen from the figure that the total energy provided under the OTO matching approach is less for a certain amount of energy demanded by the ECS, and the ESWM-StM mechanism proposed in this paper can better meet the total energy demanded. Because compared to the OTO matching method, the energy provided by one IoTD is always lower than the energy demanded by the ECS, in the OTM matching method, multiple IoTDs provide energy to one ECS, and the required energy is guaranteed to be provided during the energy collection time period, so the OTM matching method can better meet the energy demand of the ECSs.

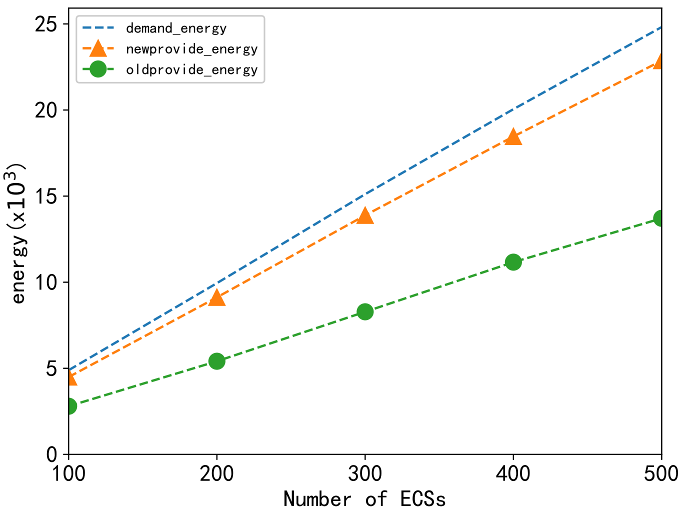

Figure 5. Differences in energy supply and demand under different incentive mechanisms.

Figure 6 gives the comparison between basic social welfare and expected social welfare under different incentive mechanisms. As the number of ECSs increases, social welfare tends to increase. For the analysis of the basic social welfare, the basic social welfare of the ESWM-StM incentive mechanism proposed in this paper is lower than the baseline method, but for the expected social welfare, the ESWM-StM incentive mechanism proposed in this paper is better than the baseline method. Because the ESWM-StM incentive mechanism proposed in this paper aims to better consider the decline of the task valuation of ECS over time in realistic situations and the punctuality of IoTDs to complete the energy collection task, the basic social welfare is lower than that of the baseline method if only the energy collection time period is considered, but in terms of expected social welfare, the expected social welfare in this paper is higher and can achieve long-term attraction of IoTDs participation in energy collection.

Figure 7 gives a comparison between the fees charged by the platform to the ECS and the fees paid to the IoTD under different incentive mechanisms. It can be seen from the figure that before the maximum number of task requests is 700, the fees paid to the platform by the two incentive mechanisms are similar, but for the fees paid to the IoTD it is obvious that the ESWM incentive mechanism in this paper is higher, which leads to a decrease in the utility of the platform but the IoTD receives more fees and is able to attract the IoTDs to participate in the energy collection task in the long term; for the maximum number of task requests, the sharp decrease in revenue and expense due to exceeding 700 is due to the fact that the platform does not execute the winner selection algorithm when the break-even condition of the auction mechanism is not satisfied, thus canceling the auction process, which is reflected in Algorithms 1 and 2.

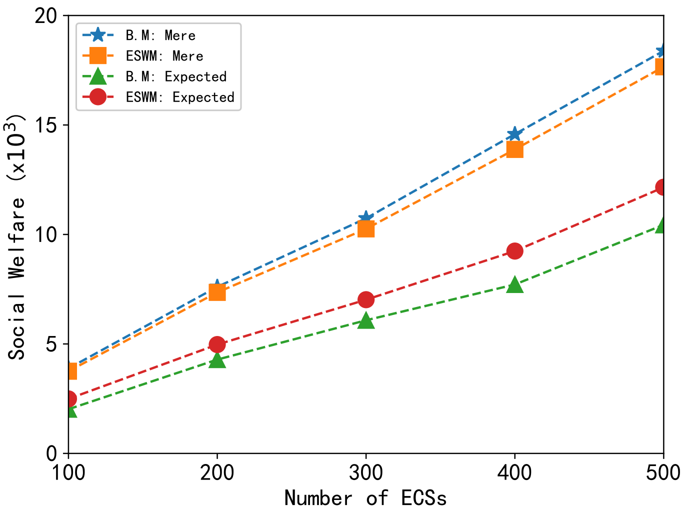

Figure 6. Comparison of expected social welfare under different incentive mechanisms.

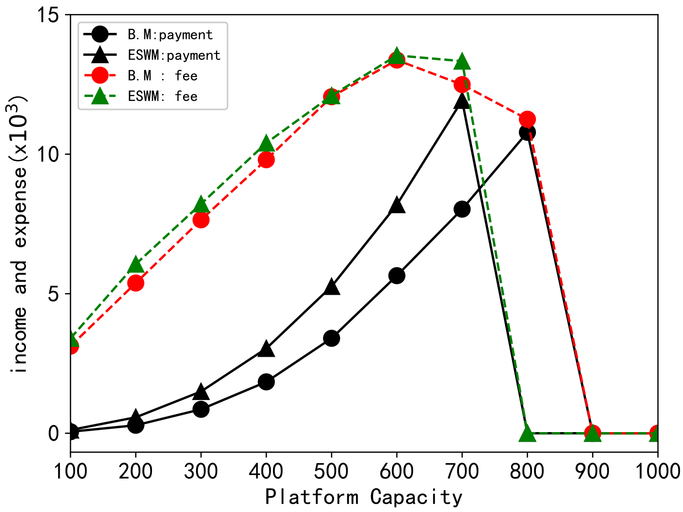

Figure 7. Comparison of income and expenses under different incentive mechanisms.

8. Conclusions

In this paper, we propose a trading mechanism in a blockchain-assisted energy harvesting marketplace designed to enable automated, efficient and verified transactions between decentralized network entities.Considering the unrealistic nature of dichotomous task valuation and the punctuality of IoTDs' energy supply, a double auction mechanism named ESWM-StM for IoTDs and ECSs in blockchain-enabled IoT is proposed, where multiple IoTDs dynamically and adaptively energy the edge ECSs. We proved that the proposed ESWM-StM mechanism is individually rational and budget balanced. Meanwhile, ESWM-StM is truthful for the ECSs and IoTDs. Most importantly, we showed that ESWM-StM has high computational efficiency. It is shown that the proposed ESWM-StM mechanism can provide more energy per unit cost during the energy collection period, effectively relieving the energy consumption pressure, and attracting more participants to enhance the expected social welfare compared with the Benchmark mechanisms. In future work, we will extend the design of the smart contract-based double auction algorithm to the case where multiple ECSs compete for single or multiple IoTD energies, and will consider the use of artificial intelligence-based heuristic algorithms to solve the complex problem of matching two sides of a transaction presented in the algorithm.

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