

Privacy-Preserved Task Offloading in Mobile Blockchain with Deep Reinforcement Learning

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Abstract—Blockchain technology with its secure, transparent and decentralized nature has been recently employed in many mobile applications. However, the mining process in mobile blockchain requires high computational and storage capability of mobile devices, which would hinder blockchain applications in mobile systems. To meet this challenge, we propose a mobile edge computing (MEC) based blockchain network where multi-mobile users (MUs) act as miners to offload their mining tasks to a nearby MEC server via wireless channels. Specially, we formulate task offloading and user privacy preservation as a joint optimization problem which is modelled as a Markov decision process, where our objective is to minimize the long-term system offloading costs and maximize the privacy levels for all blockchain users. We first propose a reinforcement learning (RL)-based offloading scheme which enables MUs to make optimal offloading decisions based on blockchain transaction states and wireless channel qualities between MUs and MEC server. To further improve the offloading performances for larger-scale blockchain scenarios, we then develop a deep RL algorithm by using deep Q-network which can efficiently solve large state space without any prior knowledge of the system dynamics. Simulation results show that the proposed RL-based offloading schemes significantly enhance user privacy, and reduce the energy consumption as well as computation latency with minimum offloading costs in comparison with the benchmark offloading schemes.

Index Terms—Blockchain, mining, task offloading, mobile edge computing, optimization, privacy, deep reinforcement learning.

I. INTRODUCTION

In recent years, blockchain technology has been employed widely in various industrial applications such as Internet of Things (IoT), healthcare, industrial applications, etc. [1], [2]. Blockchain works as a peer-to-peer public ledger where users can store data (i.e., records of transactions) and share information with other blockchain nodes in a trustworthy and decentralized manner. With the advancement of mobile technologies, blockchain now can be implemented in mobile devices to provide more flexible blockchain-based solutions for IoT applications [3], [4]. The foundation of the efficient and secure operation of blockchain is a computation process known as *mining* [5]. In order to append a new transaction to

the blockchain, a blockchain user, or a miner, needs to run a mining puzzle, i.e. *proof of work* (PoW) which is generally complicated and requires intensive computations. Resource-limited IoT nodes or mobile devices, therefore, cannot participate in the mining operation, which can restrict the application of blockchain in mobile systems.

With the emergence of mobile edge computing (MEC) technology, the problem of computing high computational tasks on mobile devices can be solved effectively. Edge computing, which enables mobile devices to offload their computation tasks to a nearby computationally powerful MEC server, provides a highly effective solution to bridge the gap between constrained resources of local mobile devices and growing demands of executing the computation tasks [6]-[8]. By employing highly computational resources available on the edge server, the performance of MEC-based mobile systems may be improved significantly, such as saving system energy, reducing computation latency and improving the quality of computation experience for mobile devices [9], [10]. As a result, the MEC technology has been studied and used widely to support computation offloading from mobile systems [8], [9], [11].

In order to improve system performances for mobile applications, various offloading approaches have been proposed in the literature. Some offloading strategies in [12], [13] were introduced with the objective of minimizing the energy usage or task execution latency by leveraging Lyapunov or convex optimization methods. But such conventional offloading optimization algorithms only work well for low-complexity online models and usually require prior knowledge of system statistics that cannot be acquired in practical scenarios. To overcome such challenges, Reinforcement Learning (RL) emerges as a strong alternative, which allows a learning agent to adjust its policy and derive an optimal solution via trial and error to achieve the best long-term goal without requiring any prior environment information [14]. Nevertheless, in high-dimensional offloading problems, the dimension of state and action space can be extremely high that makes RL-based solutions inefficient [15], [16]. Fortunately, Deep Reinforcement Learning (DRL) methods [17] such as deep Q-network (DQN) have been introduced as a strong alternative to deal with such high-dimensional problems and demonstrates its scalability and offloading efficiency in various MEC-based applications, such as multi-base station virtual MEC [18], multi-user MEC system [19], and multi-IoT networks [20].

In mobile blockchain applications, MEC-based computation offloading strategies to optimize mining services [21]

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have been considered in some previous studies. A computation offloading scheme was proposed in [22] for a wireless blockchain networks where mobile users can offload their blockchain mining tasks to a MEC server or to a network of device-to-device (D2D) users, subject to probabilistic backhaul and latency constraints. By using stochastic geometry methods, performance metrics including latency, energy cost and orphaning probability were analysed, showing feasibility of the proposed offloading scheme with reduced latency and improved long-term system revenues. Meanwhile, the problem of computation power allocation for proof-of-work offloading in the multi-access MEC-enabled blockchain was investigated in [23] with the main focus on reward optimization for mobile terminals. Further, the work [24] considered an optimization problem of offloading scheduling, resource allocation and adaptive block size scheme for a blockchain-based video streaming system with MEC. The user targets to offload computation to MEC nodes or D2D users such that transcoding revenue is maximized while achieving the high latency efficiency.

In addition to mining efficiency, privacy of blockchain users is another important issue that needs to be considered for mobile offloading in MEC-based blockchain networks [25]-[27]. However, most existing computation offloading frameworks for blockchain mining services [22]-[24] have ignored user privacy. A user privacy model was proposed for MEC-based mobile networks where mobile devices can select efficient offloading decisions using a constrained Markov decision process (CMDP) [28]. The proposed approach can protect location privacy and usage pattern privacy against potential threats from curious MEC servers. Meanwhile, the work in [29] proposed a privacy-aware computation offloading scheme using reinforcement learning, which enables IoT devices to learn an offloading policy so as to protect their personal information while achieving minimum system utility loss. These solutions provide insights into how to develop privacy mechanisms for computation offloading in mobile applications.

However, we find that the study that can achieve optimal policies of offloading mining tasks with enhancing privacy awareness in mobile blockchain is still missing. Many pioneering blockchain schemes [22]-[24] have concentrated on only offloading of mining tasks without considering user privacy preservation, which has been one of the key challenges in MEC-based blockchain networks. Different from existing works, this paper not only considers computation delay and energy consumption aspects of mobile offloading, but also takes user privacy issues into account. This study aims to fill the gap in the joint optimization of task offloading and privacy preservation in MEC-enabled mobile blockchain.

Moreover, in the offloading decision game, the users can decide to handle their mining tasks at the local mobile device when receiving blockchain transactions to reduce execution latency due to no transmission delay. However, running mining puzzle locally can cost extensive energy of mobile devices. On the other hand, offloading mining tasks to edge server will significantly save energy for local devices, but the network latency can occur from task transmission and queuing delay at the MEC server. Thus, in the task offloading, it is important to

analyze the tradeoff between computation latency and energy consumption which has a great impact on the performance of blockchain applications.

To this end, we propose a DRL-based dynamic task offloading scheme for a MEC blockchain network where each mobile user (MU) acts as a miner that can offload its mining tasks to MEC server for computing services. Particularly, we formulate task offloading and user privacy preservation as a joint optimization problem. Then we develop a RL-based algorithm to solve the proposed optimization problem with a simplified blockchain model. Next, to break the curse of high dimensionality in state space when increasing the number of blockchain users, a DRL-based method called deep Q-network (DQN) algorithm is proposed. The objective of the proposed scheme is to obtain optimal offloading actions for all blockchain miners such that the user privacy level is maximized while minimizing computation latency and energy consumption for both local mining execution and edge task offloading. To our best knowledge, MEC-enabled mobile blockchain with mining task offloading and privacy preservation has been not studied well in previous works. The main differences between our study and the existing blockchain offloading schemes [21], [23]-[24] can be highlighted as follows.

- 1) We consider a new mobile blockchain network where mobile users act as miners to learn dynamic computation offloading policies to perform the computation-intensive mining tasks on edge server. Specially, we propose a joint framework of task offloading and user privacy preservation by taking into account the dynamics of blockchain transaction states and channel states between miners and edger server.
- 2) We propose a dynamic task offloading policy for each miner with two offloading modes, i.e. offloading to edge server or executing at the local mobile device to solve the mining problem in blockchain.
- 3) To obtain optimal offloading policies for all miners, we propose a DRL-based algorithm by using a deep Q network to implement our proposed offloading strategy, aiming to achieve the best privacy performance while minimizing offloading latency and energy cost.
- 4) We analyze the tradeoff between the computation latency and energy consumption in the mining task offloading to evaluate the quality of network of our proposed blockchain application.

