A Blockchain-Based Reward Mechanism for Mobile Crowdsensing

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***Abstract*—Mobile crowdsensing (MCS) is a novel sensing scenario of cyber-physical-social systems. MCS has been widely adopted in smart cities, personal health care, and environment monitor areas. MCS applications recruit participants to obtain sensory data from the target area by allocating reward to them. Reward mechanisms are crucial in stimulating participants to join and provide sensory data. However, while the MCS applications execute the reward mechanisms, sensory data and personal private information can be in great danger because of malicious task initiators/participants and hackers. This article proposes a novel blockchain-based MCS framework that preserves privacy and secures both the sensing process and the incentive mechanism by leveraging the emergent blockchain technology. Moreover, to provide a fair incentive mechanism, this article has considered an MCS scenario as a sensory data market, where the market separates the participants into two categories: monthly-pay participants and instant-pay participants. By analyzing two different kinds of participants and the task initiator, this article proposes an incentive mechanism aided by a three-stage Stackelberg game. Through theoretical analysis and simulation, the evaluation addresses two aspects: the reward mechanism and the performance of the blockchain-based MCS. The proposed reward mechanism achieves up to a 10% improvement of the task initiator's utility compared with a traditional Stackelberg game. It can also maintain the required market share for monthly-pay participants while achieving sustainable sensory data provision. The evaluation of the blockchain-based MCS shows that the latency increases in a tolerable manner as the number of participants grows. Finally, this article discusses the future challenges of blockchain-based MCS.**

***Index Terms*—Blockchain, mobile crowdsensing (MCS), reward mechanism, sensory data market, Stackelberg game.**

I. Introduction

THE development of network technology, sensing devices, and social networks has increased the deployment of the next generation of Internet of Things (IoT)—mobile crowdsensing (MCS). MCS is a novel sensing framework, which is assisted by smartphone sensors and with the inclusion of human intelligence in the loop. MCS has become a typical application in the cyber-physical-social systems (CPSSs) [1], [2], because it adopts the multidisciplinary approach where knowledge from communication, computer science, computer network, economic, psychology, and social research unites to provide a solution of a sensing task.

Compared with the traditional IoT Frameworks, MCS has the advantages of broad sensing coverage, spatiotemporality of sensory data, feasibility and flexibility of deployment, and so on. MCS has been widely adopted in different scenarios, such as personal health care [3], smart cities [4], [5], environmental monitoring [6], and disaster recovery [7], [8]. Furthermore, it has drawn the attention of both academia and industry. The challenges in MCS that have been studied include the incentive mechanism [9], sensory data transmission [10], sensing tasks execution [11], [12] and offloading [13], quality of sensory data [14], and coverage [15].

MCS is becoming an essential part of daily life, and it collects the sensory data along with the participants' private data (such as location data). The leakage of participants' private data is inherent when the participants join an MCS application. In addition, an MCS scenario faces several challenges during deployment and operation.

1) *Untrustworthy Participants:* A participant who may forge his identity or reputation, for example, adversary attack. A malicious participant may steal sensory data causing privacy leakage.
2) *Untrustworthy Task Initiator:* A task initiator may publish a sensing task without a reward guarantee, and it may also try to steal the private information from participants when there is communication between them.
3) *Untrustworthy Reward Transaction:* Due to the mobility of the participants in the MCS, the reward allocation procedure will be disturbed when a mobile user/participant moves from one target area to another. As a result, a participant will have difficulty in redeeming his/her reward.
4) *High Operational Cost of the System:* MCS needs an authority to process all the communications between the sensing task initiator and the participants. Considering that the architecture of MCS is usually centralized, MCS may suffer a single-point failure and add an additional operational cost to the whole scenario.

To address the above privacy and security challenges, this article has proposed a blockchain-based reward mechanism to provide the privacy and security features to the MCS.

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The concept of Bitcoin [16] has drawn more attention than the blockchain technology. Bitcoin was created in 2009, following with a white paper, which provided all the details of the blockchain technology. The blockchain technology is a disruptive technology and often stated to be the fifth computing revolution after the mainframe, personal computer, Internet, and social networking [17]. The vital feature of the blockchain technology is that it is a distributed ledger that records transactions in a conventional and permanent way, which makes it a potential solution for a distributed sensing scenario.

Blockchain technology has the potential to collaborate with the MCS, because it operates the transactions in a decentralized, anonymous, and trustful fashion [18]. First, by adopting the blockchain technology, it will reduce the additional cost of the third party in MCS. Second, considering the anonymity feature of the blockchain, it can protect the participants' private information when they participate in the sensing task. Last but not least, the smart contract [19] can support the automation of sensing task allocation, participant selection, sensing task execution, and reward allocation. The smart contract can make it easier for the intricate reward allocation. We will address this in detail in Section II.

This article proposes a blockchain-based MCS, which can achieve participant identity anonymization, decentralized reward allocation, and transparent transactions without an ordinary trusted third party. The main contribution of this article involves three aspects.

1) Proposing a blockchain-based MCS framework, which provides the protection of participants' privacy, as well as a secure sensing process and reward allocation mechanism by leveraging the novel blockchain technology. The proposed work uses hybrid base stations as miners to verify and validate the identities of the participants and the sensing task, the sensing procedure, and the reward allocation.
2) Designing the workflow of the blockchain-based MCS and a set of smart contracts to assist the sensing task execution automation of the MCS. Once all the identities of the participants are verified on the blockchain, the sensing task execution procedure will be triggered. When the task initiator has collected the sensory data, the reward allocation procedure will start to execute. Smart contracts can guarantee the automation and security of the MCS framework.
3) Studying the features of the sensory data market and the participants. This article classifies the participants into monthly-pay participants, instant-pay participants, and the task initiator. It provides an economic approach to analyze the incentive mechanism. By leveraging a three-stage Stackelberg game reward mechanism, it can achieve a fair and efficient sensory data market in the MCS.

The remainder of this article is organized as follows. Section II presents the related work. The blockchain-based MCS framework and smart contracts are introduced in Section III. The three-stage Stackelberg game and the incentive mechanism are presented in Section IV, respectively. The performance and simulation of the mechanism are analyzed in Section VI. This article also identifies the future challenges of the blockchain-based sensing technology in Section VII. In Section VIII, the conclusions of this article are presented.

II. Related Work

This article adopts the blockchain in cooperation with MCS to deploy an automated, secured sensing paradigm. The blockchain technology with its disruptive features has made it possible to connect the world seamlessly, including computers, sensors, smartphones, tablets, and wearable devices. Application scenarios of blockchain technology are not merely limited to the financial sector as before. New applications, such as energy supplement chain, secure information transmission, and so on, have also emerged.

IoT and MCS applications have deployed in the distributed fashion. The deployment depends on a centric server to support the sensing tasks, which is in danger of single-point failure. Furthermore, in an environment with a large number of sensors, the traditional framework is short of proper security guarantee. By adopting the blockchain technology, it would solve the challenges of the traditional IoT faces. Reference [20] surveyed the research issues and the challenges of the IoT security aspects in cooperation with the blockchain technology. Kshetri [21] proposed a blockchain-based identity and access management systems, which can be leveraged to strengthen IoT security. As defined in this article, many companies have joined a group that hopes to establish a blockchain protocol to build the IoT devices, applications, and networks. Christidis and Devetsikiotis [22] adopted the blockchain technology into IoT, which used a smart contract to deploy the automation of the complex multi-process in the IoT. Alphand *et al.* [23] proposed IoTChain, a scheme that combined the object security architecture (OSCAR) for the IoT and the authentication and authorization for the constrained environment (ACE) framework to provide an end-to-end solution for secure authorized access to IoT resources. This article addressed the details of the whole framework and the authorization flow. It simulated the proposed framework with an Ethereum private testnet. Zhang and Wen [24] proposed a blockchain-based IoT in the E-business aspect to support the feature of decentralization and traceability. Cao *et al.* [25] discussed the main ideas of the consensus mechanisms and their limitations in IoT. Blockchain can solve the authentication of the IoT devices, because it uses the consensus mechanism to verify the identities of the IoT devices without the third party. However, the consensus mechanism of sensing task execution has not been well investigated in these works. Thus, it motivates us to consider proposing a secure task execution by leveraging the blockchain.

Related works on the collaboration of the MCS and the blockchain were proposed to provide the secure sensing procedure to MCS. Li *et al.* [26] proposed a novel framework of blockchain and crowdsensing, which deployed a software prototype on Ethereum. In [27], a privacy-preserved incentive mechanism was proposed for crowdsourcing applications.

This article used a series of encryption algorithms to solve the security issues in crowdsourcing. Delgado-Segura *et al.* [28] presented Paysense, a general framework that incentivizes user participation and provides a mechanism to validate the quality of the collected data based on users' reputation. This article focused on analyzing user participation, data sensing quality, and user anonymity. The related works focused on the improvement of security by proposing new encryption algorithms. However, spatiotemporality is crucial to the MCS task, and complicated encryption algorithms may lead to long latency. The features of MCS need to be considered when adopting the blockchain.

