Incentive-Driven Computation Offloading in Blockchain-Enabled E-Commerce

SHUIGUANG DENG, GUANJIE CHENG, and HAILIANG ZHAO, Zhejiang University, China
HONGHAO GAO, Shanghai University, China
JIANWEI YIN, Zhejiang University, China

Blockchain is regarded as one of the most promising technologies to upgrade e-commerce. This article analyzes the challenges that current e-commerce is facing and introduces a new scenario of e-commerce enabled by blockchain. A framework is proposed for mining tasks in this scenario offloaded onto edge servers based on mobile edge computing. Then, the offloading issue is modeled as a multi-constrained optimization problem, and evolutionary algorithms are utilized and re-designed as solvers. The experimental results validate the efficiency of the framework and algorithms and also show that the lower bound of computation resources exists to obtain the maximum overall revenue.

CCS Concepts: • **Networks** → *Mobile networks*;

Additional Key Words and Phrases: Blockchain, e-commerce, computation offloading, edge computing

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1 INTRODUCTION

With the rapid development of the mobile Internet industry, e-commerce, as an advanced business model, is rising prosperously. The consumption habits of mainstream consumer groups are shifting to the Internet with the popularization of e-commerce. Besides, the professional e-commerce services are provided in all aspects of transactions and transaction costs are effectively reduced. Thus, more and more offline traditional enterprises are actively carrying out e-commerce transformation. In 2019, the transaction volume of China's e-commerce market is about 32.7 trillion yuan. Though e-commerce has great development potential, there remain many serious problems to be

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Authors' addresses: S. Deng, Zhejiang University, 38 Zheda Rd, Hangzhou, China; email: dengsg@zju.edu.cn; G. Cheng, Zhejiang University, 38 Zheda Rd, Hangzhou, China; email: guanjiech@126.com; H. Zhao, Zhejiang University, 38 Zheda Rd, Hangzhou, China; email: hliangzhao97@gmail.com; H. Gao, Shanghai University, 99 Shangda Rd, Shanghai, China; email: gaohonghao@shu.edu.cn; J. Yin, Zhejiang University, 38 Zheda Rd, Hangzhou, China; email: zjuyjw@zju.edu.cn.

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solved. We divide the challenges of e-commerce into four angles—trust issues, trading security, data privacy, and logistic problems.

— **Trust issues**: For people who are accustomed to traditional shopping, e-commerce is tough to accept. In traditional scenarios, customers can try themselves and then pick out their favorite items when shopping. They can even bargain with the merchant for a cheaper price. While in an e-commerce environment, we can't judge the real quality of the products. The advertisement exaggerates the untrue description of the goods excessively, which results in trust issues. The lack of trust affects the creation of transactions greatly.
— **Trading security**: In the process of trading, the security of transaction is a key problem that troubles the development of e-commerce. The two sides trade through a virtual network that could be attacked by malicious hackers. Besides, the transaction between two parties involves not only consumers and merchants, but also the business administration, customs, insurance, taxation, banking, and other departments in different regions and countries. Every link between these roles can be a serious security risk.
— **Data privacy**: The transaction data and user data always face serious privacy concerns in online platforms. Even some of the most famous companies are stealing data privacy in order to make extra profits [3]. Huge amounts of data are generated in the e-commerce environment at every second, so data privacy protection is also a critical issue in e-commerce. However, the general public do not know how e-commerce platforms store our transaction data and identity information, or whether they would sell these data to other companies for profit. Privacy leaks have a huge impact on our lives.
— **Logistic problems**: After the deal, how to deliver the goods to consumers quickly and safely is also a big concern of e-commerce personnel and consumers. The quality of logistic services greatly affects users' experience of using e-commerce platforms. However, the logistic service awareness and service quality of some platforms are not satisfactory due to the lack of supervision. We always hear bad news about lost packages, broken packages in transit, and the like. Therefore, how to reach an efficient consensus between e-commerce businesses and logistic service providers so as to provide customers with faster and safer logistics services is crucial.

All of the above challenges perform great restrictions on the growth of e-commerce. To handle these issues, we introduce blockchain technology. Due to the trustless nature of blockchain network, we no longer need to worry about the trust problems between customers and sellers in the e-commerce environment. Through the consensus mechanism, we can effectively prevent the evil behaviors, thus ensuring the safety of the e-commerce system. The privacy problems can also be addressed naturally because transaction data in the block can never be tampered. The consumers will encrypt the data using their private keys while making transactions, so every piece of data has their stamp on it. If someone wants to use the transaction data, the owner can easily know and then charge a fee for that or just refuse. In addition, by adapting blockchain in e-commerce environment, merchants can use smart contracts to sign terms with logistics service providers to cooperate and bind each other [34]. Under such regulatory, e-commerce users can gain better logistics experience.

A key component in blockchain is the computational process called *mining* [36]. After the broadcast of the need-to-be-packed transactions, each consumer selects a certain number of them and competes for the packing right. They strive to solve a difficult and computation-intensive mathematical problem called Proof-of-Work (PoW) puzzle. The one who achieves the result firstly obtains the packing right and propagates the new block composed of the transactions and other information about the block to the global network. Only if the consensus is reached, the packed block can be successfully appended to the current blockchain. The consumer who successfully contributes a new block to the blockchain will get rewards, which leads to the fact that all consumers would try their best to solve the PoW puzzle; even their computing power is deemed insufficient. In fact, mobile devices of these consumers can not afford the expensive computing power and other energy consumptions to solve the puzzle at all. This can explain why blockchain applications are still so rare in mobile environments. Therefore, how to break the ice to provide e-commerce consumers with enough computing power (a.k.a. hashrate) to meet the PoW requirements forms a stern reality.

To tackle this issue, we bring in Mobile Edge Computing (MEC) to support blockchain-enabled e-commerce, where consumers can offload their mining tasks onto edge servers. Nevertheless, in MEC systems, computation offloading is complicated, which is influenced by many factors [14]. Firstly, the wireless signal coverage of adjacent edge servers partially overlaps, which significantly increases the difficulty of edge server selection. Secondly, edge servers' computing power is still limited. Consumers have to compete for depletable resources of available edge servers. Thirdly, from the perspective of the overall revenue of consumers, we are obliged to decide whether the mining tasks are executed locally with constrained computing power or offloaded to edge servers. The complicated situation encourages us to design an efficient offloading mechanism for multiple users and model it as a multi-constrained optimization problem. Concretely, the maximization of the overall revenue of e-commerce consumers is adopted as performance metrics. With the constraints on computing power and the overlap of signal coverage of edge servers considered, we schedule the number of transactions and the edge server selection for each consumer. Several evolutionary algorithms are adopted and re-designed as solvers for achieving asymptotic optimality against two representative baseline approaches: Random and Greedy. To the best of our knowledge, we are the first to study computation offloading mechanism for PoW in blockchain-enabled e-commerce system. The main contributions of this work are as follows.