We conduct numerical simulations to verify the effectiveness of the proposed offloading algorithm in terms of various performance metrics and compare with other offloading schemes. The simulation results with our proposed schemes show the performance of computation offloading for mobile blockchain networks can be significantly improved in terms of enhanced privacy level and reduced system costs, compared with other blockchain offloading schemes.

The remainder of this paper is organized as follows. The Section II introduces the system model of the proposed task offloading scheme for mobile blockchain networks. We also present the formulation of computation model with two offloading modes, which leads to an offloading optimiza-

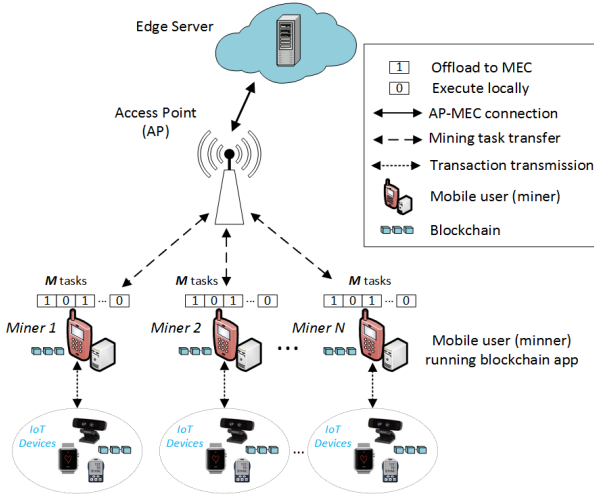


Fig. 1: The proposed mobile blockchain model.

tion problem. To solve that problem, we propose offloading schemes in Section III by using reinforcement learning and then deep reinforcement learning to achieve the optimal offloading performances for miners. Simulation results for two proposed offloading solutions are given in Section IV. Finally, our conclusions are drawn in Section V.

II. SYSTEM MODEL AND PROBLEM FORMULATION

In this section, we present the system model for a mobile blockchain network. We first propose the mobile blockchain network model, and then describe the computation model and problem formulation in details.

A. System model

In this paper, we consider a MEC-based mobile blockchain network as shown in Fig. 1. The blockchain network consists of a MEC server, an wireless access point (AP), a network of many IoT devices and N MUs denoted by a set $\mathcal{N} = \{1, 2, \dots, N\}$. In this system, data generated from IoT devices (i.e. sensor devices in a blockchain-based smart home [2]) is recorded as transactions and is transmitted wirelessly to the mobile user (MU). Each MU acts as a miner to run a computation-extensive mining process to process and append transactions to the blockchain. (MU, miner and mobile miner terms are used interchangeably throughout the paper). Without loss of generality, it is assumed that each MU n has multiple mining tasks denoted by a set $\mathcal{M} = \{1, 2, \dots, M\}$. Therefore, we denote R_{nm} as the m -th mining task of user n . We also assume that the MEC server has sufficient computation resources with high-frequency CPU cores and storage capacity, and can provide mining services for a certain number of mobile miners in the blockchain network.

It is also assumed that time is slotted and at each time slot t , the miner n generates a task R_{nm} . For each miner n , the mining task at the timeslot t can be formulated as a variable tuple $R_{nm}^t \triangleq (D_{1nm}^t, D_{0nm}^t, X_{nm}^t, \tau_{nm}^t) \in \mathcal{R}$. Here D_{1nm}^t (in bits) denotes the data size of blockchain transactions newly received from IoT devices by the miner n at the timeslot t .

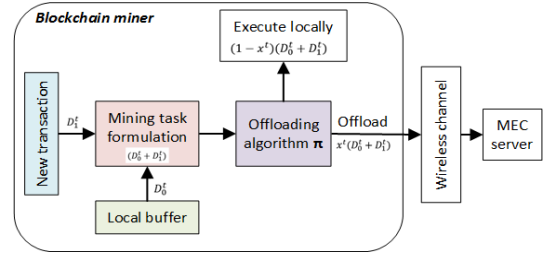


Fig. 2: The offloading process for mining tasks.

D_{0nm}^t (in bits) is the data size of blockchain transaction in the buffer of the miner n . X_{nm}^t (in CPU cycles/bit) denotes the total number of CPU cycles required to accomplish the computation for the task R_{nm}^t . Moreover, τ_{nm}^t (in seconds) reflects the maximum tolerable delay of task R_{nm}^t .

In this paper, we consider a realistic blockchain scenario where the transactions from IoT devices are highly dynamic. That means at a certain time, the transaction volume can be very large (i.e. during the data collection of IoT devices) and at another time, this can be very small (i.e. idle mode of IoT devices). Based on that, at the timeslot t , if the size of mining task is too large, the miners has to divide the current transaction data into two parts: mining task for execution and the rest for storage in the buffer for future process. The mining strategy with task offloading is shown in Fig. 2 and can be explained as follows.

At each time slot t , the miner receives new transaction data D_{1nm}^t from IoT devices and adds it into a block based on the blockchain concept [1]. Besides, the miner also has to process the previous transaction data D_{0nm}^t stored in the buffer. Moreover, for simplicity, we assume that each block contains only a transaction which will be verified by the miner through a mining process (i.e. proof-of-work) so that the verified transaction can be appended to blockchain. As a result, the total blockchain data of a transaction at each time slot t is $(D_{0nm}^t + D_{1nm}^t)$ which can be formulated as a mining task R_{nm}^t . The miner will choose to offload the mining task to the MEC server or execute it locally and store the rest mining tasks into the local buffer for processing in the future.

Accordingly, we consider two computing modes in this paper, namely:

- *Offloading computing*: The miner n offloads its mining tasks to the nearby MEC server.
- *Local computing*: The miner n executes its mining tasks at the local mobile devices.

Specially, we introduce an offloading decision policy denoted by a binary variable $x_{nm}^t \in \{0, 1\}$. Here $x_{nm}^t = 1$ means that the miner n offloads the task m to the MEC server with the wireless channel power gain $g(t)$, and $x_{nm}^t = 0$ means that the miner n decides to process the task m locally. For simplicity, the wireless channel power gain $\{g^t\}_{t \geq 0}$ can be formulated as a Markov chain model with $Pr(g^{t+1} = m | g^t = n) = h_{nm}, \forall n, m \in \mathcal{G}$, where \mathcal{G} is the wireless channel state set. Particularly, we define that $g^t = 1$ or ($g^t = 0$) represents the good (or bad) channel state at the timeslot t . This policy will be used to analyze channel

TABLE I: List of notations

Notation	Description
D_{1nm}^t	Blockchain transaction for task m at miner n at time slot t
D_{0nm}^t	Blockchain transaction in the buffer of miner
X_{nm}^t	The total number of CPU cycles per task
τ_{nm}^t	Completion deadline for mining a task
x_{nm}^t	The task offloading policy
g^t	Wireless channel power gain
f_{nm}	MEC computational capacity
$L_{nm}^{o,t}$	Latency of edge computation
$E_{nm}^{o,t}$	Energy consumption of edge computation
$L_{nm}^{l,t}$	Latency of local computation
$E_{nm}^{l,t}$	Energy consumption of local computation
P_{nm}^t	The total task offloading privacy level

conditions for ensuring user privacy during task offloading. The notations used in this paper are summarized in Table I.

In the task offloading process, the MEC server is assumed to be curious about the personal information of miners. Motivated by [28], in this paper, we consider two privacy issues in the task offloading process, namely *user location privacy* and *usage pattern privacy* of the miner. By monitoring task offloading history of the miner, the MEC server can infer channel state records to obtain location information. Further, the MEC server can infer personal information of the miner by tracking mining data through the task offloading period, which may raise a concern of privacy threat based on the usage pattern of the miner. Thus, how to build an optimal task offloading policy that improves user privacy while guaranteeing low computation/power/latency costs in the dynamic wireless environment is important to any MEC-based mobile blockchain applications. In the next subsection, we present the offloading problem formulation for the proposed model.