Related works attempted to provide the secure incentive mechanism of the MCS aided by the blockchain. Chatzopoulos *et al.* [29] proposed a truthful, cost-optimal auction that minimizes the payments from the crowdsensing providers to mobile users based on a blockchain-aided MCS architecture. With the help of four smart contracts, it deployed a novel incentive mechanism in the blockchain. Feng *et al.* [30] investigated the limitation of the existing IoT frameworks and proposed a purely decentralized platform of crowdsensing by adopting the permissionless blockchain technology. The author formulated a noncooperative game to analysis the competitive situations among the sensors. Cai *et al.* [31] addressed several challenges including the sensory data safeguarding issue, knowledge monetization, and streamlined sensory data in the crowdsensing scenario. This article proposed a crowdsensing framework that enables the privacy-preserving knowledge discovery and the full-fledged blockchain-based knowledge monetization. However, it did not give the detail on how to allocate the reward to each participant. Shi *et al.* [32] proposed a fault-tolerant incentivization mechanism for the mobile P2P crowd service (MPCS). They designed an MPCSToken smart contract to facilitate the service auction, task execution, and payment settlement process with the help of the blockchain technology. Jia *et al.* [33] proposed a blockchain-based location privacy protection incentive mechanism in MCS. It took privacy protection as a supplement of the monetary incentive mechanism and addressed the problem in a cryptographic approach. However, related works only used the classic incentive mechanisms, such as auction, noncooperative game, and so on, for one-time stimulation. They have not considered providing MCS application-sustainable sensory data. The related works have not considered that blockchain can improve the security of the system when the transactions keep growing.

Thus, this motivates us to propose a novel blockchain-based MCS framework that preserves privacy and secures both the sensing process and the incentive mechanism by leveraging the emergent blockchain technology. First, we proposed the architecture of the blockchain-based MCS and its workflow. We design a novel set of smart contracts such as participants' registration, sensing task execution, and reward allocation. Based on the framework, we provide the solution of participants' privacy and sensing procedure security. Second, different from the related works, we consider the participants into different roles and propose a three-stage Stackelberg game. This incentive mechanism makes sure the sensory data are sustainable provided by the participants, and the utility of the task initiator is maximized. Third, we have simulated the proposed framework on the Ethereum testnet to proof the efficiency.

III. Blockchain-Based MCS Framework

A. Architecture of Blockchain-Based MCS

This section introduces the framework of blockchain-based MCS and the entities in the framework. In an MCS scenario, a task initiator would like to collect as much good quality sensory data as possible under a specific budget. In some particular application, he even prefers long-term sensory data gathering. Thus, according to an enterprise system, we classify the workers (participants) in MCS into contract workers who are paid monthly and temporary workers who are paid instantly after work. In this case, contract workers will contribute to the sensory data in a long-term and stable manner and the temporary worker can make compensation whether the budget is limited or the sensory data are not sufficient. In the following article, we will call contract workers "monthly-pay participants" and temporary workers "instant-pay participants." Thus, this framework includes the following.

1) *Task Initiator:* The initiator who publishes the sensing task and allocates the reward to monthly-pay and instant-pay participants through blockchain.
2) *Participant:* The participants are classified into two different roles: participants who will get paid instant after finishing the sensing task and participants who will get paid monthly. The instant-pay participants' reward is according to the sensory data quality and his reputation and the monthly-pay participants' reward is their salaries according to the number of the tasks they accomplish and their reputation.
3) *Miner:* Adding authorized miners aims to verify all the participants' identity and transactions between them. In this scenario, the hybrid base stations serve as authorized miners in the blockchain-based MCS. A hybrid base station not only can execute the communication but also can serve as the storage and computation resource. By using the blockchain, the task initiator, participants, and miners are on the blockchain working in cooperation anonymously. In addition, the authorized miners also verify the identities of the task initiator and participants before continuing the sensing task of the MCS. Smart contracts are deployed on the miners for the sensing task execution. The miners store all the blocks in the storage, and thus, they are in charge of verifying the registration of the task initiator and participants, transactions, and quality control of sensory data.

The architecture of the blockchain-based MCS is shown in Fig. 1. This article proposes a three-layer architecture for the blockchain-based MCS, which consists of a data plane, a blockchain plane, and an application plane. Fundamental functions, such as sensing, data forwarding, and storing, can be operated on the data plane by smartphone users. This architecture introduces an extra abstract layer called the blockchain plane to help an MCS application to verify the identities of the participants, allocate the sensing task/rewards, operate

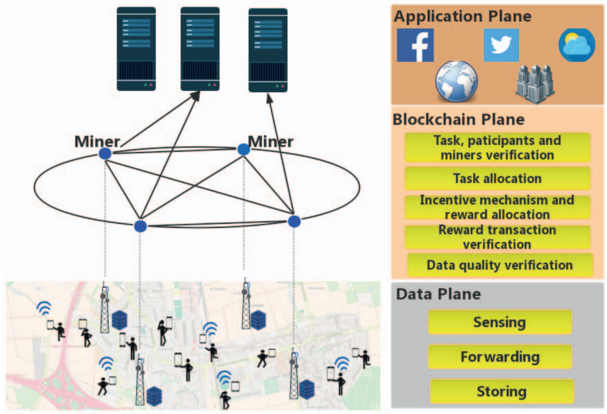

Miner
Miner
Application Plane
Blockchain Plane
Task, paticipants and miners verification
Task allocation
Incentive mechanism and reward allocation
Reward transaction verification
Data quality verification
Data Plane
Sensing
Forwarding
Storing

Fig. 1. Architecture of blockchain-based MCS.

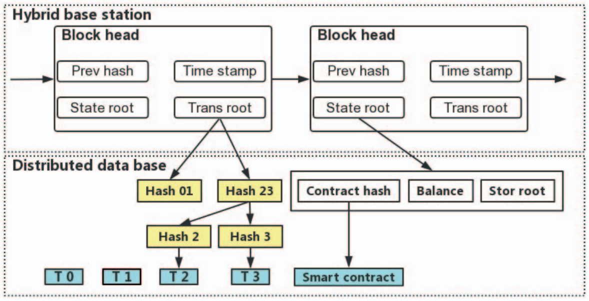


Fig. 2. Structure of block in the blockchain-based MCS.

the transactions, and control the sensory data quality. The application plane can deal with the request from a specific organization and process the sensory data to extract the knowledge.

In this article, hybrid base stations are equipped with servers and capable to operate communication and computation tasks. The miners store the whole blockchain information locally. The blockchain and structure of a block are shown in Fig. 2. The chain in the miner starts with a genesis block. The new blocks the system generates are appended after the genesis block. In each block, it consists of the blockhead, the previous hash of the block, the timestamp, the state root, the transactions root, and so on. The state root and the transactions root are the root of the Merkel tree. The transactions root stores all the hash value of the transactions between the participants. In the state root, it includes the contract hash, which is the hash value of the smart contract, balance, and storage root. All the actual data are stored in the distributed database, which could be in the server of the hybrid base station.

B. Workflow of Blockchain-Based MCS

This section presents the workflow of the blockchain-based MCS. Fig. 3 depicts the workflow of the smart contracts between each entity in the blockchain-based MCS. The task initiator communicates with the participants through the set of smart contracts, which are deployed on the miner. The details of the smart contracts will be introduced in Section III-C. We assume that the participants (including the task initiator) have registered and enrolled with the certificate authority (CA) and received back necessary cryptographic material, which is used to authenticate when the sensing task starts.

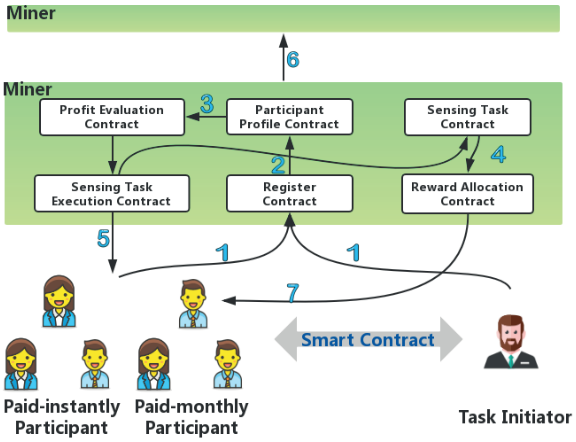

Miner
6
Miner
Profit Evaluation Contract
3
Participant Profile Contract
Sensing Task Contract
2
4
Sensing Task Execution Contract
Register Contract
Reward Allocation Contract
5
1
1
7
Smart Contract
Paid-instantly Participant
Paid-monthly Participant
Task Initiator

Fig. 3. Workflow of the blockchain-based MCS.