(1) An efficient offloading mechanism for multiple e-commerce users is proposed. The limitations on computing power, overlapped coverage of wireless signal, and the number of transactions to be packed in a block are taken into consideration.
(2) We formulate the computation offloading problem as a explicit Mixed Integer Non-Linear Programming (MINLP) problem. Several evolutionary algorithms are performed as solvers against two representative baseline approaches.
(3) We find that the lower bound of computation resources exists to obtain the maximum overall revenue. It is instructive for service providers on renting edge servers with maximum earnings and minimum costs. This conclusion is achieved with not-so-rigorous mathematical proofs.

The organization of this article is as follows. Section 2 introduces the background of blockchain technology as well as mobile edge computing. Section 3 presents the system model and the formulated optimization problem. In Section 4, several evolutionary algorithms are conducted and the results are analyzed. Extensive experiments against two baseline approaches are discussed in Section 5. The threats to validity of this study are described in Section 6. Then, the state-of-the-art is shown in Section 7. Section 8 concludes this article.

2 PRELIMINARY KNOWLEDGE

2.1 Blockchain

The world has witnessed a flourish of research activities on blockchain in recent years. As the key technology of Bitcoin, blockchain has subverted the traditional centralization technology by

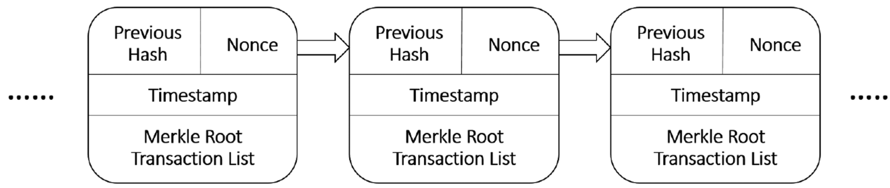


Fig. 1. Typical structure of blockchain.

creating a peer-to-peer (P2P) network. It provides us with a distributed system where the data is tamper-resistant, safe, and private without any trusted third parties. Besides, it proposes an efficient incentive mechanism among users to achieve the consensus. The consensus mechanism creates an environment where we don't need to build trust but can operate efficiently [15]. Thus, blockchain technology has been applied in various fields, such as Internet of Things [8], Healthcare [29], and video transcoding [22].

As shown in Figure 1, blockchain is a data structure that is sequentially linked from back to front by blocks containing transaction information. Each block contains a summary of all the transactions in the block using a Merkle tree data structure. Merkle tree is a hash binary tree, which is a data structure used for fast generalization and verification of large-scale data integrity [20]. In the bitcoin network, the Merkle tree is used to summarize all the transactions in a block, generate the digital fingerprint of the entire transaction set, and provide an efficient way to verify the existence of a transaction in the block. For simplicity, the Merkel tree structure provides a quick way to find and verify transaction information. Furthermore, each block contains a unique identifier value for the previous block (previous hash), which means that each block has a unique parent block. Any change in the parent block's information immediately invalidates the original identity value. Thus, the parent block identifier value is strongly associated with the parent block information. If someone wants to tamper with one of the trading information in the blockchain, the corresponding block of the trading information will change, and its sub-blocks must also be changed. On one hand, only the miners controlling the computing power of more than 50% of the entire blockchain network can modify the data recorded in the block so as to realize block reorganization. The requirement of 50% computing power is nearly impossible to achieve. On the other hand, the misbehaving nodes have to consider whether the benefits of tampering transactions can make up for the computing power costs they need to contribute, which is a dilemmatic tradeoff. Therefore, this special structure realizes the transparency and tamper-resistant characteristics of the blockchain.

One of the most promising innovations in blockchain is the creation of incentive mechanisms. The purpose of the incentive mechanism is to encourage nodes to participate in the security verification of the blockchain. The security of the blockchain depends on the participation of numerous nodes. For example, the security of the Bitcoin blockchain is based on the huge amount of calculation brought by the participation of plentiful nodes in the proof of work, making it impossible for attackers to provide a higher amount of calculation. The verification process of a node usually requires expensive computing resources and power. In order to encourage node participation, the blockchain usually uses digital currency to reward participants. Almost all of the existing cryptocurrency projects are the products of this mechanism. Taking Bitcoin as an example, the reward mechanism includes two parts. The first part is the system-generated bitcoin after the new block being generated. The second part is that each transaction will deduct some expenses as a transaction fee. In the early stage, the creator of each block will receive a certain amount of bitcoins. The genesis block provides 50 bitcoins, and then as the number of bitcoins in the system continues to increase, the quantity of bitcoins provided by this model is halved every 4 years. When the total amount of bitcoins reaches 21 million, the newly generated block will no longer generate bitcoin. At this time, the second commission is mainly used as a reward mechanism. This incentive mechanism is inherently suitable for e-commerce scenarios, which efficiently stimulate mobile users to participate in e-commerce platforms and maintain the security in a cooperation manner. What's more, the blockchain makes business logics programmable through smart contract technology. The related rules are automatically triggered based on corresponding events without need of any trusted central party. By leveraging smart contracts, complex interaction rules between various e-commerce entities can be simply implemented and superivised, creating an easy-to-use environment.

In summary, all the above features show that blockchain technology is quite appropriate for being adapted into e-commerce.

2.2 Mobile Edge Computing

Recently, mobile devices (such as Mobile Phone, Smart Phone, Tablet, etc.) are emerging as an important tool for learning, entertainment, social networking, updating news, and businesses. However, mobile users do not get the same service experience compared to desktop due to resource constraints of mobile devices, including processing power, battery lifetime, and storage capacity [12]. Fortunately, with the development of mobile cloud computing, many services are directly accessible from the mobile devices [2]. However, the centralized risks, high network load, growing demand of network bandwidth, and high latency become serious bottlenecks that limits the user experience. To overcome these issues, mobile edge computing is proposed where mobile devices can offload computational tasks to the less resourceful server near the users' proximity [1].

Mobile edge computing provides IT and cloud-computing capabilities within the Radio Access Network (RAN) in close proximity to mobile subscribers [25]. For application developers and content providers, the RAN edge offers a service environment with ultra-low latency and high-bandwidth as well as direct access to real-time radio network information (such as subscriber location, cell load, etc.) that can be used by applications and services to offer context-related services; these services are capable of differentiating the mobile broadband experience. Mobile edge computing allows content, services, and applications to be accelerated, increasing responsiveness from the edge via resource provisioning [21] and service composition [28]. Therefore, the mobile subscriber's experience can be improved through efficient network and service operations.