B. Computation model

In this subsection, we derive the expression of performance metrics on network latency, energy consumption and user privacy under two offloading modes.

1) *Offloading computing model*: We model the case when the MU n selects to offload its mining tasks to the MEC server ($x_{nm} = 1$). Offloading latency and energy consumption problems are considered in our offloading formulation.

Offloading latency: The computation latency is the key performance indicator for evaluating the quality of mining task offloading. For the miner n , ($\forall n \in \mathcal{N}$), the whole computation latency to offload the mining task m to the MEC server at the timeslot t can be decomposed into three parts, namely uploading, queuing and processing [11], which is given as

$$L_{nm}^{o,t} = L_{nm}^{u,t} + L_{nm}^{p,t} + L_{nm}^{q,t} \quad (1)$$

where $L_{nm}^{u,t}$, $L_{nm}^{p,t}$, $L_{nm}^{q,t}$ are uploading latency, task processing latency and queuing latency on MEC server, respectively.

- *Uploading latency*: We consider the latency when the user n uploads the mining task m to the MEC server. We use r_n to denote the upload transmission rate of the user n in the wireless channel. For simplicity, we assume that the transmission rate

is the same for all users n . Thus, we can express the required time to upload the mining task m to the MEC server as

$$L_{nm}^{u,t} = \frac{D_{0nm}^t + D_{1nm}^t}{r_n}. \quad (2)$$

- *Queuing latency*: In our task offloading model, we are interested in the queuing latency caused by waiting in the task buffer for processing at the MEC server. Let Q denote as the total number of CPU cycles in the mining task buffer, the queuing latency can be given by

$$L_{nm}^{q,t} = \frac{Q}{f_{nm}}. \quad (3)$$

- *Processing latency*: The time consumed by the miner n to execute the mining task m on the MEC server at the timeslot t can be formulated as [22]

$$L_{nm}^{p,t} = \frac{(D_{0nm}^t + D_{1nm}^t)X_{nm}^t}{f_{nm}} \quad (4)$$

where f_{nm} is defined as the computational resource (in CPU cycles per second) allocated by the MEC server to accomplish the task R_{nm} . Note that this computation capacity is assumed to be large enough to serve all miners our blockchain system.

Once the execution of mining task on MEC server finishes, the processed result is downloaded to the miner. Thus the downloading time latency can be given by $L_{nm}^d = \frac{G_{nm}}{S_{nm}}$ where G_{nm} defines the size of executed data and S_{nm} is the data rate of the MU n . However, the processed data from the MEC server is very small and the download rate is very high in general [12], and thus the latency (and energy cost) for the download process will be ignored in this paper.

Energy consumption: The entire energy consumption for the task offloading can be formulated as the sum of energy costs for task uploading, task processing and MEC operation. Thus it is easy to express the total energy consumed by the computation offloading for the mining task m of the MU n at the time slot t as

$$E_{nm}^{o,t} = P^M L_{nm}^{u,t} + \gamma(f_{nm})^3 L_{nm}^{p,t} + P^C L_{nm}^{q,t} \quad (5)$$

where γ is the energy consumption efficiency coefficient of the MEC server, P^M is the transmit power of miner and P^C denotes the baseline circuit power [13].

2) *Local computing model*: When the MU n decides to execute its task m locally ($x_{nm} = 0$), it uses computation resource of the local device to process the mining puzzle. In this case, we consider the time cost and energy consumption for the local mining process.

We denote the local executing time per data bit as t_{nm}^l (in sec/bit), then the total time cost consumed by the miner n to complete the task m at the timeslot t can be expressed by

$$L_{nm}^{l,t} = (D_{0nm}^t + D_{1nm}^t)t_{nm}^l. \quad (6)$$

Meanwhile, we use e_{nm}^l (in J/bit) to denote the energy consumption per data bit of the MU n . Accordingly, the energy cost required for the MU n to execute the mining task at the timeslot t is

$$E_{nm}^{l,t} = (D_{0nm}^t + D_{1nm}^t)e_{nm}^l. \quad (7)$$

3) *User privacy model*: In this subsection, we consider user privacy issues that have been largely ignored in previous studies in MEC-based mobile blockchain networks. Motivated by the privacy-aware offloading framework proposed by [28], here we consider two privacy criteria, i.e. usage pattern privacy and location privacy.

- *Usage pattern privacy*: Naturally, if the wireless channel state is good, the miner tends to offload their mining task with all blockchain transaction data ($D_{offload}^t = D_{1nm}^t + D_{0nm}^t$) to the MEC server to reduce processing time and energy cost on the mobile device. More specially, if the mobile user n moves near to the access point, it is more likely to have $D_{offload}^t = D_{1nm}^t$ (due to $D_{0nm}^t = 0$). Obviously, the data usage pattern of the miner can be obtained by the MEC server through monitoring the mining task $D_{offload}^t$. We denote ϵ as the pre-defined good channel power gain state, similar to [28], the level of usage pattern privacy can be estimated by

$$P_{nm}^{u,t} = |D_{0nm}^t - x_{nm}^t(D_{0nm}^t + D_{1nm}^t)| \cdot \mathbb{I}(g^t \geq \epsilon) \quad (8)$$

where \mathbb{I} denotes the indicated function that equals 1 (or 0) if the statement is true (or false). The equation (3) means that the miner n deliberately changes the amount of transaction data processed by local device under the good channel state, aiming to create a difference between the actual transaction data size D_{0nm}^t and the offloading data size ($D_{0nm}^t + D_{1nm}^t$) to preserve usage pattern privacy.

- *Location privacy*: Besides usage pattern privacy, the location privacy is another critical issue that should be considered to improve the performance of blockchain mining task offloading. According to the system model formulation in the previous subsection, the MU will offload its mining task to the MEC server if the wireless channel has a good transmission state ($g_{nm}^t = 1$). Otherwise, the mining task will be executed locally or stored in the buffer for future process when the channel state is bad ($g_{nm}^t = 0$). However, since the wireless channel power gain is highly correlated to the distance between the miner and MEC server, this offloading strategy can expose location information of miner. Applying the privacy metric in [28], we can formulate the location privacy level as

$$P_{nm}^{l,t} = \mathbb{I}[x_{nm}^t(D_{0nm}^t + D_{1nm}^t)] \cdot \mathbb{I}(g^t < \epsilon) \quad (9)$$

which means that the miner should keep offloading its mining task to MEC server under poor transmission channel quality to preserve its location privacy. In summary, to protect privacy during task offloading, miners should mitigate the offloading rate under good channel quality while increasing the offloading rate under poor channel quality.

Combining the result (8) and (9), the total task offloading privacy level at the timeslot t can be given as

$$P_{nm}^t = P_{nm}^{u,t} + \lambda P_{nm}^{l,t} \quad (10)$$

where λ scales the importance of the location privacy relative to the usage pattern privacy ($0 < \lambda < 1$).

C. Problem Formulation

In this section, we formulate the mining task offloading and edge resource allocation as a joint optimization problem. The

objective in this work is to maximize the offloading privacy while minimizing the sum cost of computation latency and energy consumption.