1) *System Initialization:* Task initiator and participants sign in for the MCS application. They will send their identities, public/private keys, certificates, and so on to the closest miner. The miner will run the “Registration Contract” and verify the identities of the participants and the task initiator with other miners by consensus mechanism. Then, the miners will send confirmations to the task initiator if the participants’ identities are valid. When the registration procedure completes, it will trigger the next step. Task initiator will send the description of the sensing task to the corresponding miners. The miners will verify the sensing task and then broadcast the sensing task to all the registered participants.
2) *Incentive Mechanism Deployment (Three-Stage Stackelberg Game):* After system initialization, the role of each identity will be clarified. Thus, the incentive mechanism will be triggered by running the “Participant Profile Contract” and the “Sensing Task Contract.” We will introduce this procedure in detail in the following sections.
3) *Token Allocation:* After the incentive mechanism completes, all the participants receive the message of the reward and size of the sensory data. They need to inspect the message, if the message is legitimate, and then, they execute the sensing task according to the reward. Each of the participants will be allocated with a token, which indicates the sensing task and reward. For this function, we set a “credit & token bank” in every miner to enable token allocation.
4) *Sensory Data Uploading:* Since every participant had the promised reward for accomplishing the sensing task, they will upload the promised sensory data to the task initiator via miner. At this step, instant-pay participants will get their reward from the credit bank of the miner.
5) *New Block Generation:* The miners will process the proof of work (PoW) and build the new block with all the transactions of the sensing task on the chain. The new block will be audited and finally added on the blockchain.

TABLE I
REGISTRATION CONTRACT

ID	Address	Type
P_1	Addr$\{P_1\}$	Initiator
P_2	Addr$\{P_2\}$	Instant-pay participant
P_3	Addr$\{P_3\}$	Monthly-pay participant
P_4	Addr$\{P_4\}$	Miner

TABLE II
PARTICIPANT PROFILE CONTRACT

Address	Profile	Sensing Task ID	Reward of Task
Addr$\{P_1\}$	Profile$\{P_1\}$	T_1	R_1
Addr$\{P_2\}$	Profile$\{P_2\}$	t_1	r_1
Addr$\{P_3\}$	Profile$\{P_3\}$	t_2	r_2
Addr$\{P_4\}$	Profile$\{P_4\}$	t_2	0

6) *Token Redemption and Task Accomplishment:* After the new block is added, all the participants have the tokens, and when the sensing task completes, the tokens will be redeemed whenever or wherever the participants need.

C. Smart Contracts of Blockchain-Base MCS

The concept of the smart contract was first introduced in 1997 [19]. A smart contract is an agreement, which tells each party how to act when they trust each other. We assume that all the smart contracts are authorized before deployment. In the proposed blockchain-based MCS framework, a novel set of smart contracts is designed to operate the transactions and verification. According to the workflow of the blockchain-based MCS, the novel set of smart contracts is proposed.

1) *Registration Contract:* All the participants including the task initiator register run the registration contract, as shown in Table I. All the participants will send their address and roles in the secure communication channel to the miner to verify their identities. After the consensus among the miners finishes, the participants without the legitimate signature will be detected. This article omits the technical details of the cryptography algorithms in the blockchain. We adopt the asymmetric cryptography algorithms to provide the secure communication channel.
2) *Participant Profile Contract:* When the miners collect all the information from the participants, their profile will be built to assist the participant selection procedure, sensing task execution procedure, and reward allocation procedure. A participant's profile contains the participant's reputation, expecting the reward of sensing task, participant's status, and so on, as it is shown in Table II.
3) *Sensing Task Contract:* The sensing task contract consists of the ID, execution status, deposit, and rewards plan of the sensing tasks. The execution status of a sensing task is a binary variable in Table III. When the status is 0, it means the sensing task is unfinished and vice versa. There are also parameters, such as sensing task's deposit, which can guarantee the promised rewards to the participants and its reward plan, which gives guidance for reward allocation.

TABLE III
SENSING TASK CONTRACT

Sensing Task ID	Status	Deposit	Reward Plan
T_1	0	D_1	R_1
T_2	1	D_2	R_2

TABLE IV
PROFIT EVALUATION CONTRACT

ID	Expecting reward	Sensing task ID	Device ability	Profit $U(\cdot)$
P_1	r_1	T_1	$D(P_1)$	$U_1(\cdot)$
P_2	r_2	T_2	$D(P_2)$	$U_2(\cdot)$

TABLE V
SENSING TASK EXECUTION CONTRACT

ID	Profit $U(\cdot)$	Sensing task ID	Status
P_1	$U_1(\cdot)$	T_1	0
P_2	$U_2(\cdot)$	T_2	1

TABLE VI
REWARD ALLOCATION CONTRACT

Sensing Task ID	Status	Participant's ID	Token
T_1	0	P_1	$Token_1$
T_2	1	P_2	$Token_2$

4) *Profit Evaluation Contract:* When the participants register on the chain, the miners obtain all the information to evaluate the reward allocation plan by running the profit evaluation contract. Due to the deployment of the three-stage Stackelberg game, all the participants, including the task initiator, have the profit evaluation contract to calculate if a specific scenario will maximize their profit, according to (1), (3), and (4). This procedure will be introduced in the following sections. We denote $U(\cdot)$ as the profit function of the participant with the sensing plan in Table IV.
5) *Sensing Task Execution Contract:* When the participants calculate the maximum profit according to the details of the sensing task, reward, and so on, they will obtain the sensing plan, including the quality of the sensory data and the sensory data size. The participants will follow the sensing task execution contract, in Table V, to execute the sensing task. Therefore, the sensing task execution contract will be triggered.
6) *Reward Allocation Contract:* The key algorithms of this article will be deployed in a sensing task contract according to the participant profile contract. This algorithm will give the result of the reward plan of the sensing task. Meanwhile, during this procedure, reward will be allocated as tokens to the participants, which is enabled by the reward allocation contract in Table VI.

D. Consensus Mechanism of Blockchain-Base MCS

In this article, we use PoW as the consensus mechanism. PoW requires a great amount of computation power to create a set of transactions (the block). PoW is the practice of solving block equations to verify if the each transaction is legitimate in the block. The miner starts PoW by choosing a number "nonce," and along with the hash of the previous block and the Merkel root, he could get an answer of the equation. He repeats changing the "nonce" until he calculates the right answer. Once the PoW completes, the block of transactions is confirmed and becomes public. PoW can reduce the risk of a 51% attack, because the equation is very hard to solve. In addition, it does not rely on any third party, which enables to build a transparent network.

In this article, we adopt the PoW in Ethereum without any optimization. In the future work, our study will be focused on the distributed consensus mechanism.

IV. System Model of the Incentive Mechanism

The incentive mechanism is the crucial research aspect in the MCS. A task initiator can obtain the sensory data and price the sensory data in the MCS framework as a sensory data market. A sensory data market should conform to market rules. Thus, adopting a primary economic method is necessary.

In the blockchain-based MCS, the framework consists of a set $\mathbf{p}$ of participants. We consider a set of the instant-pay participants as $\mathbf{p^I} = \{1, 2, \dots, p^I\}$ and a set of the monthly-pay as $\mathbf{p^M} = \{p^I + 1, p^I + 2, \dots, p^I + p^M\}$, where $\mathbf{p^I} \bigcup \mathbf{p^M} = \mathbf{p}$. In this scenario, there exist multiple hybrid base stations acting as miners. We denote miner as $\mathbf{m} = \{1, 2, \dots, m\}$. A task initiator will publish a sensing task $t = (R, D, B)$ to the participants. Here, D denotes the required sensory data size, R denotes the reputation of the participants, and B denotes the budget of reward. The sensory data size each participant in $\mathbf{p^I}$ and $\mathbf{p^M}$ provides is $\mathbf{d} = \{d_1, \dots, d_{p^I}, \dots, d_{p^I+p^M}\}$. The notations of the system model are shown in Table VII.

In this blockchain-based MCS sensory data market, to have more sustainable participants for sensing tasks, the task initiator prefers more monthly-pay participants. Thus, in the first stage of the game, monthly-pay participants dominate the market over the task initiator. In the second stage, the task initiator should dominate the market when he/she negotiates with the instant-pay participants. In the third stage, instant-pay participants adjust the sensory data size according to the reward the task initiator provides. The formal definitions of the players and their strategies in the three-stage Stackelberg game [34] are as follows.

1) Monthly-pay participant signs in for long term and gets paid monthly. The strategy profile of the monthly-pay participants is their salary, which denote as a set $\mathbf{r_{p^M}} = \{r_{p^I+1}, \dots, r_{p^I+p^M}\}$. They can only redeem their payments monthly.
2) Task initiator starts a sensing task, selects the monthly-pay participants according to the sensing task's requirements, and then offers the instant-pay participants the reward to execute the sensing task. Thus, the strategy profile of the task initiator includes two parts: sensory data size $\mathbf{d_{p^M}} = \{d_{p^I+1}, \dots, d_{p^I+p^M}\}$ and the reward to instant-pay participants $\mathbf{r_{p^I}} = \{r_1, \dots, r_{p^I}\}$.
3) Instant-pay participant gets paid after each task according to the sensory data size and reputation. According to the reward offered by the task initiator, instant-pay participants can decide the sensory data size. The strategy profile is the sensory data size $\mathbf{d_{p^I}} = \{d_1, \dots, d_{p^I}\}$.