Figure 2 shows the architecture of mobile edge computing. In the bottom are various kinds of mobile devices, which lack processing resources. Edge servers are edge service providers located in each mobile base station. Public cloud is the cloud infrastructure hosted on the Internet. In consideration of the existing blockchain frameworks, the security of the system relies on the total computing power participating in the network. Furthermore, to ensure stable operation of blockchain system, all nodes have to reach a consensus on every instruction, resulting in high costs of computing and storage resources. Nevertheless, mobile devices are both short of storage resources and computing power, making them unsuitable for running blockchain applications. In spite of the abundant resources that the cloud computing framework can provide, there exist many defects such as single node attack, high latency, and privacy issues, making it unsuitable for blockchain-based applications. Luckily, mobile edge computing offers a promising solution to handle with these challenges. As shown above, the edge servers enable the execution of computation-sensitive tasks on blockchain in a low-latency manner. Therefore, in the e-commerce environment, the consumers can chase the rewards by offloading the PoW puzzle to edge servers for faster resolution. The distributed nature of mobile edge computing makes e-commerce users easy to find a close server for offloading tasks. Thus, the mobile edge computing architecture makes up for

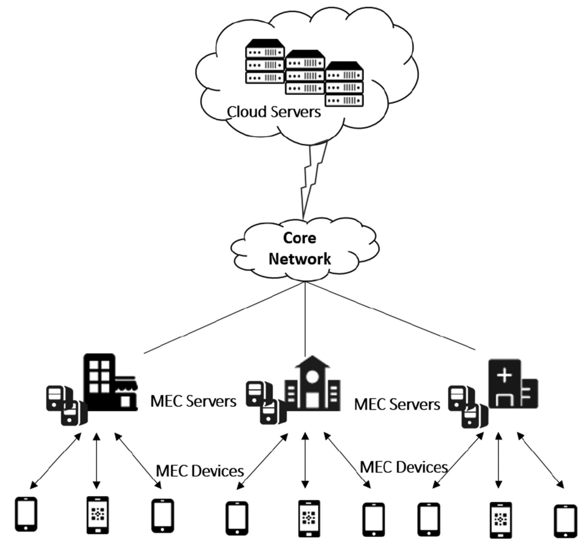


Fig. 2. Mobile edge computing architecture.

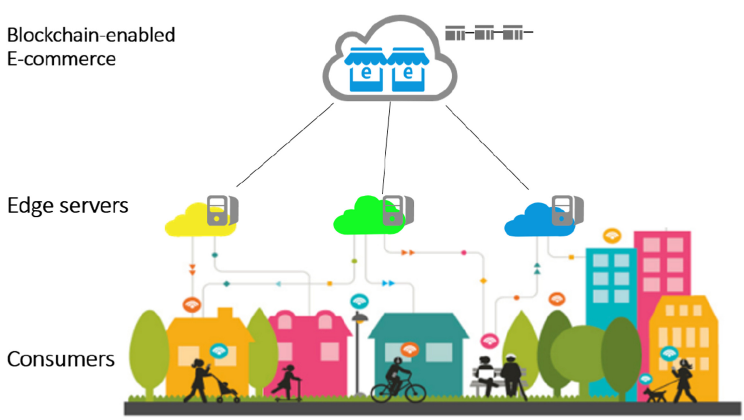


Fig. 3. Blockchain-enabled e-commerce scenario.

the shortage of resources in mobile devices and makes the employment of blockchain technology in the e-commerce environment more feasible and efficient. Additionally, taking the quality of e-commerce services into account, the consumers' using experiences will be significantly improved due to the faster response and higher bandwidth.

3 SYSTEM MODEL

3.1 Scenario Motivation

Blockchain is a natural fit for e-commerce, since it was designed for storing transaction data. The applications of using blockchain in e-commerce are limitless, including Alternative Payment Methods [17], Private Transactions [19], Fast Authentication [35], More Secure Payments [39], and so on. We bring in a simple blockchain-enabled e-commerce scenario, as shown in Figure 3.

Assuming there are many consumers using mobile devices to buy coffee in an online coffee shop (a.k.a. e-shop), a large number of trades may happen at the exact same time. Then, a mass

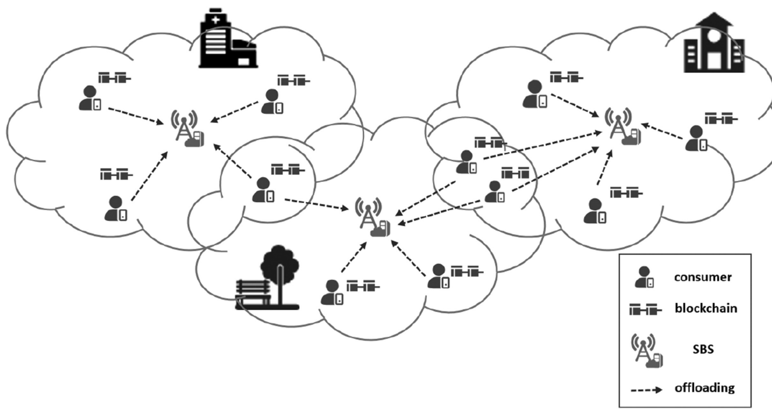


Fig. 4. Simplified scenario.

of different transactions are generated, such as outside catering, purchase orders, payments, and refunds. Various transactions are different in sizes. In order to handle with the challenges we discussed above, we consider that the e-commerce system after the e-shop is implemented based on blockchain technology. As the underlying consensus machanism in Bitcoin, the PoW algorithm has experienced years of tests and proved its extraordinary security in distributed systems. A lot of novel consensus algorithms have appeared recently with the goal of improving the scalability of the current blockchain systems. However, these new algorithms either sacrifice system security and decentralization, or require complex verification and participation mechanisms, which raises the threshold for user's participation in consensus. Thus, in consideration of system security and decentralization, we adopt the PoW mechanism in our system. Besides, merchants can offer coupons in the form of tokens to attract customers and increase revenue. Tokens can be circulated in the whole blockchain network, thereby coupons can also be easily circulated in the whole e-commerce platform and accepted by the public quickly [6].