We first formulate the computation latency as the maximum of the local task processing time and the task execution time on MEC server, that can be expressed as

$$L_{nm}^t = \max\{L_{nm}^{o,t}, L_{nm}^{l,t}\}. \quad (11)$$

Meanwhile, the total energy consumption includes the local energy consumption $E_{nm}^{l,t}$ and energy cost for the task offloading $E_{nm}^{o,t}$. Therefore, we can denote C as the cost function that is the weighted sum of the time latency and energy consumption, as

$$C_{nm}^t = \sum_{n=1}^N \sum_{m=1}^M [\alpha_1(x_{nm}^t E_{nm}^{o,t} + (1 - x_{nm}^t) E_{nm}^{l,t}) + \alpha_2 L_{nm}^t] \quad (12)$$

where $\alpha_1, \alpha_2 \in (0, 1)$ denote the weight of energy consumption and task processing latency. Now we can formulate the optimization problem to jointly optimize the system privacy (10) and the system cost (12) under the constraint of maximum task mining latency and MEC computation capacity, which can be expressed as follows

$$P1 : \quad \max_{\mathbf{x}} \sum_{n=1}^N \sum_{m=1}^M (P_{nm} - C_{nm})$$

s.t.

$$x_{nm} \in \{0, 1\}, \forall n \in \mathcal{N}, m \in \mathcal{M}, \quad (13a)$$

$$x_{nm} L_{nm}^o + (1 - x_{nm} L_{nm}^l) \leq \tau_{nm}, \forall n \in \mathcal{N}, m \in \mathcal{M}. \quad (13b)$$

In (13), $\mathbf{x} = [x_{11}, x_{12}, \dots, x_{1M}; \dots; x_{N1}, x_{N2}, \dots, x_{NM}]$ is the offloading decision vector. Here, the constraint (13a) represents the binary offloading decision policy of the miner n for the task m , or offloading to the MEC server or processing locally at the mobile device. Further, the execution time to complete a mining task should not exceed a maximum time latency value, which is expressed in the constraint (13b). It is worth noting that the optimization problem (P1) is not convex due to the non-convexity of its feasible set and objective function with the binary variable \mathbf{x} . Further, the size of the problem (13) can be very large when the number of miner in the blockchain network increases rapidly. To tackle this problem, the existing blockchain offloading studies, such as [22], assume that the probability of offloading decision selection is known so that the binary variable can be relaxed. In this way, the original offloading problem can be approximated and transformed into a convex programming problem, and the objective function can be converted into a smooth form. As a result, the primal optimization problem can be solved analytically to obtain the optimal offloading policy. However, this assumption is too ideal in real blockchain scenarios. The size of blockchain transactions to miners is time-varying based on demands of blockchain entities, i.e. the different rate of data collection and transaction of different IoT devices on blockchain. Therefore the action to offload tasks to edge server or execute locally needs to be decided adaptively according to the current state of blockchain transactions at

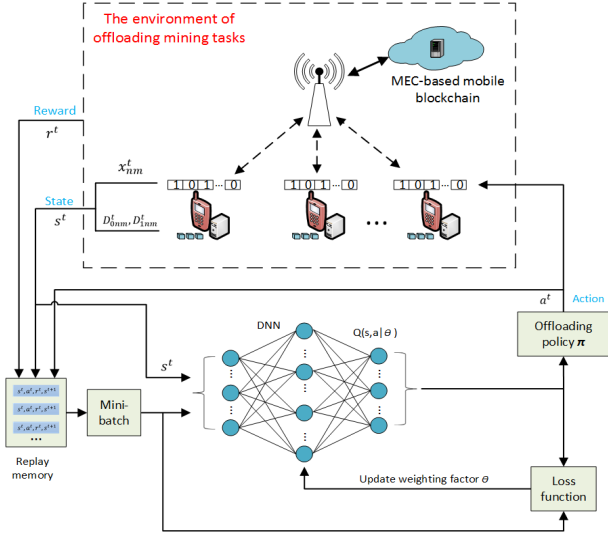


Fig. 3: RL-based offloading for mobile blockchain.

each time slot, instead of following to a pre-defined policy. Furthermore, when the number of miners in the blockchain network increases rapidly, the state space becomes very large, which makes the conventional optimization algorithms [22]-[24] infeasible. To overcome such challenges, we propose a dynamic offloading scheme using deep reinforcement learning (DRL). The advantages of our algorithm are twofold. First, it enables miners to obtain an optimal offloading action at each system state based on current blockchain transaction data and channel state without requiring prior knowledge of system dynamics. Second, as the DRL-based method is efficient in solving complex problems with large state space [18], it can achieve a better offloading performance to improve the quality of large-scale blockchain applications. Details of our design are presented in the next section.

D. Reinforcement Learning formulation

In our blockchain scenario, each miner acts an agent which interacts closely with the mobile blockchain environment at the timeslot t to find a task offloading action a for a state s using a policy π as shown in Fig. 3. This policy is defined as a mapping from the action to the state, i.e., $\pi(s) = a$. The main goal of the blockchain miner is to find an optimal policy π , aiming to maximize the total amount of award r over the long run. To implement the RL-based algorithms, we first define the specific state, action and reward for the proposed task offloading. We formulate the main elements of a reinforcement learning approach for our blockchain offloading as follows.

- **State:** The system state is chosen as $s^t = \{D_1^t, D_0^t, g^t\}$ where D_1^t, D_0^t represent the new and buffered blockchain transaction data of the miner at the timeslot t , respectively. g^t is the power gain state of wireless channel between the miner and MEC server as defined in the system model.
- **Action:** The action space can be formulated as the offloading decision vector $\mathbf{x}^t = [x_{11}^t, x_{12}^t, \dots, x_{1M}^t; \dots; x_{N1}^t, x_{N2}^t, \dots, x_{NM}^t]$. Therefore, the action vector can be expressed as $a^t = x_{nm}^t (\forall n \in \mathcal{N}, m \in \mathcal{M})$.

- **Reward:** The objective of the RL agent is to find an optimal offloading decision action a at each state s with the aim of achieving the maximum privacy level $P(s, a)$ while minimizing the sum cost $C(s, a)$ of time and energy consumption in the task offloading. Specially, the reward function should be positively related to the objective function of the optimization problem (P1) in the previous section. Accordingly, we can formulate the immediate system reward $r^t(s, a)$ as

$$r^t(s, a) = P^t(s, a) - C^t(s, a). \quad (14)$$

In the next section, we propose task offloading schemes using Reinforcement Learning with two algorithms: RL-based task offloading (RLO) and deep RL-based task offloading (DRLO).

III. RL-BASED ALGORITHMS

To solve the mining problem in blockchain networks, we propose a RL-based strategy to obtain the optimal offloading policies for miners. Next, to further improve offloading performances, we then develop a DRL-based scheme using deep Q-network algorithm.

A. RL-based task offloading algorithm

The principle of Reinforcement Learning (RL) can be described as a Markov Decision Process (MDP) [15]. In the RL model, an agent can make optimal actions by interacting with the environment without an explicit model of the system dynamics. In our blockchain scenario, we consider miners as agents to develop the RL scheme. At the beginning, the miner has no experience and information about the blockchain environment. Thus it needs to *explore* for every time epoch by taking some actions at each offloading state, i.e. the size of current blockchain transaction data. As long as the miner has some experiences from actual interactions with the environment, it will *exploit* the known information of states while keep exploration. In this paper, as a combination of Monte Carlo method and dynamic programming, a temporal-difference (TD) approach is employed to allow the agent to learn offloading policies without requiring the state transition probability which is difficult to acquire in realistic scenarios like in our dynamic mobile blockchain. In this subsection, we focus on developing a dynamic offloading scheme using a free-model RL. To this end, the state-action function can be updated using the experience tuple of agent (s^t, a^t, r^t, s^{t+1}) at each time step t as

$$Q(s^t, a^t) \leftarrow Q(s^t, a^t) + \alpha[r(s^t, a^t) + \gamma * \max_{a'} Q(s^{t+1}, a^{t+1}) - Q(s^t, a^t)] \quad (15)$$

which is called as Q-learning algorithm [15]. Here α is the learning rate, γ is the discount factor between (0,1) and $\sigma^t = r(s^t, a^t) + \gamma * \max_{a'} Q(s^{t+1}, a^{t+1}) - Q(s^t, a^t)$ is the TD error which will be zero for the optimal Q-value. Further, under the optimal policy π^* which can be obtained from the maximum Q-value ($\pi^*(s) = \operatorname{argmax}_a Q^*(s, a)$), the Bellman optimality

equation [15] for the state-action equation can be expressed as

$$Q^*(s^t, a^t) = \mathbb{E}_{s^{t+1} \sim E}[r(s^t, a^t) + \gamma * \max Q^*(s^{t+1}, a^{t+1})]. \quad (16)$$

It is noting that the Q-learning algorithm is proved to converge with probability one over an infinite number of times [15] and achieves the optimal Q^* . Specially, we focus on finding the optimal policy π^* which maximizes the reward $r(s, a)$ in (14). The details of task offloading implementation for mobile blockchain using Q-learning (RLO) are summarized in Algorithm 1.