TABLE VII
NOTATION AND DESCRIPTIONS

Notation	Description
$\mathbf{p}$	A set of participants
$\mathbf{p^I}$	A set of instant-pay participants
$\mathbf{p^M}$	A set of monthly-pay participants
$\mathbf{m}$	A set of base stations / miners
$\mathbf{d}$	A set of sensory data size
$R_\mathbf{p}$	Reputation of participant $\mathbf{p}$
$\mathbf{r}$	A set of payment/reward to participants
α	Market domination indicator
γ	Default value of reputation
$\omega_\mathbf{p}$	Processing ability of sensing device in participant set $\mathbf{p}$
β	Network condition
B	Reward Budget of task initiator
D	Total sensory data size of the task

A. Problem Formulation

1) Utility of Task Initiator: A task initiator aims to maximize his profit, which consists of two parts: revenue by accomplishing the sensing task and cost by paying the participants. When a task initiator announces a sensing task to all the participants, they must have a set of specific parameters to guarantee the quality of the result of the sensing task. Moreover, task initiator will consider the reputation [14], [35], [36] of the participant as well. Task initiator will have a set of payment $\mathbf{r} = \{r_1, \dots, r_{p^I}, \dots, r_{p^I+p^M}\}$ to participants, where $\mathbf{r}$ is the value of one unit of the sensory data. We also denote the data quantity as $\mathbf{d} = \{d_1, \dots, d_{p^I}, \dots, d_{p^I+p^M}\}$. Let d_i denote the instant-pay participants where $i \in \mathbf{p^I}$ and d_j denote the monthly-pay participants where $j \in \mathbf{p^M}$.

In order to obtain long and stable sensory data, a sensing task initiator is willing to recruit more monthly-pay participants. Instant-pay participants are part-time workers, who complement the sensory data market. For example, when the budget is limited, possibly more instant-pay participants will join the market. Thus, in this model, monthly-pay participants will dominate the market. In this article, the Stackelberg game is adopted to naturally grand monthly-pay participants the "first mover advantage," which means the first mover in the game will dominate the market [37].

The profit a task initiator can gain depends on the sensory data size d_i and d_j, the reputation of the participants R_i and R_j, and his expense to pay them r_i and r_j as well. The utility function of the task initiator is defined as

$$U_I = \sum_{i \in \mathbf{p^I}} d_i h(R_i) + \sum_{j \in \mathbf{p^M}} {d_j}^2 \; h(R_j) - \left(\sum_{i \in \mathbf{p^I}} r_i d_i + \sum_{j \in \mathbf{p^M}} r_j d_j \right) \tag{1}$$

where $h(\cdot)$ is the reputation function of the participants. Note that we have added quadratic d_j, which indicates the task initiator prefers monthly-pay participants to obtain more income. The reputation function [38] $h(\cdot)$ of the participants $\mathbf{p}$ is defined as

$$h(R_{\mathbf{p}}) = \begin{cases} \gamma + (1-\gamma)ln(1+\varepsilon), & \text{if } R \leq R_{\mathbf{p}} \leq R_{\max} \\ \gamma\, e^{(R_{\mathbf{p}}-R)}, & \text{if } R_{\min} \leq R_{\mathbf{p}} \leq R \end{cases} \tag{2}$$

where γ is a default value and R is the required reputation of the task initiator. Here, $\varepsilon = ((e-1)(R_{\mathbf{p}} - R)/R_{\max} - R)$. The reputation function implies that when the reputation of a participant is lower than the required reputation of the sensing task, $h(\cdot)$ will decrease sharply; conversely, $h(\cdot)$ will markedly increase.

2) Utility of Monthly-Pay Participant: The utility function of the participant $j \in \mathbf{p^M}$ who gets paid monthly is based on the sensory data size d_j and the cost of sensing and uploading. We assume that every participant keeps the sensing history on record to estimate the expecting salary for the next month and then report the salary to the task initiator. Thus, we have the utility function of monthly-pay participant j

$$U_j^{PM} = r_j d_j - [s_j(d_j, R_j) + u(d_j)] \tag{3}$$

where $s_j(\cdot)$ is the function of the sensing cost and $u(\cdot)$ is the function of the sensory data uploading cost. Function $s_j(\cdot)$ and $u(\cdot)$ increase as the size of sensory data increases. A rational participant will keep his utility function positive.

3) Utility of Instant-Pay Participant: Instant-pay participant $i \in \mathbf{p^I}$ will receive a reward offer from the task initiator. Then, according to the reward, he will decide the sensory data size d_i he can contribute to the task initiator. The revenue for p_i^I will be the reward r_i he/she can get after accomplishing a single sensory task. The cost depends on the size of sensory data d_i, the participant's reputation $h(R_i)$, and the uploading cost $u(d_i)$. The objective of the participants is to maximize their individual expected utility. Thus, the utility function U_i^{PI} of the instant-pay participant i is

$$U_i^{PI} = r_i d_i - [s_i(d_i, R_i) + u(d_i)]. \tag{4}$$

Furthermore, the sensing cost function $s_i(\cdot)$ and the sensory data uploading function $u(\cdot)$ are defined in detail

$$s_i(d_i, R_i) = \omega_i \cdot h(R_i) {d_i}^2 \tag{5}$$

$$s_j(d_j, R_j) = \omega_j \cdot h(R_j) d_j \tag{6}$$

$$u(d_{\mathbf{p}}) = \beta \cdot d_{\mathbf{p}} \tag{7}$$

where $\omega_{\mathbf{p}}$ represents the processing ability of the sensing devices, which is the CPU ability of encoding the data before sending them out. The network condition denoted as β, which means that a greater β indicates a poorer network condition, will require more cost to upload the sensory data. Note that we design different sensing cost functions for different participants, and the instant-pay participants will have greater cost than the monthly-pay participants, because the task initiator prefers more monthly-pay participants in the system.

V. Three-Stage Game and Equilibrium

This section will present the solution of the three-stage Stackelberg game. This game aims to maximize the utility of the task initiator and maximize the utility of the participants, and, at the same time, achieve the maximum sensory data quality.

To solve a traditional Stackelberg game, we adopt backward induction, which solves the equilibria of the subgames first. In the three-stage Stackelberg game, there are three subgames, which means we need to obtain three perfect equilibria [39] of the three subgames.

A. Subgames Equilibria and Stackelberg Equilibrium

For every player i with the strategy profile τ_i, we assume that the state after executing the strategy profile τ_i is $O_{\mathfrak{h}}(\tau_i)$ according to history $\mathfrak{h}$.

1) Definition (Subgame Perfect Equilibrium): The strategy profile τ^* is a subgame perfect equilibrium if the utility of state $O_{\mathfrak{h}}(\tau^*)$ is at least as good as the utility of state $O_{\mathfrak{h}}(\tau_i, \tau_{-i}^*)$, where the strategy profile (τ_i, τ_{-i}^*) represents that player i chooses τ_i while every other player $-i$ chooses τ_{-i}^*. Equivalently, for every player i and every history $\mathfrak{h}$ after which it is player i's turn to move

$$U_i(O_{\mathfrak{h}}(\tau^*)) \geq U_i\left(O_{\mathfrak{h}}\left(\tau_i, \tau_{-i}^*\right)\right) \tag{8}$$

where U_i is an utiltiy function that represents player i's preferences.

The definition above is the general definition for subgame perfect equilibrium. For example, in this article, when an instant-pay participant wants to decide his strategy of sensory data size d_i, he will take the previous stage's strategy as given, which is the reward strategy r_i from the task initiator, to derive his optimal strategy ${d_i}^*$. The subgame perfect equilibrium can be interpreted in the following two aspects.

1) The subgame is Nash equilibrium, so the follower's strategy is optimal, given the leader's strategy: in the three-stage Stackelberg game, the leader is the monthly-pay participant and the follower is the task initiator in Stage I. Then, the leader is the task initiator and the followers are the instant-pay participants in Stage II. Finally, the players are instant-pay participants in noncooperate game Stage III. Thus, in this three-stage Stackelberg game, the Nash equilibrium can be obtained.
2) According to the strategy history, the followers' strategy is optimal: as it is in a Stackelberg game, the subgame will be played dynamically. According to the strategy history and preferences of the leader, the followers will repeatedly engage in the same game with different strategy profiles until they reach the optimal solutions.

When every subgame can admit a subgame perfect equilibrium, the Stackelberg game achieves the Stackelberg equilibrium. Now, we give the definition of the Stackelberg equilibrium of the proposed game.