In order to fulfill the requirements of faster transactions and more secure payments, the consumers are performed as *miners* who will validate each transaction they generate during the whole purchase process and then transfer the valid transaction to other consumers. After that, each *miner* selects a certain number of transactions to pack into a block and start to calculate the *Nonce*, which we mentioned above as PoW puzzle. All of the consumers are eager to get the coupons and the rewards of successfully submitting the block onto the main chain, which may even offset the cost of coffee. So, most of the consumers will make efforts to solve the puzzle. However, mobile devices of these consumers can not support the computing power to solve the puzzle at all. In this case, they have the option of offloading computing tasks to the edge servers around them. As is depicted in Figure 3, the consumers offload the puzzle to edge servers, which cover them. Edge computing framework performs as an excellent paradigm to provide e-commerce users with sufficient computing power to compete for the coupons. The fastest valid block will be appended to the tail of the main chain of the e-commerce system. Consequently, all transactions will be stored safely and permanently. And the consumer who contributed the valid block wins a considerable revenue. After a valid block is appended onto blockchain, the next block starts to be competed among e-commerce users. Therefore, a new round of user-system interaction begins, according to the generation time of a certain block.

For the sake of simplicity, the scenario is simplified in Figure 4. We refer to a blockchain-enabled e-commerce network consisting of N consumers, who are also referred to as *miners*, indexed by

$\mathcal{N}$, and M geo-distributed Small Base Stations (SBSs), indexed by $\mathcal{M}$. Each SBS is bound with a Small Cell (SC) for data transmission and communication. Besides, each SBS is equipped with a multi-core server for the offloaded mining tasks. As illustrated in Figure 4, signal coverage overlap is considered in our research. Thus, let us denote the set of SBSs covering the ith consumer as $\mathcal{M}_i$. Correspondingly, $\mathcal{N}_j$ denotes the set of consumers covered by the jth SBS. Users who are outside the coverage of an edge server will not be able to offload tasks to it.

Each mobile user runs a blockchain-enabled e-commerce platform where the transactions performed in the group are recorded by underlying block structure. Those mobile users play against each other in a race to find the solution of a mathematical problem, which is solved by a *try-and-guess* strategy. The occurrence of a new block can be modeled as a random variable following *a Poisson process*. Besides, the owner of the mobile blockchain application can dynamically adjust the complexity of the PoW puzzle so as to ensure that T seconds are needed for block generation in expectation [18].

3.2 Mobile Blockchain Mining

After the creation of *the genesis block*, each e-commerce user chooses a set of transactions to pack into a block. After that, each user needs to broadcast his solution to the network and his solution must reach a *consensus*. In general, each user competes to be the first to solve the PoW puzzle with correct *Nonce* value. Let us denote the number of transactions included in the block mined by the ith e-commerce user as Q_i, which is used to describe the size of block body (in bits). The number of transactions in T seconds in expectation is denoted as $\widehat{Q}$. Apparently, Q_i follows the constraint below:

$$0 \leq Q_i \leq \widehat{Q}, \forall i \in \mathcal{N}. \tag{1}$$

In general, the block header includes block version, parent block hash, Merkle tree root hash, timestamp, nBits (current hash target), and Nonce [32]. Without loss of generality, we assmue that the size of block header is fixed (for Bitcoin blockchain, it is 80 Bytes).

Generally, the mobile users do not have competitive *hashrate* to cope with the hard puzzle, as we discussed above. Fortunately, the PoW puzzle can be offloaded to a nearby SBS for execution. Let us denote $I_{i,j} \in \{0,1\}, j \in \mathcal{M}_i$ as the SBS-selection indicator for whether the ith mobile user would decide to offload the task to the jth server. $I_{i,j} = 1$ indicates that the jth SBS is chosen for execution while $I_{i,j} = 0$ represents that the ith user prefers not to offload any task to the jth server. $\mathbf{I}_i \triangleq [I_{i,1}, \ldots, I_{|\mathcal{M}_i|}]$ is defined as the SBS-selection vector. Each mobile user's mining task can only be offloaded to *one* SBS, although the user may be covered by several SBSs. It is the initial block that needs to be offloaded to the chosen SBS, whose size is $\overline{u} \cdot Q_i + h$, where $\overline{u}$ is the average size of transactions created in the edge computing group, and h is the size of the remaining part. After that, each chosen SBS allocates the computation resource to the connected mobile users. Different from Mobile Cloud Computing (MCC), the computing capability of SBSs is limited [23]. Let us denote the the maximum computing power of the jth SBS as ψ_j; thus, we have the following constraint:

$$\sum_{i \in \mathcal{N}_j} I_{i,j} \cdot \alpha_{i,j} \leq \psi_j, \forall j \in \mathcal{M}, \tag{2}$$

where $\alpha_{i,j}$ is the allocated computation power from the jth SBS for the ith mobile user. For those mobile users who do not offload mining task to any SBS under current scheduling policy, the computing power comes from himself, which is denoted by β_i. As a result, the *relative* computing power of the ith mobile user γ_i is calculated by

$$\gamma_i = \frac{\sum_{j \in \mathcal{M}_i} I_{i,j} \cdot \alpha_{i,j} + \mathbb{1}\{\mathbf{I}_i = \mathbf{0}\} \cdot \beta_i}{\sum_{i' \in \mathcal{N}} \left[\sum_{j \in \mathcal{M}_{i'}} I_{i',j} \cdot \alpha_{i',j} + \mathbb{1}\{\mathbf{I}_{i'} = \mathbf{0}\} \cdot \beta_{i'} \right]}, \forall i \in \mathcal{N}. \tag{3}$$

In mobile blockchain, the first miner who successfully mines a block that reaches a consensus earns the mining rewards. The rewards consist of a fixed while decreasing reward R and the transaction fee $r \times Q_i$, which is directly proportional to the number of transactions included in the block.

However, there exists a possibility that the new block can not achieve global consensus after being propagated to the network, known as a fork. This kind of mined blocks that cannot be appended to the blockchain is called orphaned blocks [31]. In the Bitcoin network, the miners who produced orphaned blocks will not achieve any rewards regardless of how much resources they have sacrificed in order to mine the blocks. The transactions in the orphaned block then transfer to an unverified state and wait for revalidation and package. This accounts for why each transaction in Bitcoin needs to obtain the validation of six blocks so as to guarantee its successful uploading to the blockchain. Therefore, we need to ensure the mined block will not become an orphaned block. Hence, the probability that the ith mobile user successfully contributes a block to the blockchain $\Pr(\gamma_i, Q_i)$ is equal to the probability of successfully finishing the PoW puzzle times the probability of reaching consensus. The former can be represented by the relative computing power, i.e., γ_i. The latter can be described by the chance that the mined block is not *orphaned* [36]. Obviously, a larger block needs more propagation time, which incurs higher delay for consensus. Without loss of generality, we assume that the propagation time of a block is directly proportional to the size of it. Besides, the time consumed by transmitting the offloading task to the edge server can not be ignored as well. Whatever communication mechanism is adopted, such as Frequency Division Multiple Access (FDMA) or Code Division Multiple Access (CDMA), we reasonably assume that the transmission time is directly proportional to the size of the initial block, i.e., $\overline{u} \cdot Q_i + h$.