Algorithm 1 RL-based task offloading (RLO) algorithm for mobile blockchain networks

- 1: **Initialization:**
 - 2: Initialize parameters: learning rate α , discount factor γ , exploration rate $\epsilon \in (0, 1)$
 - 3: Initialize the action-value function Q with initial pair (s, a) , and create a Q-table with $Q(s^0, a^0)$
 - 4: Set $t = 1$
 - 5: **Procedure:**
 - 6: **while** $t \leq T$ **do**
 - 7: **** Plan the task offloading on blockchain ****
 - 8: Observe blockchain transaction (D_1^t, D_0^t)
 - 9: Estimate the channel gain state g^t
 - 10: Set $s^t = \{D_1^t, D_0^t, g^t\}$
 - 11: Select a random action a^t with probability ϵ , otherwise $a^t = \text{argmax} Q(s^t, a, \theta)$
 - 12: Offload mining task $x^t(D_1^t + D_0^t)$ to MEC server or execute $(1 - x^t)(D_1^t + D_0^t)$ locally
 - 13: Calculate the system reward r^t by (14)
 - 14: Estimate the privacy level $P(s, a)^t$
 - 15: Estimate the system cost $C(s, a)^t$
 - 16: **** Update ****
 - 17: Set $s^{t+1} = \{D_1^{t+1}, D_0^{t+1}, g^{t+1}\}$
 - 18: Update $Q(s^t, a^t)$ by (15)
 - 19: $t \leftarrow t + 1$
 - 20: **end while**
-

Using the Algorithm 1, the optimization problem (P1) can be solved to obtain the optimal offloading policy for miners. The RLO algorithm consists of two phases, the planning phase and the updating phase. The inputs are system states, i.e. blockchain transaction data and channel states, and actions, i.e. offloading tasks to MEC server or executing locally. The outputs are the resulting $Q^t(s, a)$ with maximum reward $r^*(s, a)$ which corresponds to the offloading policy $\pi^*(s, t)$ in each state. In the planning phase (lines 6-15), we use a ϵ -greedy policy to balance the exploration and exploitation [15] for updating the Q function (15). At each time epoch, the miner observes the blockchain state, selects an offloading action, and estimates the privacy value and system costs. After each action, the miner moves to the next step, updates the new state (lines 17-19) and iterates the offloading algorithm to obtain the optimal offloading policy.

Although the RLO algorithm can solve the problem (P1) by obtaining the optimum reward, there are still some remaining

problems. The state and action values in the Q-learning method are stored in a two-dimensional Q table, but this method can become infeasible to solve complex problems with a much larger state-action space. This is because if we keep all Q-values in a table, the matrix $Q(s, a)$ can be very large, which makes the learning agents difficult to obtain sufficient samples to explore each state, leading to the failure of the learning algorithm. Moreover, the algorithm will converge very slow due to too many states that the agent has to process. To overcome such challenges and consider a realistic blockchain scenario with multiple miners, in the next subsection, we propose to use deep learning with Deep Neural Network (DNN) to approximate the Q-values instead of using the conventional Q-table. Besides, we also combine it with reinforcement learning to develop a deep Q-network (DQN) algorithm for a Deep Reinforcement Learning offloading scheme (DRLO) for in our mobile blockchain model.

B. DRL-based task offloading algorithm

In the DRL-based algorithm, a DNN is used to approximate the Q-values $Q(s^t, a, \theta)$ with weights θ as shown in Fig. 3. Further, to solve the instability of Q-network due to function approximation, the experience replay solution is employed in the training phase with the buffer \mathcal{B} which stores experiences $e^t = (s^t, a^t, r^t, s^{t+1})$ at each time step t . Next, a random mini-batch of transitions from the replay memory is selected to train the Q-network. Here the Q-network is trained by iteratively updating the weights θ to minimize the loss function, which is written as

$$L^t(\theta^t) = \mathbb{E}[(r^t + \gamma * \max Q(s^{t+1}, a' | \theta') - Q(s^t, a^t | \theta^t))^2] \quad (17)$$

where the $\mathbb{E}[\cdot]$ denotes the expectation function. The detailed DQN-based task offloading algorithm for the proposed blockchain network is summarized in Algorithm 2.

The DRLO algorithm can achieve the optimal task offloading strategy in an iterative manner. As shown in Algorithm 2, the procedure generates a task offloading strategy for miners based on system states, i.e. blockchain transaction data, and observes the system reward at each time slot so that the offloading policy can be optimized (lines 6-12). Then the procedure updates the history experience tuple and train the Q-network (lines 14-18) with loss function minimization. This trial and error solution will avoid the requirement of prior information of offloading environment. Over the training time period, the trained neural network can characterize well the environment and therefore, the proposed offloading algorithm can dynamically adapt to the real mobile blockchain environment.

IV. SIMULATION RESULTS

In this section, we evaluate the proposed task offloading algorithms through numerical simulations. First, simulation setup is described. Then the performance of the proposed algorithms is analyzed for two scenarios, mobile blockchain with single user and multiple user.

Algorithm 2 DRL-based task offloading (DRLO) algorithm for mobile blockchain networks

```

1: Initialization:
2: Set replay memory  $\mathcal{D}$  with capacity  $N$ 
3: Initialize the Q network with input pair  $(s, a)$  and estimated action-value function  $Q$  with random weight  $\theta$ ; initialize the exploration probability  $\epsilon \in (0, 1)$ 
4: for  $t = 1, 2, \dots$  do
5:   /* ** Plan the task offloading on blockchain ** */
6:   Observe blockchain transaction  $(D_1^t, D_0^t)$ 
7:   Estimate the channel gain state  $g^t$ 
8:   Set  $s^t = \{D_1^t, D_0^t, g^t\}$ 
9:   Select a random action  $a^t$  with probability  $\epsilon$ , otherwise  $a^t = \text{argmax} Q(s^t, a, \theta)$ 
10:  Offload mining task  $x^t(D_1^t + D_0^t)$  to MEC server or execute  $(1 - x^t)(D_1^t + D_0^t)$  locally
11:  Observe the reward  $r^t$  calculated via (14) and next state  $s^{t+1}$ 
12:  Evaluate the achieved privacy  $P(s, a)^t$ , and system cost  $C(s, a)^t$ 
13:  /* ** Update ** */
14:  Store the experience  $(s^t, a^t, r^t, s^{t+1})$  into the memory  $\mathcal{D}$ 
15:  Sample random mini-batch of state transitions  $s^t, a^t, r^t, s^{t+1}$  from  $\mathcal{D}$ 
16:  Calculate the Q-value by  $y^k = r^k + \gamma * \text{max} Q(s^{k+1}, a', \theta)$ 
17:  Perform a gradient descent step on  $(y^k - Q(s^k, a^k, \theta))^2$  as loss function
18:  Train the Q-network with updated  $\theta^t$ 
19: end for

```

A. Simulation settings

In our simulation, a mobile blockchain network is considered with a MEC server with a varying number of mobile users (miners) and mining tasks. The simulation is conducted over $T = 10,000$ timeslots, and each timeslot t lasts 1s. The computational capacity of the MEC server F is set to 10 GHz/sec. At each mobile user, we set the local computation time and computing energy consumption as $4.75 * 10^{-7}$ s/bit and $3.25 * 10^{-7}$ J/bit, respectively [9]. We assume that the size of blockchain transactions generated from IoT devices is randomly distributed between 50kb and 150kb. The local computation workload X is set to 18000 CPU cycles/bit, and the delay threshold τ is assumed as 15s. Further, the energy consumption efficiency coefficient and static circuit power of MEC server are set to 10^{-26} and 0.05W, respectively [22], and the channel gain factor σ is set to 0.8.

In the DQN-learning algorithm, we consider a DNN including one input layer, two hidden layers and one output layer. The first and second hidden layer has 300 and 200 neurons, respectively. The discount factor γ equals 0.85; and the replay memory capacity and training batch size are set to 10^5 and 128, respectively. All simulations were implemented in Python with TensorFlow 2.0 [30] on a computer with an Intel Core i7 3.2GHz CPU and 16 GB memory.