Definition (Stackelberg Equilibrium): The strategy profile $(\mathbf{r}_{\mathbf{p^M}}^*, \mathbf{d}_{\mathbf{p^M}}^*, \mathbf{r}_{\mathbf{p^I}}^*, \mathbf{d}_{\mathbf{p^I}}^*)$ is a Stackelberg equilibrium if it satisfies

$$U^{PI}\left(\mathbf{d}_{\mathbf{p^I}}^*\right) \geq U^{PI}\left(d_i, \mathbf{d}_{-i}^*\right) \tag{9}$$

$$U^I\left(\mathbf{d}^*_{\mathbf{p}^\mathbf{M}}, \mathbf{r}^*_{\mathbf{p}^\mathbf{I}}\right) \geq U^I\left(d_j, \mathbf{d}^*_{-j}, r_i, \mathbf{r}^*_{-i}\right) \tag{10}$$

$$U^{PM}\left(\mathbf{r}^*_{\mathbf{p}^\mathbf{M}}\right) \geq U^{PM}\left(r_j, \mathbf{r}^*_{-j}\right) \tag{11}$$

where $\mathbf{d}^*_{\mathbf{p}^\mathbf{I}}$ is the equilibrium sensory data size strategies of the instant-pay participants, d_i is the sensory data size strategy of participant i, and d^*_{-i} is the equilibrium strategies of all the participants expect participant i in (9). The rest of the notation in (10) and (11) has the same meaning as in (9). Equations (9)–(11) are the subgame equilibria of Stage III, Stage II, and Stage I, respectively, in the whole Stackelberg game. When all the subgames admit perfect equilibria, we derive the Stackelberg equilibrium. The subgame perfect equilibria of the three subgames will be analyzed in the following sections.

B. Stage III: Instant-Pay Participants' Strategy Profile

According to backward induction, the task initiator's reward plan $\mathbf{r}_{\mathbf{p}^\mathbf{I}}$ is taken as given to solve the profit maximization problem of instant-pay participants in Stage III. According to (4), (5), and (7)

$$\begin{aligned} \max_{d_i \in \mathbf{d}_{\mathbf{p}^\mathbf{I}}} \ & U_i^{PI} = r_i d_i - \omega_i h(R_i) {d_i}^2 - \beta d_i \\ \text{s.t. } & U_i^{PI} > 0 \\ & R_i \geq R \end{aligned} \tag{12}$$

where $h(\cdot)$ is defined in (2). First, the utility function should be greater than 0, because every participant is rational. Second, there is a requirement in the sensing task description, which indicates the participants' reputation to fulfill R. Equation (12) is the concave maximization problem in the strategy space $[d_{\min}, d_{\max}]$. According to the derivation of d_i, the optimal ${d_i}^*$ is

$${d_i}^* = \frac{r_i - \beta}{2\omega_i h(R_i)}. \tag{13}$$

The optimal strategy profile of sensory data size $d_i^*(r_i)$ of instant-pay participant i is obtained, which is a subgame perfect equilibrium. This article assumes that the task initiator will set a minimum sensory data size $d_{\min}$ for every participant, and participants' sensing ability is fixed, which is not more than $d^{\max}$.

C. Stage II: Task Initiator's Strategy Profile

Given salary plan $\mathbf{r}_{\mathbf{p}^\mathbf{M}}$ of monthly-pay participants, the task initiator aims to maximize his profit by deciding the equilibrium strategy profile of reward $\mathbf{r}_{\mathbf{p}^\mathbf{I}}$ for instant-pay participants and the strategy profile of the sensory data size $\mathbf{d}_{\mathbf{d}^\mathbf{M}}$ for the monthly-pay participants. Since the salary plan of the monthly-pay participants is given, the sensory data size of them obtains. According to (3), (6), and (7)

$$\begin{aligned} \max_{r_i \in \mathbf{r}_{\mathbf{p}^\mathbf{I}}, d_j \in \mathbf{d}_{\mathbf{p}^\mathbf{M}}} \ & U^I \\ \text{s.t. } & \sum_i r_i + \sum_j r_j \leq B \\ & \sum_i d_i + \sum_j d_j \geq D \\ & d_j \leq D_j^{\max} \\ & U^I > 0. \end{aligned} \tag{14}$$

The first constraint is the total reward to all the participants under budget B. The second constraint means that the total sensory data size is greater than the required sensory data size D. The third constraint is the sensory data of monthly-pay participants whose contribution cannot exceed the maximum sensory data $D_j^{\max}$. The last constraint requires that the utility should not be below 0. It shows the concavity of (14) and the convexity of the constraints. Thus, it is a concave maximization problem. Given the monthly-pay participants' strategy r_j and the optimal data strategy ${d_i}^*$ of the instant-pay participants from (13), the Lagrange function of (14) is

$$\begin{aligned} &\mathcal{L}\left(\mathbf{r}_{\mathbf{p}^\mathbf{I}}, \mathbf{d}_{\mathbf{p}^\mathbf{M}}, \lambda, \mu, \kappa_{\mathbf{p}^\mathbf{M}}\right) \\ &= -\sum_{i \in \mathbf{p}^\mathbf{I}} \frac{r_i(r_i - \beta)}{2\omega_i h(R_i)} - \sum_{j \in \mathbf{p}^\mathbf{M}} r_j d_j \\ &\quad + \left(\sum_{i \in \mathbf{p}^\mathbf{I}} \frac{r_i - \beta}{2\omega_i h(R_i)} h(R_i) + \sum_{j \in \mathbf{p}^\mathbf{M}} \eta {d_j}^2 \ h(R_j) \right) \\ &\quad + \lambda \left(B - \sum_{i \in \mathbf{p}^\mathbf{I}} r_i - \sum_{j \in \mathbf{p}^\mathbf{M}} r_j \right) \\ &\quad + \mu \left(\sum_{i \in \mathbf{p}^\mathbf{I}} \frac{r_i - \beta}{2\omega_i h(R_i)} + \sum_{j \in \mathbf{p}^\mathbf{M}} d_j - D \right) + \sum_{j \in \mathbf{p}^\mathbf{M}} \kappa_j \left(D_j^{\max} - d_j \right) \end{aligned} \tag{15}$$

where λ, μ, and $\kappa_{\mathbf{p}^\mathbf{M}}$ are the nonnegative Lagrange multipliers associated with the constraints in (14). According to (15), we can solve r_i and d_j from (14) by the derivations of all the r_i and all the d_j, respectively.

By adopting the Karush–Kuhn–Tucker (KKT) conditions [40], the optimal strategy profile of the instant-pay participants' rewards $\mathbf{r}_{\mathbf{p}^\mathbf{I}}{}^*(r_j)$ and $\mathbf{d}_{\mathbf{p}^\mathbf{M}}{}^*(r_j)$ can be obtained by solving the linear equations. The results depend on r_j from Stage I. The subgame perfect equilibrium can be derived by obtaining the optimal value in Stage II.

Lemma 1: In Stage II, given the strategy $\mathbf{r}_{\mathbf{p}^\mathbf{M}}$ of the monthly-pay participants, the task initiator's optimal strategy can be obtained.

The solution of Stage II and proof of Lemma 1 can be found in the Appendix.

D. Stage I: Monthly-Pay Participants' Strategy Profile

In Stage I, given the monthly-pay sensory data strategy of $\mathbf{d}_{\mathbf{p}^\mathbf{M}}(\mathbf{r}_{\mathbf{p}^\mathbf{M}})$, monthly-pay participants will adjust their salary strategy $\mathbf{r}_{\mathbf{p}^\mathbf{M}}$ to maximize their profit function. According to (3), that is

$$\begin{aligned} \max_{r_j \in \mathbf{r}_{\mathbf{p}^\mathbf{M}}} \ & U_j^{PM} = r_j d_j - \omega_j h(R_j) d_j - \beta d_j \\ \text{s.t. } & U_j^{PM} > 0 \\ & R_j \geq R_{\mathbb{I}}^b \end{aligned} \tag{16}$$

where $h(\cdot)$ is defined in (2). According to (28), the optimal data size strategy $\mathbf{d}_{\mathbf{p}^\mathbf{M}}{}^*(r_j)$ of the monthly-pay participant is an increasing function on r_j; as a result, the objective function in (16) is convex. Due to the constraints, the optimal salary strategy for the monthly-pay participants can be obtained.

Lemma 2: In Stage I, the strategy $\mathbf{r}_{\mathbf{p}^{\mathbf{M}}}$ of the monthly-pay participants satisfies

$$U_j\left(\mathbf{r}^*_{\mathbf{p}^{\mathbf{M}}}\right) \geq U_j\left(r_j, \mathbf{r}^*_{-j}\right). \quad (17)$$

By analyzing the optimal strategy $\mathbf{d}_{\mathbf{p}^{\mathbf{M}}}{}^*$ in (28), the salary of one monthly-pay participant relates to all the other monthly-pay participants. This indicates that the subgame in Stage I is a cooperative game, which means the coworkers (monthly-pay participants) work in the union form and fight for each other for a better salary. The optimal strategy $\mathbf{r}_{\mathbf{p}^{\mathbf{M}}}{}^*$ can be achieved.