Thus, the orphaning probability can be approximated by

$$\mathbb{P}_{orphan}(Q_i) = 1 - \exp\left(-\frac{\zeta_1 \cdot Q_i + \zeta_2 \cdot \sum_{j \in \mathcal{M}_i} I_{i,j}(\overline{u} \cdot Q_i + h)}{T}\right) \tag{4}$$

as the arrival of a new block follows a Poisson process [18]. ζ_1 and ζ_2 are corresponding constants. Thus, we have

$$\Pr(\gamma_i, Q_i) = \gamma_i \cdot \left(1 - \mathbb{P}_{orphan}(Q_i)\right) = \gamma_i \cdot e^{-\frac{\zeta_1 \cdot Q_i + \zeta_2 \cdot \sum_{j \in \mathcal{M}_i} I_{i,j}(\overline{u} \cdot Q_i + h)}{T}}, \forall i \in \mathcal{N}. \tag{5}$$

As a result, the expected reward of the ith mobile user is given by

$$\Theta_i \triangleq (R + r \times Q_i) \cdot \Pr(\gamma_i, Q_i), \forall i \in \mathcal{N}. \tag{6}$$

3.3 Revenue Maximization on Mining Offloading

The goal of our research is to maximize the overall revenue of e-commerce users by scheduling the number of transactions Q_i, the SBS-selection vector $\mathbf{I}_i$, and the computing power of SBS $\alpha_{i,j}$ according to the geographical distribution and the computation loads of SBSs.

Consequently, the revenue maximization problem is formulated as follows:

$$\begin{aligned} \mathcal{P}: \quad & \max_{\forall i, \mathbf{I}_i, Q_i, \forall j \in \mathcal{M}_i, \alpha_{i,j}} \sum_{i \in \mathcal{N}} \Theta_i \\ s.t. \quad & (1), (2), \\ & I_{i,j} \in \{0, 1\}, j \in \mathcal{M}_i, \forall i \in \mathcal{N}, \end{aligned} \tag{7}$$

Table 1. Mathematical Notations

Symbol	Description
$\mathcal{M}$	The numbers of Small Base Stations (SBS)
$\mathcal{N}$	The numbers of consumers (mobile users)
$\mathcal{M}_i$	The set of SBSs covering the ith user
$\mathcal{N}_j$	The set of mobile users covered by the jth SBS
T	The time needed for block generation in expectation
Q_i	The number of transactions packed by the ith user
$\widehat{Q}$	The number of transactions in T seconds
$I_{i,j}$	The indicator for whether the ith user will offload to the jth server
$\mathbf{I}_i$	The SBS-selection vector of the ith user
$\overline{u}$	The average size of transactions
h	The size of the remaining part of the block
ψ_j	The maximum computing power of the jth SBS
$\alpha_{i,j}$	The allocated computing power from the jth SBS for the ith mobile user
β_i	The personal computing power of the ith user
γ_i	The relative computing power of the ith user
R	The fixed bonus for mining a new block
r	The transaction fee rate
$\Pr(\gamma_i, Q_i)$	The probability of mining a block by the ith user
$\mathbb{P}_{orphan}(Q_i)$	The orphaning probability of the block mined by the ith user
ζ_1, ζ_2	Corresponding constants
Θ_i	The expected rewards of the ith user

$$\sum_{j \in \mathcal{M}_i} I_{i,j} \leq 1, \forall i \in \mathcal{N}. \tag{8}$$

The symbols used in our model are summarized in Table 1.

4 NUMERICAL RESULTS

The model we formulated is a highly complex MINLP problem that is *NP*-hard and not well figured out so far [4]. In this section, we conduct some evolutionary algorithms to cope with it. All the experiments are implemented on macOS Mojave equipped with Intel core i7 (6 CPUs, 2.2GHz) and 16GB RAM.

4.1 Evolutionary Algorithms

We introduce four of the most widely-used evolutionary algorithms and re-design them to be more adaptive to our scenario.

The Genetic Algorithm (GA). The GA is one of the most popular evolutionary algorithms that is widely used for service computing researches to solve complicated optimization problems. To be specific, the individuals in the algorithm denote each feasible solution in the offloading problem while the population means the set of all feasible solutions. In our article, the solution is composed of Q_i and $\mathbf{I}_i$ of the whole blockchain users. And the fitness function is represented by the need-to-be-maximized overall revenue. Technically, we randomly generate a floating number in the interval of 0 to 1. Then, we take two decimal places to represent Q_i. Thus, we encode Q_i into a 7-bit binary string. Considering $\mathbf{I}_i$ is another decision variable, we eventually encode a feasible solution as a binary string with $7 \cdot N + N$ bits. Finally, we strive to find out the optimal solution through the iterations of selection, crossover, and mutation operations.

The Simulated Annealing Algorithm (SA). SA is another popular evolutionary algorithm. In SA, local optimal solution will be abandoned with a certain probability so as to pursue the global optimal solution of the target function. This efficiently avoids the algorithm from getting trapped in local optimum. Concretely, we separate Q_i and $\mathbf{I}_i$ from the solution to make a disturbance, respectively. For Q_i, We make it fluctuate in a small range. For $\mathbf{I}_i$, we change the value with a given probability. And then the new solution is evaluated as to whether we will accept it. As the temperature goes down, we find the optimal solution iteratively.

The Artificial Bee Colony Algorithm (ABC). ABC is a novel global optimization algorithm based on swarm intelligence. Its intuitive background comes from the colony behavior of honey bees. The bees can find the optimal solution to the problem via the benign information sharing and communication mechanism. Specifically, the food sources in ABC represent feasible solutions of our model. We make a modification in the food resource updating operation. Firstly, we make a small change to Q_i. Then, we alter $\mathbf{I}_i$ according to a given probability. After that, we generate an updated food resource (solution) based on these two variables.

The Particle Swarm Optimization (PSO) Algorithm. The PSO is a kind of evolutionary computation technology that comes from the study of the hunting behaviors of birds. The basic idea of PSO algorithm is to seek the optimal solution through cooperation and information sharing among individuals in the group. The particle determines its next move based on the best position it has found and the best position all particles have found so far. Specifically, the position of the particle indicates a feasible solution while the velocity denotes the disturbing variable, which is updated during each iteration. Because $\mathbf{I}_i$ is a binary variable that cannot be subtracted directly, we solve this problem by comparing $\mathbf{I}_i$ with the personal best solution and global best solution separately. If one of them is not equal, we will change its value with a certain probability. If both values are equal, we will ignore the change of $\mathbf{I}_i$. In addition, we introduce an inertia factor to improve the performance of PSO.