To evaluate the task offloading performance for mobile blockchain, we focus on the following three metrics.

- The computation latency for offloading and local execution.
- The energy consumed by mining process on MEC server and local computation.
- The privacy level during the mining task offloading process.

To highlight the advantage of the proposed offloading schemes in terms of latency and energy metrics, we compare our RLO and DRLO algorithms with two baseline schemes, i.e.

- Non-offloading scheme (NO): All mining tasks are executed at the local devices, (i.e, setting offloading decision vector $x_{nm} = 0 (\forall n \in \mathcal{N}, m \in \mathcal{M})$).
- Edge offloading scheme (EO): All miners offload their mining tasks to the MEC server (i.e, setting offloading decision vector $x_{nm} = 1 (\forall n \in \mathcal{N}, m \in \mathcal{M})$).

Further, to evaluate the privacy performance metric, we compare our algorithms with the constrained Markov decision process (CMDP)-based scheme [28] and RL-based design in [29].

Specially, we introduce a tradeoff factor $\beta \in [0, 1]$ for each miner to analyze the influence of computation latency and energy consumption on the quality of mobile blockchain offloading. In this way, the weighted factors in (12) can be represented by $\alpha_1 = \beta$ and $\alpha_2 = 1 - \beta$. Therefore, the reward function (14) can be rewritten as

$$r^t(s, a) = P^t(s, a) - [\beta E^t(s, a) + (1 - \beta)L^t(s, a)] \quad (18)$$

where $E^t(s, a)$ and $L^t(s, a)$ are the sum offloading energy and latency cost, respectively.

B. Numerical results

We first evaluate the convergence performance of our mining task offloading algorithms, namely RLO and DRLO with tradeoff factor settings $\beta = 0.5$ and $\beta = 0.8$ through the training process. Fig. 4 shows the learning curve obtained by the offloading policy using the proposed algorithms over 10,000 timeslots. The results show that the total system reward is very small at the beginning of the learning process. However, as the number of timeslot increases, the total reward increases rapidly and become stable after about 2500 timeslots, which validates the convergence performance of the proposed DQN-learning scheme. Further, it can be seen that the DRLO algorithm can achieve a better long-term reward in both cases, compared to the RLO scheme. For instance, in the case of $\beta = 0.5$, the DRLO-based learning strategy converges to 4.5, which is approximately 12.5% higher than that of the RLO-based learning scheme, which converges to 4 after about 2500 timeslots. Moreover, for a larger tradeoff value with $\beta = 0.8$, the DRLO scheme converges to about 5, which is roughly 16.3% higher than that of the RLO scheme. Overall, the DRLO algorithm using deep learning achieves the best performance after convergence, which demonstrates that the DRLO algorithm is more efficient in exploring the action space when comparing to the RLO scheme.

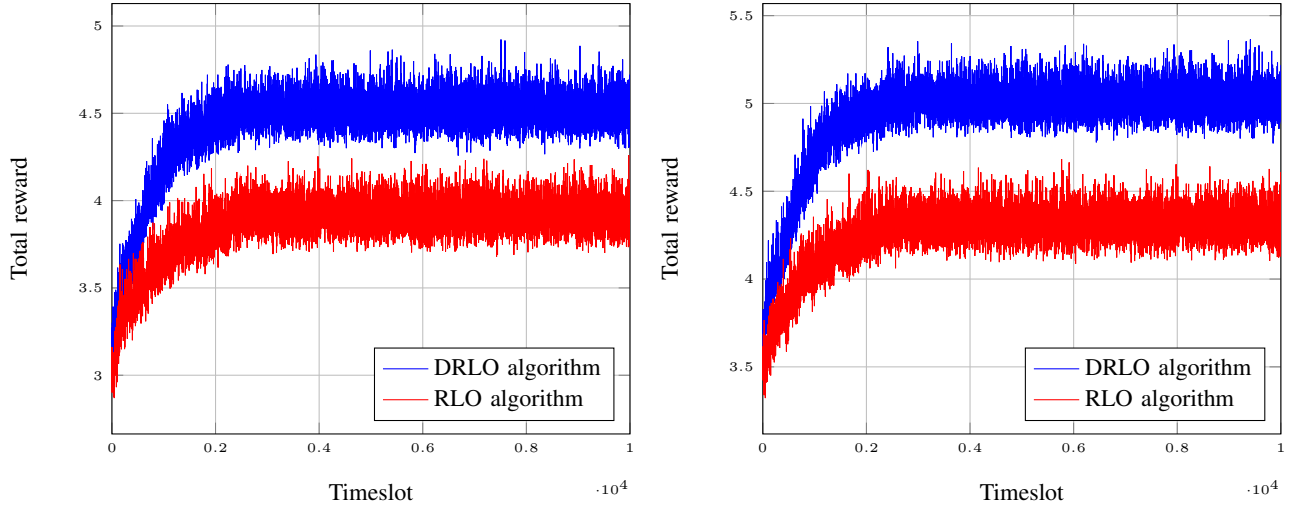


Fig. 4: Convergence performance of proposed offloading algorithms with $\beta = 0.5$ and with $\beta = 0.8$, respectively.

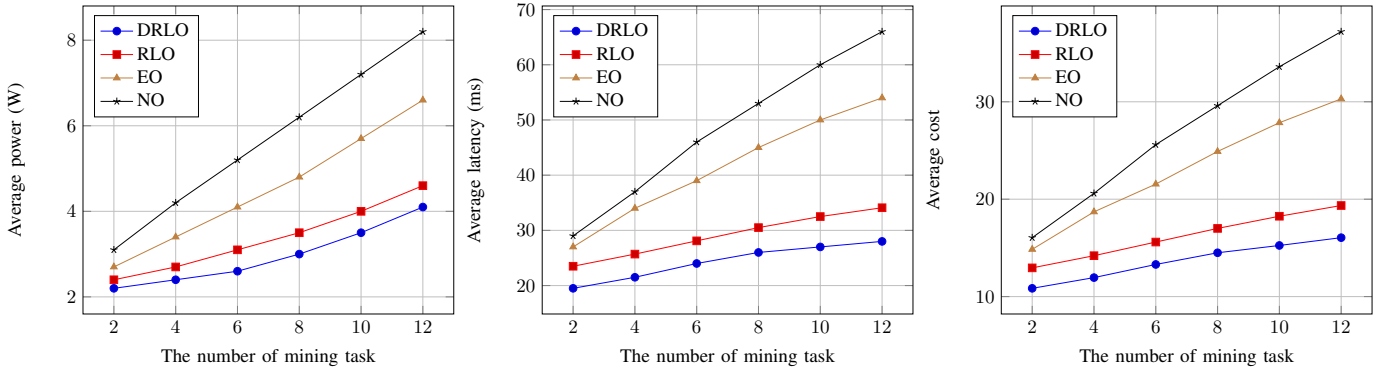


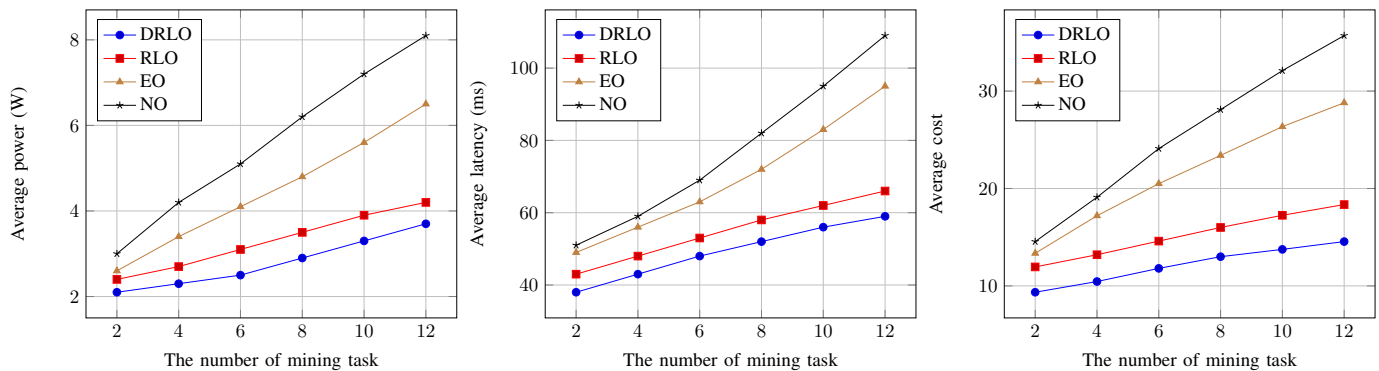
Fig. 5: Comparison results for single user scenario with $\beta = 0.5$

By using offloading policies obtained from the learning phase, we evaluate the performance of the proposed offloading algorithms for single user and multiple user scenarios. To compare the performance of different offloading schemes, the simulation results are averaged from 50 runs of numerical simulations.