1) When $d_j^* = D_j^{\max}$, the objective function is an increasing function; thus, $r_j^* = r_j^{\max}$.
2) When $d_j^* = (r_j/2h(R_j))$, the objective function is

$$U_j^{PM} = \frac{r_j^2}{2h(R_j)} - \omega_j h(R_j)\frac{r_j}{2h(R_j)} - \beta\frac{r_j}{2h(R_j)}$$

and it is concave; thus, $r_j^* = r_j^{\max}$.

3) When

$$d_j^* = \xi\left(D - \tau + \sum_{i\in\mathbf{p}^{\mathbf{L}}} A_i \sum_{j\in\mathbf{p}^{\mathbf{M}}} r_j + \sum_{j\in\mathbf{p}^{\mathbf{M}}} \frac{r_j - r_{j-1}}{2h(R_{j-1})}\right)$$

d_j^* is a function on $\sum_j r_j$, which is $d_j^* = \sum_j r_j$. The objective function is a binary primary concave function; at the same time, the constant terms are all greater than zero. Thus, r_j^* is in the range of $[r_j^{min}, r_j^{\max}]$.

Thus, the optimal strategy $r_j{}^*$ of the monthly-pay participants of Stage I can be obtained. The subgame equilibrium of Stage I can be reached in the situations above.

E. Existence and Uniqueness of Nash Equilibrium

Theorem 1 *(Existence of Subgame Perfect Equilibrium):* Every finite extensive game with perfect information has a subgame equilibrium.

Proof: The proposed three-stage Stackelberg game is an extensive game with all the given information; also, it is with a finite strategy space, such as $[d_{\min}, d_{\max}]$ and $[r_{\min}, r_{\max}]$. Thus, the subgame equilibrium can be obtained.

Theorem 2 *(Existence of Stackelberg Equilibrium):* There exists Stackelberg equilibrium in the proposed three-stage game.

Proof: The existence of Stackelberg equilibrium depends on the subgame perfect equilibrium. In the proposed three-stage game, the set of subgame perfect equilibria of a finite-strategy space-extensive game with perfect information is equal to the set of strategy profiles isolated by the procedure of backward induction [39]. According to the analysis of the proposed three-stage game, Stackelberg equilibrium can be obtained.

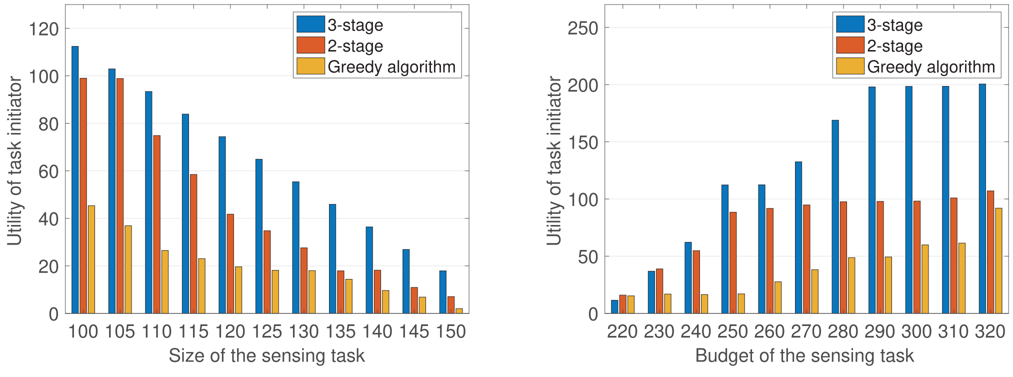
VI. Simulation

This section presents the simulation results of the proposed framework in two aspects. We first evaluate the three-stage Stackelberg algorithms. Then, the performance of the blockchain-based MCS architecture is assessed by the Ethereum testnet.

A. Incentive Mechanism Performance Analysis

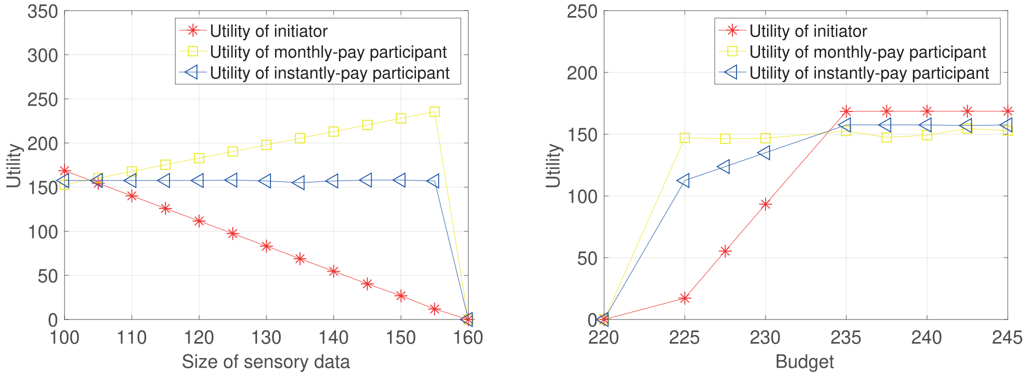
To benchmark the performance of the proposed algorithm, we implement the traditional Stackelberg algorithm [11] and the greedy reward allocation algorithm. Note that the traditional Stackelberg algorithm takes only one kind of participants, and the greedy algorithm is centralized. We show the dynamics of the task initiator's utility in terms of different sensory data requirements with a limited budget. Fig. 4(a) shows that when the size of the sensing task increases, the task initiator's utility decreases slower than the two-stage and the greedy algorithm. Fig. 4(b) demonstrates the three different algorithms with different budgets and the same size of the sensing task. We observe that when the budget increases, the proposed algorithm can achieve higher initiator's utility. It can provide the sensory data market with a reasonable pricing strategy, which leads the system to a better utility. To investigate the impact of sensory data size and budget, we then implement the simulations with different sizes of sensory data requirement B in Fig. 5(a). We see that when the size of the sensing task increases, the task initiator's utility decreases. However, the utility of the monthly-pay participants increases. There is a joint point when the size is 105 MB, which means the equilibrium point in this setting of the simulation. When the size of the sensing task is too big, there is not enough budget, which makes the utilities become zero. We also implement the simulations with different budgets D in Fig. 5(b). We see that when the budget increases, the utilities become stable, because the computation ability of the participants is bounded.

Fig. 6(a) demonstrates the domination of the monthly-pay participants in the proposed sensory data market considering a scenario with different CPU abilities w_j of the monthly-pay participants. With higher CPU ability, the sensing cost will increase for monthly-pay participants; then, more instant-pay participants will join the sensing task. However, because of the "first mover's advantage" of the monthly-pay participants, they will still dominate the sensory data market. For a further understanding of the "first-mover advantage" and the sensory data market share, this article evaluates the proposed model with different ratios of monthly-pay participants and instant-pay participants, considering 20 participants in this scenario with a sensory data amount of 50, 60, and 70 MB. As shown in Fig. 6(b), when the ratio increases, the task initiator's utility gradually increases. However, with a small sensory data amount requirement, the utility stays stable at some point. The result is because the ratio of participants is sufficient for the specific scenario. To verify that the proposed algorithms can reach convergent, we further the dynamics of the reward for participants in Fig. 7. There are 20 participants with 500 units of reward and 200 units of sensory data.



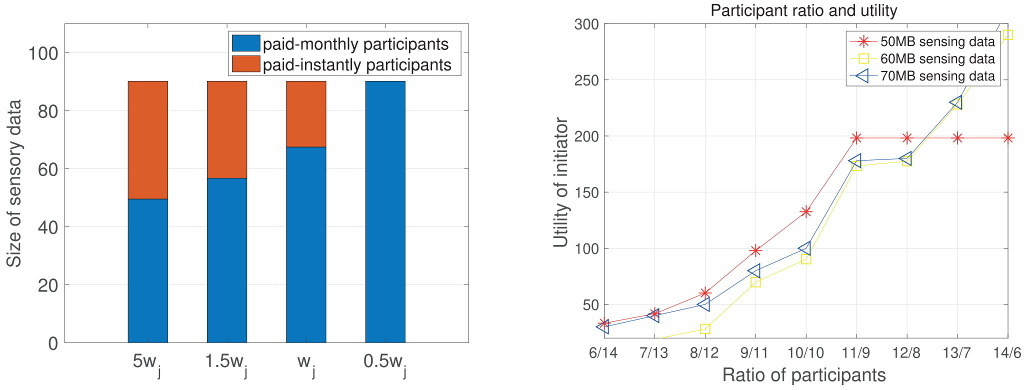
(a) (b)

Fig. 4. Utility of task initiator. (a) With different sensory data sizes D. (b) With different budgets B.



(a) (b)

Fig. 5. Utilities of participants and the task initiator. (a) With different sensory data sizes D. (b) With different budgets B.



(a) (b)

Fig. 6. Market share in blockchain-based MCS. (a) Monthly-pay participants with different computation ability values w_j. (b) With different ratios of participants in the sensory data market.