4.2 Results Analysis

We conduct two sets of experiments in this section. The first set of experiments aims to evaluate the effectiveness of the algorithms discussed above by comparing their optimality and convergence rate. The algorithm with the highest fitness value and the quickest convergence rate is the most effective one. The second set of experiments targets to analyze the effects of some key parameters in our model.

Parameter Setting. Since no standard platforms and datasets are available in this blockchain-enabled e-commerce system, we generate our experimental data in a synthetic way. We set the number of mobile blockchain users and the edge servers according to the scenario in Figure 4 as a simple template, which means our model and approach can be easily adapted to larger mobile blockchain groups in more complex scenarios. Specifically, there are 11 miners (mobile users) and three edge servers in the blockchain network. In addition, there are two overlapping areas. A user located in the overlapping area can only offload tasks to one of the edge servers covering them, in order to achieve the maximum rewards. We keep the key parameters fixed to observe the performance of each algorithm. The computing power of each SBS is set as 200, 60, and 100, respectively. We set the expected generation time for one block T as 10 minutes (600 seconds), which is generally accepted in the Bitcoin network. We fix $\overline{u} = 10$, $h = 1$, $R = 50$, and $r = 10$. Moreover, the positive constant ζ_1 and ζ_2 are set as 0.5 without the loss of generality.

Experimental Results. As we can see in Figure 5, the PSO approach outperforms the others in terms of convergence rate while SA performs worst. In SA, the fitness value is pulsing irregularly

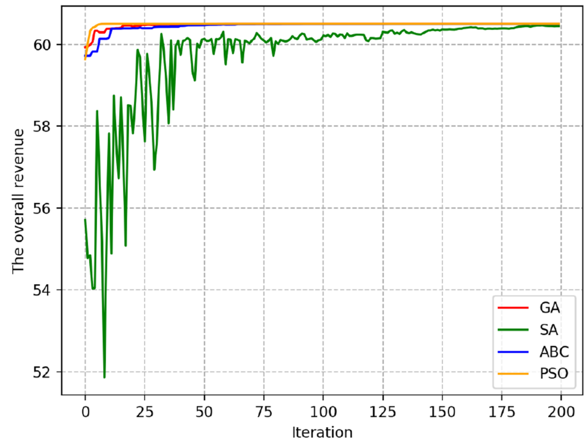
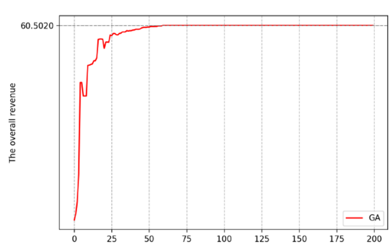
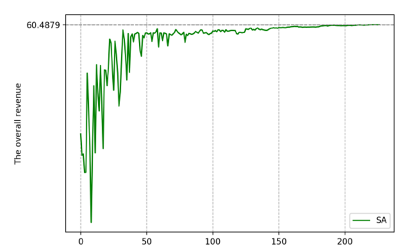


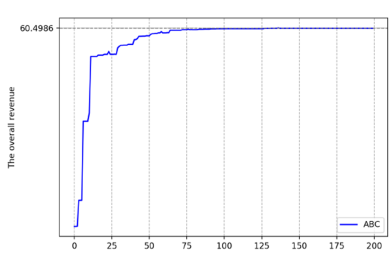
Fig. 5. Performance of the four algorithms.



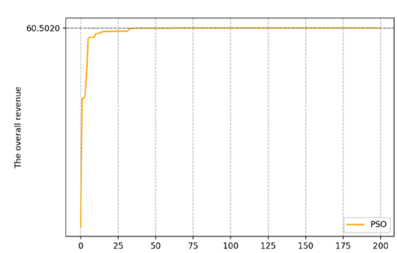
(a) Results of GA



(b) Results of SA



(c) Results of ABC



(d) Results of PSO

Fig. 6. Experimental results of each algorithm.

during the first 100 iterations because there is a random perturbation on Q_i and $\mathbf{I}_i$ during each iteration. The goal is to jump out the local optimum and achieve the global optimal solution gradually. Besides, we can find that PSO shows the quickest convergence speed due to that all particles in the particle swarm adjust their speed and position according to the current individual optimal value and the current global optimal value shared by the whole swarm, which is quite an efficient way to achieve the best value. As is illustrated in Figure 6(a)–(d), the convergence results of GA and PSO are identical, while the results of ABC and SA are a bit smaller than the other two algorithms. From the above, we can draw a conclusion that PSO is more suitable than the other three algorithms for our model.

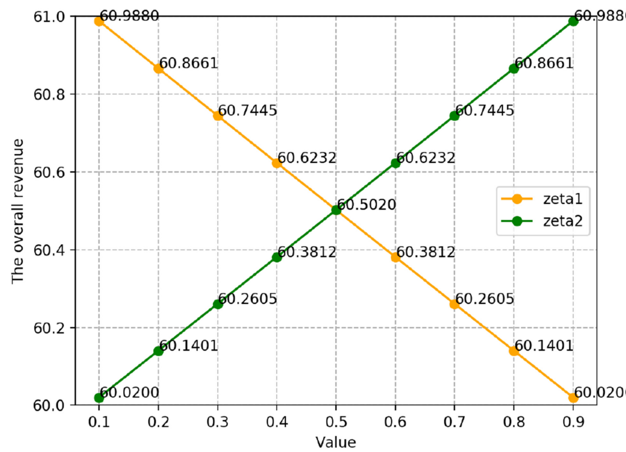


Fig. 7. Impact of parameter ζ_1 and ζ_2.

It is obvious that the overall revenue will increase if we enhance the fixed bonus R of generating a new block for the network or increase the transaction fee r. Furthermore, the security of the blockchain networks is associated with the computing power dedicated to mining the block [5]. Also, as we can speculate, if we expand the group of users $\mathcal{N}$ and edge servers $\mathcal{M}$, the overall rewards will absolutely increase because the whole computing power improves a lot. What's more, the rewards given to miners will increase since the blockchain network is more stable and secure. Thus, we investigate the impacts of ζ_1 and ζ_2 on the overall revenue of mobile users. As is shown in Figure 7, the overall revenue decreases as ζ_1 increases, while the overall revenue increases as ζ_2 increases. We can deduce from Equation (4) that the orphaning probability will increase with ζ_1 getting bigger. Therefore, the possibility of successfully contributing a block will become smaller. And then it will naturally result in the lower revenue of blockchain users. However, the performance of ζ_2 is just the reverse, which means that the transmission time of the offloading task is negatively correlated to the block-orphaning probability. Hence, in order to narrow their impacts on the orphaning probability, we pursue a balance between ζ_1 and ζ_2 by taking 0.5 as their value.