1) *Single user scenario*: In the single user model, we consider a blockchain network with a single miner $N = 1$ and change the number of tasks at each miner ($M=2\sim 12$). Note that the size of each task is the same for all miners. The simulation results for $\beta = 0.5$ and $\beta = 0.8$ are shown in Figs. 5 and 6 which exhibit the offloading performances of mobile blockchain users in terms of energy consumption, computation latency and sum offloading cost. In Fig. 5 with $\beta = 0.5$, it is observed that when the number of task increases, the cost of four approaches increases due to the growing size of transaction data on the blockchain network. For example, in the EO strategy, the average offloading cost of all miners increases from 15 at $M = 2$ to 30 at $M = 12$, and that of the RLO scheme also increases to 9 at $M = 12$. Further, the NO algorithm always incurs a higher energy cost than the other schemes and has the largest increasing rate of 125%, reaching 36 at $M = 12$. The reason behind this observation is that when the number of mining task grows, the computational

capacity of the mobile miner becomes less sufficient to provide mining services for computing all tasks. Thus newly generated blockchain transactions have to wait to be processed in the buffer of local devices, increasing the mining latency as formulated in equation (6). Further, the higher cost comes from a higher computation delay and a power consumption. Specially, the DRLO scheme achieves the best performance with minimum energy consumption, offloading latency and sum cost for all mining tasks.

Fig. 6 shows the simulation results with a larger tradeoff factor $\beta = 0.8$. According to the formulated reward function (18), a larger tradeoff factor will give more penalty to energy consumption. In this case, the gap between the DRLO scheme and the other baselines is larger than that in the case of $\beta = 0.5$, which is caused by the increased offloading delay and lower power cost. Particularly, the DRLO algorithm exhibits the best performance again among four schemes with minimum offloading efficiency index. For instance, when the miner has 12 mining tasks, the offloading cost averaged over 50 simulations of the DRLO scheme is 18.7%, 57%, and 65% lower than those of the RLO, EO, and NO schemes, respectively. Such results demonstrate the efficiency of the DRLO-based scheme in task offloading for mining blockchain transactions.

Fig. 6: Comparison results for single user scenario with $\beta = 0.8$ TABLE II: Comparison results for multi-user scenario with $\beta = 0.5$.

Schemes	Average power (W)		Average latency(ms)		Average cost	
	$N=5$	$N=10$	$N=5$	$N=10$	$N=5$	$N=10$
DRLO	3.5	6.9	32.6	55.8	19.8	34.8
RLO	4.2	8.6	35.3	63.2	21.9	40.2
EO	6.2	14.3	53.2	94.6	32.8	53.5
NO	4.5	9.1	39.7	75.4	24.6	46.8

TABLE III: Comparison results for multi-user scenario with $\beta = 0.8$.

Schemes	Average power (W)		Average latency(ms)		Average cost	
	$N=5$	$N=10$	$N=5$	$N=10$	$N=5$	$N=10$
DRLO	3.3	6.5	55.9	90.7	13.8	23.3
RLO	3.9	8.3	59.1	98.5	14.9	26.3
EO	6.0	13.9	82.2	163.8	21.2	35.6
NO	4.2	8.5	66.3	116.7	16.6	30.1

2) *Multi-user scenario*: Next, we analyze the task offloading performance for the blockchain network with multiple users. We consider two cases, $N=5$ miners and $N=10$ miners. We also assume that there are 2 mining tasks at each miner, and the size of each task is the same for all miners. The comparison results are shown in TABLE II and TABLE III for tradeoff factor $\beta = 0.5$ and $\beta = 0.8$, respectively. Under the scenario with $\beta = 0.5$ in TABLE II, the DRLO scheme exhibits the lowest average power consumption, computation latency in both cases $N=5$ and $N=10$, and thus achieves the minimum total offloading cost, followed by the RLO scheme with a small gap. Another observation is that among the four schemes, the highest offloading cost comes from the EO-based scheme, instead of the NO-based scheme. This is because the more miners offload mining tasks to MEC server, the more computing capacity is required to provide enough computation resources for running the mining tasks of all blockchain users. It is also noteworthy that the computation capacity of the MEC server is only sufficient to provide resources for a certain number of miners and high mining demands from multiple users can result in a significant increase in network latency and system cost.

Using a higher tradeoff value $\beta = 0.8$, we present comparison results in TABLE III. Similar to the single user scenario, the larger tradeoff factor gives more penalty to energy consumption, and therefore, the energy consumed by all miners is lower than that of the case of $\beta = 0.5$, while the offloading delay becomes larger for both cases of $N=5$ and $N=10$. Based on such observations, we can minimize energy consumption with respect to task offloading latency by

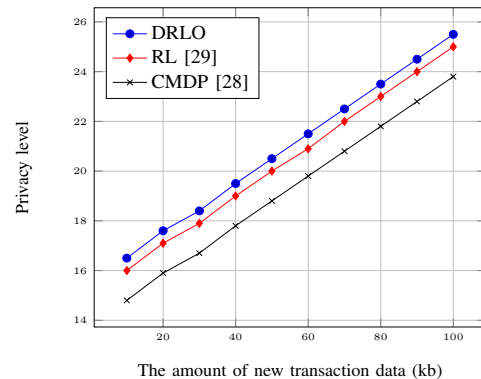


Fig. 7: The achieved privacy level.

adjusting the tradeoff factor for a better offloading efficiency. It is also worth mentioning that the DRLO-based scheme still exhibits the best offloading performance with minimum power usage, mining delay and resulting offloading cost. For instance, in the case of $N=10$, the offloading cost of the DRLO-based strategy is 12.7%, 52.5%, and 30.4% lower than those of the RLO, EO, and NO schemes, respectively. The numerical results clearly show that the DRLO algorithm outperforms the other baseline schemes in improving offloading cost efficiency in multi-user scenarios.

3) *Privacy performance*: Finally, we analyse the performance of the proposed offloading design in terms of the privacy metric as shown in Fig. 7. We compare the privacy performance of our DRLO-based scheme with the RL-based scheme [28] and CMDP-based scheme [29]. It can be observed from Fig. 7 that the privacy level of the blockchain miner increases when the amount of transaction data increases from 10kb to 100kb in each time slot for all offloading schemes. However, the proposed DRLO method can achieve the best privacy performance, compared to the other benchmarks. For instance, as the mobile user mines 10kb blockchain transactions, the proposed DRLO scheme achieves 5.2% and 12.7% higher privacy levels compared with the RL-based and CMDP-based schemes, respectively. Further, in the case of mining 100kb blockchain transactions, the privacy level of DRLO scheme still shows the best performance, with 5.5% higher than the RL-based strategy and 13.4% higher than the CMDP-based strategy. Such simulation results confirm a

high efficiency of the proposed DRLO algorithm with a better user privacy performance in task offloading for blockchain networks, compared to the existing offloading benchmarks.