The proposed algorithm obtains the optimal reward strategy within ten iterations. The result of the simulation infers the feasibility of the proposed strategy in real life.

B. Blockchain Performance Analysis

Previous simulations on the mobile device-based blockchain have been done in [41]. In this section, the performance of the proposed blockchain-based MCS has been presented. We implemented the Ethereum testnet on a computer with Intel Core i5 CPU at 1.3 GHz and 4 GB of RAM. The simulation considers a blockchain-based MCS including different numbers of the monthly-pay participants and instant-pay participants, three miners, and one task initiator, which makes the topology of the MCS. In this topology, every participant can communicate with the miner and each other.

First, miners will run the **Registration contract** to register all the participants, including the monthly-pay/instant-pay participants and the task initiator. Second, the identities of participants are verified by the miners by running consensus mechanism. Then, the miners will broadcast the sensing task

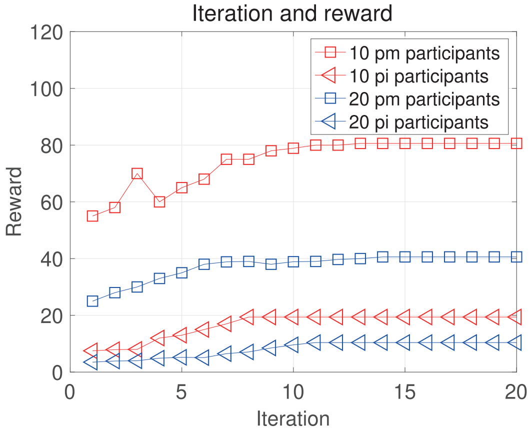


Fig. 7. Convergence of the proposed algorithm.

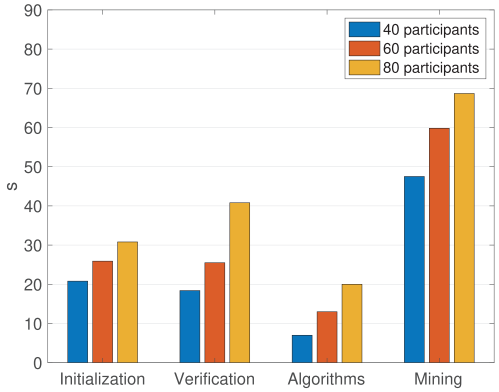


Fig. 8. Latency of blockchain-based MCS.

and run the **Participant profile contract** and the **Sensing task contract** to negotiate with task initiator. Third, all the miners will run the **Profit evaluation contract** to compute their optimal strategy individually and execute the sensing task by the **Sensing task execution contract**. At last, the miners will run the **Reward allocation contract** to compensate all the participants. Periodically, the miners will verify all the transactions and build a new block. As shown in Fig. 8, we deploy the contracts of the blockchain-based MCS framework, including the key functions, such as system initialization, verification, the three-stage game algorithms, and mining. It demonstrates the proposed framework with a different number of participants. With the expansion, the proposed framework still shows a tolerable latency of each function.

VII. Future Challenges

Blockchain technology has shown significant influence in the IoT, Internet of Vehicles, and MCS with the advantages of decentralization, trustworthiness, traceability, flexibility, and so on. However, there are still open issues need to be considered in the future when adopting the blockchain technology into the MCS.

A. Computation Overhead of Blockchain-Based MCS

Mobile devices work as sensors in the MCS with limited power supplement, computation capacity, and storage, with complex communication network conditions at the same time. For the sensing and personal data privacy, the blockchain will adopt more complicated cryptographic algorithms to resolve the issue, which mobile devices could not afford. Xiong *et al.* [42] considered edge computing as the network enabler for mobile blockchain. However, this article focused mostly on the pricing scheme of edge-computing resources, but not the details in cooperation with the blockchain technology. Moreover, MCS requires real-time sensory data, which also enhance the need for high computation capacity. The challenge is improving the performance of the blockchain-based MCS without sacrificing the security feature of the system.

B. Privacy and Trustworthiness of Blockchain-Based MCS

Although MCS is a novel form of traditional IoT, it has unique features, such as the selfishness, mobility, and intelligence of the users of the mobile devices. These features add more requirements when it comes to privacy guarantee. In the future research, dynamic access control is a crucial function to guarantee the security in the blockchain-based MCS where mobile device users may join the sensing task anytime and anywhere, due to mobility.

C. Human-in-the-Loop Framework

MCS is a human-centric sensing framework. With the feature of automation in blockchain, the human-centric feature can drift the framework from autonomy to intelligence by leveraging human-in-the-loop. For example, by designing a human-centric trust model [43], an MCS funded by grass-rooted participants can perform services like an expert.

D. Sensory Data Market

MCS needs rational incentive mechanisms to stimulate mobile device users to participate in sensing tasks. Pricing the sensory data is one of the essential incentive mechanisms in the MCS. According to the applications of the blockchain-based cryptocurrencies, such as bitcoin, a blockchain-based sensory data market will make sure that the pricing scheme is fair and secure.

E. Tradeoff Among Performance, Security, and Resource

An MCS application requires real-time sensory data from more participants, which requires higher performance from a blockchain-based MCS when participants increase. To achieve high performance and efficient resource allocates while maintaining a high security level for the system is a crucial task in the blockchain-based MCS. Initial attempt has been made by Wang and Wang [44]. This article proposed asynchronous consensus zones to scale blockchain system linearly without compromising security.

VIII. Conclusion

The work presented in this article has two main contributions toward solving the challenges of MCS. First, it proposes a blockchain-based MCS framework with a novel set of smart contracts. Second, this article designs a three-stage

Stackelberg game to maintain the number of participants by considering this MCS scenario as a sensory data market. In the three-stage Stackelberg game, the participants are classified into monthly-pay participants and instant-pay participants. This allows the monthly-pay participants to have a guarantee of the sustainable contribution of the sensory data. Furthermore, the game preserves the fairness of the sensory data market in cooperation with a secure reward allocation scheme aided by blockchain technology.

The simulation of the proposed blockchain-based MCS framework is twofold. First, we simulate the performance of the three-stage game. In terms of the utility of the task initiator, the improvement in the proposed reward strategy ranges from 2% to 10%, under the same participants' reputation, compared with the two-stage game. It also ranges from 2% to 20% compared with the average reward strategy. It can also maintain the required market share for monthly-pay participants while achieving sustainable sensory data provision. Second, we simulate the performance of the block-based MCS with a set of smart contracts to prove the feasibility of the proposed work. Finally, this article also discusses the future challenges in the cooperation of blockchain technology and MCS to enlighten future works.

Currently, the bottleneck of blockchain deployment is the consensus mechanism. Consensus mechanisms, such as the computationally intensive PoW and Byzantine fault tolerance (BFT), cannot support a large number of IoT devices. Therefore, in the future work, we will study the consensus mechanism of the blockchain to support improved efficiency and scalability.

Appendix
Proof of Lemma 1

Based on the Lagrange function (15) and according to the KKT conditions, it follows:

$$r_i\frac{\partial \mathcal{L}}{\partial (r_i)} = 0; \quad \frac{\partial \mathcal{L}}{\partial (r_i)} \le 0; \;\; r_i \ge 0 \tag{18}$$

$$d_j\frac{\partial \mathcal{L}}{\partial (d_j)} = 0; \quad \frac{\partial \mathcal{L}}{\partial (d_j)} \le 0; \;\; d_j \ge 0 \tag{19}$$

$$\begin{gathered}\lambda\left(\sum_{i\in\mathbf{p}^{\mathbf{L}}} r_i + \sum_{j\in\mathbf{p}^{\mathbf{M}}} r_j - B\right) = 0;\\ \sum_{i\in\mathbf{p}^{\mathbf{L}}} r_i + \sum_{j\in\mathbf{p}^{\mathbf{M}}} r_j - B \le 0; \quad \lambda \ge 0\end{gathered} \tag{20}$$

$$\begin{gathered}\mu\left(A\sum_{i\in\mathbf{p}^{\mathbf{L}}} r_i - \beta + \sum_{j\in\mathbf{p}^{\mathbf{M}}} d_j - D^b\right) = 0;\\ A\sum_{i\in\mathbf{p}^{\mathbf{L}}}(r_i - \beta) + \sum_{j\in\mathbf{p}^{\mathbf{M}}} d_j - D^b \le 0; \quad \mu \ge 0\end{gathered} \tag{21}$$

$$\begin{gathered}\sum_{j\in\mathbf{p}^{\mathbf{M}}} \kappa_j\left(D_j^{\max} - d_j\right) = 0;\\ D_j^{\max} - d_j \le 0; \sum_{j\in\mathbf{p}^{\mathbf{M}}} \kappa_j \ge 0\end{gathered} \tag{22}$$

where (18)–(21) denote the complementary slackness condition, and (23) and (24) are the first-order derivative conditions of (15) with respect to r_i and d_j, respectively

$$\frac{\partial \mathcal{L}}{\partial r_i} = A_i h(R_i) - A_i(2r_i - \beta) - \lambda + \mu A_i \tag{23}$$