5 PERFORMANCE EVALUATION

In this section, we evaluate the performance of our approach by extensive experiments with a comparison to two baseline approaches. Moreover, a very valuable discovery on edge servers' computing resources is elaborated in Section 5.2.

5.1 Baseline Approaches

Our model will be evaluated against two baseline approaches, namely *Random* and *Greedy*, respectively.

—*Random*: Each mobile user will offload the computation task to an edge server randomly as long as that server has sufficient computation power and has the user in its coverage.

—*Greedy*: Each mobile user will offload his task to an edge server that has the most computation power and has the user in its coverage as well.

We conduct our experiments in a synthetic way, where the number and location of edge servers is established randomly. There will be a dramatic influence on scenario topology if we vary the numbers of mobile blockchain users and edge servers for experiments due to the change in signal

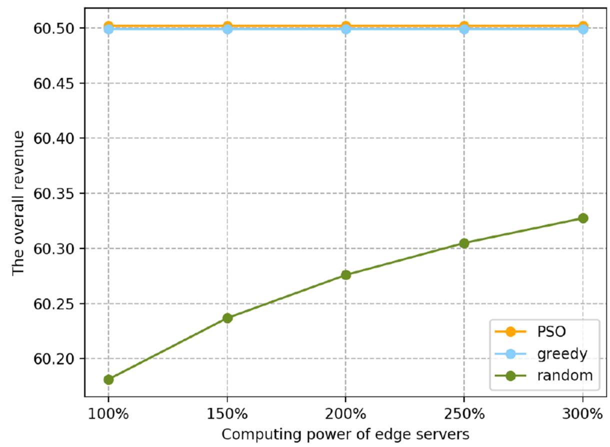


Fig. 8. Impact of edge servers' computing power.

coverage. As a result, we keep these two parameters fixed to observe the impact of edge servers' computing power on the approaches.

Computing Power of Edge Servers. The computing powers of different edge servers located in various places are absolutely different. However, the choice of users for one particular edge server will exert a great influence on their relative computing power, which directly determines whether they could make a block successfully. Hence, we set various levels of computing power to analyze the impacts on the overall revenue. To be specific, we conduct the experiments respectively by the use of three approaches. We calculate 100%, 150%, 200%, 250%, and 300% of the initial computing power of each edge server. Besides, for *Random* approach, we run the experiments 100 times to get the average revenue for each computing power, so that extreme cases are properly neutralized. Obviously, the approach with the highest revenue shows a better performance.

5.2 A Valuable Discovery

As depicted in Figure 8, the overall revenue of *Greedy* method is approximately identical to our approach, while the performance of *Random* is so poor that the revenue is far lower than the other two approaches. As we can imagine, in *Greedy* method, all mobile users are anxious to get abundant computing resources to solve the PoW puzzle so as to get rewards. Thus, they prefer to offload their tasks to edge servers rather than execute locally. In addition, they would make their minds to pack as much transactions (i.e., Q_i) as they can for more revenues, which can explain the result of *Greedy* approach is nearly identical to PSO. Note that Q_i should always be constrained under the restriction (1). On the contrary, in *Random* method, end-users casually select edge servers to offload or simply execute locally if they have enough computing power. Therefore, $\mathbf{I}_i$ of each end-user is determined in a random way. For simplicity, we fix the transaction numbers that each user chooses. As shown in Figure 8, the overall revenue shows an upward trend with more end-users deciding to offload their tasks to edge servers in order to achieve higher computing capacity. However, this figure will change with the offloading selection of users relatively.

Furthermore, when we dig deeper into Figure 8, we find an interesting discovery that the overall revenue of the system remains unchanged regardless of the increase of edge servers' computing power, both in PSO and *Greedy* approaches. As formulated in Equations (5) and (6), the formulation $(R + r \times Q_i)$ is a monotonically increasing function as Q_i increases. In addition, the function on the right side of γ_i in Equation (5) is monotonically decreasing with the increase of Q_i. Therefore, let us multiply these two functions; then, we get a new function that can not be ensured of its monotonicity. However, no matter if the new function is monotonically increasing or decreasing, we can easily draw a conclusion that this new function can always achieve a maximum value in the interval of Q_i. Let's denote $Ymax$ as the maximum value in the new function, which can be achieved by all end-users, and $Ymax_i$ as the practical value for the ith user. For simplicity and clarity, we use a_i as the computing power owned by the ith end-user and Δ to describe the whole computing power of all users. Then, we get a new formulation about revenue:

$$\Theta_i = \frac{a_i}{\Delta} \cdot Ymax_i, \forall i \in \mathcal{N}. \tag{9}$$

Obviously, $Ymax_i$ follows the constraint below:

$$0 \leq Ymax_i \leq Ymax, \forall i \in \mathcal{N}. \tag{10}$$

Therefore, we can conclude that no matter how much computing power each end-user gets, the whole revenue of users will always be less than the condition that every user picks $Ymax$ in Equation (9). Thus, in order to get the maximum overall revenue, all users always choose Q_i, which maximizes $Ymax$ and, finally, accounts for the fact shown in Figure 5.

The overall revenue has no relation with computing power anymore after converging to the optimal value. This means that there remains a lower bound of edge servers' computing capacity if we want to maximize the overall revenue in this mobile blockchain system. Clearly, this reveals a great reference for Edge Service Provider (ESP) to optimize their allocating schedules to edge servers so as to achieve lower costs and higher incomes. Besides, it's also beneficial for edge server managers to make a better price model and optimize resource management. Thus, this discovery may open up a number of research directions and exert a profound effect on practical scenarios in a blockchain-enabled e-commerce environment.

6 THREATS TO VALIDITY

In this section, we analyze the threats to validity of our study on computation offloading in a blockchain-enabled e-commerce environment.

Threats to Construct Validity. The main threat to the construct validity in our study lies in the comparison between the four evolutionary algorithms, i.e., the GA, SA, ABC, and PSO. On one hand, the computation offloading in blockchain-enabled e-commerce environment has not been investigated well before. On the other hand, the mixed-integer non-linear programming we modeled lacks concise and direct mathematical solution. Both of these factors lead to a threat where the comparison with the selected evolutionary algorithms might not properly demonstrate the effectiveness of solving the offloading problem. To minimize this threat, we selected the *Random* and *Greedy* methods as baseline approaches in our evaluation. By this way, we could reliably evaluate our approach through the comparison with the baseline methods and then perform extensive experiments on parameters.