V. CONCLUSIONS

In this paper, we have proposed reinforcement learning-based task offloading algorithms for multi-users to obtain the optimal offloading policy in a dynamic blockchain network with mobile edge computing (MEC). We formulate the task offloading and privacy preservation as a joint optimization problem. A RL-based scheme using the Q-network algorithm is employed to learn efficiently the offloading policy such that the total system cost combining computation latency and energy consumption is minimized while guaranteeing the best user privacy performance. To break the curse of high dimensionality in state space, we then develop a DRL-based approach using a deep Q-network algorithm. The offloading performances in terms of energy consumption, computation latency, and user privacy are analyzed under various conditions for both single user and multiple user offloading scenarios via numerical simulations. The experimental results show that the proposed DRL offloading scheme is superior to the other baseline methods with a reduced energy consumption, computation latency with much lower offloading costs and improved privacy level.

REFERENCES

- [1] T. M. Fernandez-Carams and P. Fraga-Lamas, "A Review on the Use of Blockchain for the Internet of Things," *IEEE Access*, vol. 6, pp. 32979-33001, 2018.
- [2] J. Xie et al., "A Survey of Blockchain Technology Applied to Smart Cities: Research Issues and Challenges," *IEEE Communications Surveys & Tutorials*, 2019.
- [3] Dinh C. Nguyen, Pubudu N. Pathirana, Ming Ding, and Aruna Seneviratne, "Blockchain for Secure EHRs Sharing of Mobile Cloud based E-health Systems," *IEEE Access*, vol. 7, pp. 66792-66806, 2019.
- [4] K. Suankaewmanee, D. T. Hoang, D. Niyato, S. Sawaditang, P. Wang and Z. Han, "Performance Analysis and Application of Mobile Blockchain," in *International Conference on Computing, Networking and Communications (ICNC)*, Maui, HI, 2018, pp. 642-646.
- [5] R. Pass and E. Shi, "FruitChains: A Fair Blockchain," in *Proc. ACM Symp. Principles of Distributed Computing*, Washington, DC, July 2527, 2017, pp. 31524.
- [6] W. Shi, J. Cao, Q. Zhang, Y. Li, and L. Xu, "Edge computing: Vision and challenges," *IEEE Internet of Things Journal*, vol. 3, no. 5, pp. 637-646, 2016.
- [7] P. Mach and Z. Becvar, "Mobile edge computing: A survey on architecture and computation offloading," *IEEE Commun. Surveys Tuts.*, vol. 19, no. 3, pp. 1628-1656, 2017.
- [8] Y. Mao, C. You, J. Zhang, K. Huang, and K. B. Letaief, "A survey on mobile edge computing: The communication perspective," *IEEE Commun. Surveys Tuts.*, vol. 19, no. 4, pp. 2322-2358, 2017.
- [9] H. Guo, J. Liu, J. Zhang, W. Sun, and N. Kato, "Mobile-edge computation offloading for ultra-dense iot networks," *IEEE Internet of Things Journal*, 2018.
- [10] M. Chen and Y. Hao, "Task Offloading for Mobile Edge Computing in Software Defined Ultra-Dense Network," *IEEE Journal on Selected Areas in Communications*, vol. 36, no. 3, pp. 587-597, March 2018.
- [11] S. Yu, X. Wang and R. Langar, "Computation offloading for mobile edge computing: A deep learning approach," in *IEEE 28th Annual International Symposium on Personal, Indoor, and Mobile Radio Communications (PIMRC)*, Montreal, QC, 2017, pp. 1-6.
- [12] X. He, H. Xing, Y. Chen and A. Nallanathan, "Energy-Efficient Mobile-Edge Computation Offloading for Applications with Shared Data," in *IEEE Global Communications Conference (GLOBECOM)*, Abu Dhabi, United Arab Emirates, 2018, pp. 1-6.
- [13] S. Li et al., "Joint Admission Control and Resource Allocation in Edge Computing for Internet of Things," *IEEE Network*, vol. 32, no. 1, pp. 72-79, Jan.-Feb. 2018.
- [14] I. Comsa et al., "Towards 5G: A Reinforcement Learning-Based Scheduling Solution for Data Traffic Management," *IEEE Transactions on Network and Service Management*, vol. 15, no. 4, pp. 1661-1675, Dec. 2018.
- [15] R. S. Sutton, A. G. Barto et al., *Reinforcement learning: An introduction*. MIT press, 1998.
- [16] K. Arulkumaran, M. P. Deisenroth, M. Brundage and A. A. Bharath, "Deep Reinforcement Learning: A Brief Survey," *IEEE Signal Processing Magazine*, vol. 34, no. 6, pp. 26-38, Nov. 2017.
- [17] Mnih, K. Kavukcuoglu, D. Silver, A. A. Rusu, J. Veness, M. G. Bellemare, A. Graves, M. Riedmiller, A. K. Fidjeland, G. Ostrovski et al., "Human-level control through deep reinforcement learning," *Nature*, vol. 518, no. 7540, p. 529, 2015.
- [18] X. Chen, H. Zhang, C. Wu, S. Mao, Y. Ji and M. Bennis, "Optimized Computation Offloading Performance in Virtual Edge Computing Systems via Deep Reinforcement Learning," *IEEE Internet of Things Journal*, 2019.
- [19] J. Li, H. Gao, T. Lv and Y. Lu, "Deep reinforcement learning based computation offloading and resource allocation for MEC," in *IEEE Wireless Communications and Networking Conference (WCNC)*, Barcelona, 2018, pp. 1-6.
- [20] M. Min, L. Xiao, Y. Chen, P. Cheng, D. Wu and W. Zhuang, "Learning-Based Computation Offloading for IoT Devices With Energy Harvesting," *IEEE Transactions on Vehicular Technology*, vol. 68, no. 2, pp. 1930-1941, Feb. 2019.
- [21] Z. Xiong, Y. Zhang, D. Niyato, P. Wang and Z. Han, "When Mobile Blockchain Meets Edge Computing," *IEEE Communications Magazine*, vol. 56, no. 8, pp. 33-39, August 2018.
- [22] M. Liu, F. R. Yu, Y. Teng, V. C. M. Leung and M. Song, "Computation Offloading and Content Caching in Wireless Blockchain Networks With Mobile Edge Computing," *IEEE Transactions on Vehicular Technology*, vol. 67, no. 11, pp. 11008-11021, Nov. 2018.
- [23] Yuan Wu, Xiangxu Chen et al., "Optimal Computational Power Allocation in Multi-Access Mobile Edge Computing for Blockchain", *Sensors Journal*, 2018.
- [24] M. Liu, F. R. Yu, Y. Teng, V. C. M. Leung and M. Song, "Distributed Resource Allocation in Blockchain-Based Video Streaming Systems With Mobile Edge Computing," *IEEE Transactions on Wireless Communications*, vol. 18, no. 1, pp. 695-708, Jan. 2019.
- [25] J. Zhang, B. Chen, Y. Zhao, X. Cheng and F. Hu, "Data Security and Privacy-Preserving in Edge Computing Paradigm: Survey and Open Issues," *IEEE Access*, vol. 6, pp. 18209-18237, 2018.
- [26] T. Salman, M. Zolanvari, A. Erbad, R. Jain and M. Samaka, "Security Services Using Blockchains: A State of the Art Survey," *IEEE Communications Surveys & Tutorials*, vol. 21, no. 1, pp. 858-880, Firstquarter 2019.
- [27] D. K. Tosh, S. Shetty, X. Liang, C. A. Kamhoua, K. A. Kwiat and L. Njilla, "Security Implications of Blockchain Cloud with Analysis of Block Withholding Attack," in *17th IEEE/ACM International Symposium on Cluster, Cloud and Grid Computing (CCGRID)*, Madrid, 2017, pp. 458-467.
- [28] X. He, J. Liu, R. Jin and H. Dai, "Privacy-Aware Offloading in Mobile-Edge Computing," in *IEEE Global Communications Conference*, Singapore, pp. 1-6, 2017.
- [29] M. Min et al., "Learning-Based Privacy-Aware Offloading for Healthcare IoT with Energy Harvesting," *IEEE Internet of Things Journal*, 2019.
- [30] A. Martn, A. Ashish et al., "TensorFlow: Large-scale machine learning on heterogeneous systems," 2015, software available from tensorflow.org. [Online]. Available: <https://www.tensorflow.org/>.