$$\frac{\partial \mathcal{L}}{\partial r_{i-1}} = A_{i-1} h(R_{i-1}) - A_{i-1}(2r_{i-1} - \beta) - \lambda + \mu A_{i-1}$$

$$\vdots$$

$$\frac{\partial \mathcal{L}}{\partial d_j} = 2d_j h(R_j) - r_j + \mu - \kappa_j \tag{24}$$

$$\frac{\partial \mathcal{L}}{\partial d_{j-1}} = 2d_{j-1} h(R_{j-1}) - r_{j-1} + \mu - \kappa_{j-1}$$

$$\vdots$$

$$\frac{\partial \mathcal{L}}{\partial \lambda} = \sum_{i\in\mathbf{p}^{\mathbf{L}}} r_i + \sum_{j\in\mathbf{p}^{\mathbf{M}}} r_j - B \tag{25}$$

$$\frac{\partial \mathcal{L}}{\partial \mu} = \sum_{i\in\mathbf{p}^{\mathbf{L}}} A_i(r_i - \beta) + \sum_{j\in\mathbf{p}^{\mathbf{M}}} d_j - D \tag{26}$$

$$\frac{\partial \mathcal{L}}{\partial \kappa_j} = D_j^{\max} - d_j \tag{27}$$

$$\frac{\partial \mathcal{L}}{\partial \kappa_{j-1}} = D_{j-1}^{\max} - d_{j-1}$$

$$\vdots$$

where $(1/2w_i h(R_i)) = A_i$. Then, we will look for the interior solutions when the following holds.

1) When $\mu = 0$, $\kappa_j = 0$, and $\lambda = 0$, by solving the equations above, we can obtain the optimal strategy

$$r_i{}^* = \frac{1}{2}(h(R_i) + \beta)$$
$$d_j{}^* = \frac{r_j}{2h_j}$$

when $\sum_{j\in\mathbf{p}^{\mathbf{M}}} r_j \in [0, \phi]$.

And when $\mu = 0$, $\kappa_j = 0$, and $\lambda \ge 0$, we can obtain the optimal strategy

$$\sum_{i\in\mathbf{p}^{\mathbf{L}}} r_i{}^* = B - \sum_{j\in\mathbf{p}^{\mathbf{M}}} r_j$$
$$d_j{}^* = \frac{r_j}{2h_j}$$

when $\sum_{j\in\mathbf{p}^{\mathbf{M}}} r_j \in (\psi, \sum_{j\in\mathbf{p}^{\mathbf{M}}} r_j^{\max})$.

2) When $\mu > 0$, $\kappa_j \ge 0$, and $\lambda = 0$, by solving the equations above, we can obtain the optimal strategy

$$r_i{}^* = \frac{1}{2}(h(R_i) + \beta)$$
$$d_j{}^* = D_j^{\max}$$

when $\sum_{j\in\mathbf{p}^{\mathbf{M}}} r_j \in (0, \psi)$.

And when $\mu = 0$, $\kappa_j = 0$, and $\lambda \ge 0$, we can obtain the optimal strategy

$$r_i{}^* = w_i\left[D - \sum_{j\in\mathbf{p}^{\mathbf{M}}} D_j^{\max} - \frac{1}{4w_i}\sum_{i\in\mathbf{p}^{\mathbf{L}}}(h(R_{i-1}) - h(R_i))\right]$$
$$d_j{}^* = D_j^{\max}$$

when $\sum_{j\in\mathbf{p}^{\mathbf{M}}} r_j \in (\psi, \sum_{j\in\mathbf{p}^{\mathbf{M}}} r_j^{\max})$.

3) When $\mu > 0$, $\kappa_j = 0$, and $\lambda = 0$, there is no solution for this optimization problem.
In addition, when $\mu > 0$, $\kappa_j = 0$, and $\lambda \geq 0$, we can obtain the optimal strategy

$$r_i{}^* = w_i \left[D - \sum_{j \in \mathbf{p}^{\mathbf{M}}} D_j^{\max} - \frac{1}{4w_i} \sum_{i \in \mathbf{p}^{\mathbf{L}}} (h(R_{i-1}) - h(R_i)) \right]$$

$$d_j{}^* = \xi \left(D - \tau + \sum_{i \in \mathbf{p}^{\mathbf{L}}} A_i \sum_{j \in \mathbf{p}^{\mathbf{M}}} r_j + \sum_{j \in \mathbf{p}^{\mathbf{M}}} \frac{r_j - r_{j-1}}{2h(R_{j-1})} \right)$$

when $\sum_{j \in \mathbf{p}^{\mathbf{M}}} r_j \in (\varphi, \sum_{j \in \mathbf{p}^{\mathbf{M}}} r_j^{\max})$.

4) When $\mu > 0$, $\kappa_j \geq 0$, and no matter $\lambda = 0$ or $\lambda \geq 0$, we can obtain the optimal strategy

$$r_i{}^* = \frac{1}{4} \left[2 \left(B - \sum_{j \in \mathbf{p}^{\mathbf{M}}} r_j \right) - \sum_{i \in \mathbf{p}^{\mathbf{L}}} (h(R_{i-1}) - h(R_i)) \right]$$

$$d_j{}^* = D_j^{\max}$$

when

$$\sum_{j \in \mathbf{p}^{\mathbf{M}}} r_j \in \left(\psi, \sum_{j \in \mathbf{p}^{\mathbf{M}}} r_j^{\max} \right).$$

We can obtain the result

$$d_j^* = \begin{cases} D_j^{\max}, & \text{if } \sum_{j \in \mathbf{p}^{\mathbf{M}}} r_j \in (0, \phi) \left(\psi, \sum_{j \in \mathbf{p}^{\mathbf{M}}} r_j^{\max} \right); \\ \dfrac{r_j}{2h(R_j)}, & \text{if } \sum_{j \in \mathbf{p}^{\mathbf{M}}} r_j \in \left(\psi, \sum_{j \in \mathbf{p}^{\mathbf{M}}} r_j^{\max} \right); \\ \xi \left(D - \tau + \sum_{i \in \mathbf{p}^{\mathbf{L}}} A_i \sum_{j \in \mathbf{p}^{\mathbf{M}}} r_j + \sum_{j \in \mathbf{p}^{\mathbf{M}}} \dfrac{r_j - r_{j-1}}{2h(R_{j-1})} \right), & \\ & \text{if } \sum_{j \in \mathbf{p}^{\mathbf{M}}} r_j \in \left(\varphi, \sum_{j \in \mathbf{p}^{\mathbf{M}}} r_j^{\max} \right) \end{cases} \tag{28}$$

$$r_i^* = \begin{cases} \dfrac{h(R_i)}{2}, & \text{if } \sum_{j \in \mathbf{p}^{\mathbf{M}}} r_j \in (0, \phi); \\ \dfrac{1}{4} \left[2(B - \sum_{j \in \mathbf{p}^{\mathbf{M}}} r_j) - \sum_{i \in \mathbf{p}^{\mathbf{L}}} (h(R_{i-1}) - h(R_i)) \right], & \\ & \text{if } \sum_{j \in \mathbf{p}^{\mathbf{M}}} r_j \in \left(\psi, \sum_{j \in \mathbf{p}^{\mathbf{M}}} r_j^{\max} \right); \\ w_i \left[D - \sum_{j \in \mathbf{p}^{\mathbf{M}}} D_j^{\max} - \dfrac{1}{4w_i} \sum_{i \in \mathbf{p}^{\mathbf{L}}} (h(R_{i-1}) - h(R_i)) \right], & \\ & \text{if } \sum_{j \in \mathbf{p}^{\mathbf{M}}} r_j \in \left(\varphi, \sum_{j \in \mathbf{p}^{\mathbf{M}}} r_j^{\max} \right) \end{cases} \tag{29}$$

where

$$\begin{aligned} \xi &= \frac{1}{1 + h(R_j) \sum_{j \in \mathbf{p}^{\mathbf{M}}} \frac{1}{h(R_{j-1})}} \\ \tau &= B \sum_{i \in \mathbf{p}^{\mathbf{L}}} A_i - \sum_{i \in \mathbf{p}^{\mathbf{L}}} A_i \beta \\ \phi &= 2 \sum_{j \in \mathbf{p}^{\mathbf{M}}} h_j D_j^{\max} \\ \psi &= B - \frac{1}{2} \sum_{i \in \mathbf{p}^{\mathbf{L}}} h_i \\ \varphi &= \sum_{j \in \mathbf{p}^{\mathbf{M}}} \frac{1}{h(R_j)} \left(D - \frac{1}{4w_i} \sum_{i \in \mathbf{p}^{\mathbf{L}}} h_i \right). \end{aligned} \tag{30}$$

Until now, this lemma is proven.

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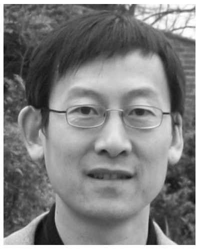

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