Threats to External Validity. A major threat to external validity is whether our findings based on the experimental dataset can be generalized to other scenarios in e-commerce environment. Since there is currently no standard platforms and real-world dataset for this type of computation offloading problems, we generate our experimental data in a synthetic way. Honestly, it is possible that different application scenarios might have different factors that could exert big impacts on the experimental results, such as the computing power of edge servers. Therefore, our approach is evaluated by varying the size of the computing power of edge servers, in order to simulate as many types of edge server as possible. This helps to reduce the threat to the external validity of our evaluation and increase the universality of our method.

Threats to Internal Validity. A threat to internal validity of our work is the comprehensiveness of our experiments and whether or not the results are not biased by the experimental parameter settings. In order to mitigate this threat, we carried out extensive experiments with systematically selected parameters. And for parametric experiments, we conducted multiple groups of experiments to take the average, which helps to eliminate the potential bias caused by misoperation. Another threat to the internal validity of our evaluation is where more complex scenarios could be simulated, e.g., those scenarios where two or more parameters in the model change at the same time. However, the results in those scenarios can be predicted with big possibility based on the results that we have obtained via experiments. For example, if the computing power of edge servers and the number of e-commerce consumers increase at the same time, the overall revenue may remain stable according to Figure 8.

Threats to Conclusion Validity. The lack of statistical tests is the biggest threat to our conclusion validity. Statistical tests will be included in our future work to prove a statistically significant relationship between the experiment settings and the results. In this article, we have compensated for this with meaningful comparison baselines and extensive experiments that cover many different scenarios. When an experimental parameter changes, the results are averaged over 100 runs of the experiment. In addition, the selection of algorithms in our experiments also results in the threat to conclusion validity. We have improved the algorithms in the process of implementation so as to minimize this threat.

7 RELATED WORKS

This section reviews related works on mobile blockchain and computation offloading in MEC, respectively.

7.1 Mobile Blockchain

Research on mobile blockchain has become an emerging trend with the explosive growth of blockchain technology and applications. However, the security and decentralization in blockchain depends on a consensus process, which requires a large volume of energy and time. Thus, there exists a trouble for mobile users to continuously run such a computationally difficult program, which becomes a major challenge for the development of mobile blockchain [16].

There have been several works bringing MEC to support blockchain-based platforms due to the outstanding features of edge computing, including low latency, high bandwidth, wide-spread geographical distribution, and sufficient resources. An innovative MEC-enabled system for mobile blockchain networks was proposed in Ref. [37], where blockchain users can enjoy various services and resources provided by the edge service provider, so as to release their workloads on running blockchain applications. In order to efficiently allocate computing resources to mobile users, Yutao Jiao et al. [16] proposed an auction-based market model to maximize the social welfare while guaranteeing the truthfulness, individual rationality, and computational efficiency. Similarly, NC Luong et al. [26] presented an optimal auction-based deep learning architecture to make resource allocation in mobile blockchain networks. In addition, a two-stage Stackelberg game was adopted to jointly maximize the profit of the ESP and the individual utilities of different miners so as to optimize the resource management in mobile blockchain [36]. Liu et al. [22] proposed a novel blockchain-based framework for video streaming systems with MEC. They formulated an optimization problem to maximize the average transcoding profit for the transcoders by the joint design of offloading scheduling, resource allocation, and adaptive block size scheme.

Despite that these excellent works have studied the area of mobile blockchain, the issue of computation offloading in blockchain-enabled e-commerce system has not been well investigated yet. This motivates us to design an efficient offloading mechanism for multiple e-commerce users.

7.2 Computation Offloading in MEC

With the thriving developments of recent innovative applications (e.g., augment reality, self-driving, and Internet of Things (IoT)), more and more computation-intensive and data-intensive tasks are considered to be offloaded onto edge servers for execution [7]. As Pavel Mach et al. [24] have classified, the researches on computation offloading in MEC can be divided into three key directions: (1) decision on computation offloading; (2) allocation of computing resources within the MEC; and (3) mobility management. He et al. [13] formulated the edge user allocation problem as a potential game and then designed a novel decentralized algorithm for finding a Nash equilibrium in the game as a solution. Deng et al. [11] investigated dynamical resource allocation in edge for IoT systems by utilizing reinforcement learning. Similarly, Wang et al. [33] proposed a reinforcement learning-based online microservice coordination algorithm to learn the optimal strategy, which can reduce the overall service delay with low costs. Deng et al. [10] explored the deployment problem of microservice-based applications in MEC environment, and proposed an approach to help optimizing the cost of application deployment with the constraints of resources and performance. Shen et al. [27] utilized multiple Deep Reinforcement Learning agents deployed on IoT devices to guide computation offloading decisions. Deng et al. [9] considered the dependency relations among component services so as to optimize execution time and energy consumption of executing mobile services. A cross-edge computation offloading framework is proposed by Zhao et al. [40], which enables the offloading of mobility-aware computation-intensive services by collaboration among edge servers. A similar work is Ref. [38], where collaborative networks are formulated based on mobile devices' density to study whether/how/what to offload tasks from various IoT devices to edge servers.

Among those latest works, what Wenda Tang et al. [30] have done seems the most similar to ours. However, several key differences should be addressed. (1) In this article, mobile users always offload their computation tasks to the nearby fog servers. In ours, we need to decide whether to offload or not and which server to offload so as to achieve the maximum overall revenue; (2) In order to deal with privacy and security issues, they brought blockchain technology into the fog environment to verify each fog server's authenticity. But we focus on achieving an efficient offloading system to support the mobile blockchain environment.

8 CONCLUSION

In this article, we bring blockchain into e-commerce and investigate a computation offloading mechanism for blockchain mining. With the maximization of the overall revenue of the e-commerce users, we model the offloading task as a multi-constrained optimization problem and give the standard formulations. We solve this problem with several evolutionary algorithms and then find out the appropriate approach. We conduct extensive experiments with two baseline approaches, and the results show that our approach is highly efficient. Last but not least, a profound discovery is found and proved via mathematical derivation, which instructs service providers to rent edge servers with lowest costs and maximum earnings. Besides, it may incur lots of new research directions.

In the future, we will try to design a more efficient algorithm with lower complexity for our model based on Branch-and-Bound methods. We will implement it on a real e-commerce scenario and adjust the algorithm by analyzing the feedback. Moreover, we will take the consumers' mobility into consideration so as to optimize our model.

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