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Research on Joint Optimization of Blockchain Consensus and Edge Computing Task Offloading Computing Power Matching Based on Double-Delay Deep Deterministic Policy Gradient Algorithm

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Abstract: With the gradual application of edge computing technology in practical scenarios, the issues of system security and credibility have become the core difficulties affecting its performance and promotion. Blockchain technology, with its characteristics of decentralization and data immutability, provides a solid guarantee for task offloading and identity authentication in edge computing. However, there is an obvious contradiction in the allocation of computing resources between the blockchain consensus process and the execution of edge computing tasks. If the resource allocation is unreasonable, it will lead to the decline of system efficiency and the waste of resources. In response to this challenge, this paper constructs a collaborative computing model including multiple terminals, multiple edge nodes and cloud servers. Systematically combining the network environment, task processing mechanism and blockchain consensus mechanism, a joint optimization strategy based on the double-delay deep deterministic policy gradient algorithm is proposed. This strategy realizes the coordinated allocation of computing resources between blockchain consensus and edge task offloading. The optimization method designed in this paper comprehensively considers task offloading decisions, transmission power control and computing resource allocation, significantly shortening the overall task processing delay of the terminal and reducing energy consumption, while ensuring the timeliness and security of the consensus mechanism. For the high-dimensional and complex resource scheduling problem, this paper adopts the double-delay deep deterministic policy gradient algorithm combined with fast numerical computing technology, which effectively improves the training efficiency and stability of the model. Through multi-scenario simulation experiments, the method proposed in this paper has improved the system performance by an average of more than 20% compared with the traditional scheme, fully verifying its superiority in improving the credibility and resource utilization rate of the system. The research results of this paper not only enrich the theoretical basis of the integration of blockchain and edge computing, but also provide practical and feasible solutions for the

rational allocation of computing resources in actual engineering.

1. Introduction

With the continuous development of mobile Internet technology, edge computing, as a distributed computing model, significantly improves the efficiency of processing delay-sensitive tasks by bringing computing resources and data storage closer to the data generation end, and is widely applied in multiple fields such as intelligent transportation, augmented reality and industrial automation. Edge intelligence technology deploies artificial intelligence models on edge devices, enabling the devices to independently complete the analysis and decision-making of local data, thereby improving the response speed and security performance of the system. However, current edge computing and edge intelligence systems still face many challenges in task offloading and computing power resource allocation. Especially in a multi-node collaborative environment, how to effectively optimize task scheduling and resource allocation to reduce latency and energy consumption while ensuring the stability and security of the system has become an urgent problem to be solved.

To address these challenges, this paper proposes a joint optimization method based on the double-delay deep deterministic policy gradient algorithm. This method integrates the distributed ledger technology of blockchain with the task offloading mechanism of edge computing, achieving the collaborative matching of blockchain consensus computing and edge computing resources. This paper constructs an edge-cloud architecture covering cloud servers, edge servers and terminal devices, and designs corresponding optimization models for key links such as task offloading decision-making, transmission power regulation and computing resource allocation. The goal is to reduce the overall task processing time and energy consumption while enhancing the security and reliability of the system. Specifically, in this paper, collaborative scheduling models for task offloading and blockchain mining are established respectively for general computing power (CPU) and heterogeneous computing power (GPU), and the offloading scheme and resource allocation strategy are jointly optimized by using the double-delay deep deterministic policy gradient algorithm.

The algorithm in this paper is superior to many traditional methods in terms of convergence speed, system performance and resource utilization efficiency, demonstrating its application value in blockchain-assisted edge intelligence scenarios. This research provides theoretical support and technical guarantee for improving the timeliness of task processing and the consensus computing capacity of blockchain in the edge computing environment. It has high practical significance and promotion potential.

2. Relevant research

2.1. Research Status in the Field of BlockChain-Assisted Edge Computing Systems

The integration of blockchain and edge computing has become an important development direction in the fields of the Internet of Things and the Internet of Vehicles, dedicated to enhancing the security and computing performance of terminal devices. With the continuous advancement of Internet of Vehicles technology, edge computing has shown great potential in assisting vehicles in handling complex tasks. However, there are risks of data leakage and tampering during the task offloading process, and it is urgent to build an effective security guarantee mechanism. In response to this issue, some studies have proposed combining the consensus algorithm of blockchain with edge computing [1], using the consensus mechanism to enhance the stability of the system and the credibility of data. Meanwhile, through theoretical models and optimization algorithms, the response time of the system is reduced to achieve efficient and reliable data processing.

Considering the limited computing power of edge devices, the traditional proof-of-work blockchain mining is difficult to apply. Therefore, a mining task offloading scheme based on direct communication between devices [2] is introduced, and the task allocation strategy is optimized through trajectory prediction technology to reduce the probability of consensus failure and improve the overall mining efficiency. Meanwhile, the resource allocation model based on game theory effectively balances the interests of miners and resource providers[3], promoting the rational allocation of resources. In the edge computing environment, edge nodes need to take into account both user task processing and blockchain maintenance tasks. Reasonably scheduling resources to ensure system performance becomes the key.

With the continuous expansion of the scale of Internet of Things (iot) applications, traditional cloud processing is facing latency and security challenges [4]. The collaborative application of blockchain and edge computing, by pushing computing and storage to the network edge, not only accelerates data processing speed but also enhances security guarantees, alleviates the pressure on resource-constrained terminals, and promotes the efficient operation of intelligent systems. Despite this, there are still challenges in this field, such as the lightweighting of consensus mechanisms, cross-network collaboration, privacy protection, and scalability. In the future, in-depth research needs to be conducted at the levels of algorithm design, system architecture, and practical applications to achieve broader application implementation.

2.2. Research Status of BlockChain-Assisted Edge Intelligence Systems

The application of blockchain technology in edge intelligent systems is becoming increasingly widespread, and it has become one of the core technologies for ensuring system security, improving resource utilization efficiency and enhancing credibility. In the field of cloud-assisted intelligent transportation, in response to the demand for the integrity protection of key data, a lightweight data verification scheme based on agents was designed. By using agent nodes to generate encrypted signatures and combining with distributed ledger technology, data tampering was effectively prevented, while reducing the burden on managers and ensuring the stable operation of the system [5]. In the federated learning scenario, the traditional model relying on centralized servers has problems such as single point of failure and insufficient trust. The blockchain-supported federated learning framework improves the allocation efficiency of computing resources and the stability of the overall system in the edge computing environment by introducing distributed auditing and consensus mechanisms. Simulation results show that the service time and resource utilization rate of the server have been significantly improved.

Aiming at the trust and privacy challenges faced by edge computing in the Internet of Things, an intelligent edge collaboration platform based on blockchain was constructed [6]. This platform combines the enhanced memory network to complete resource prediction and node screening, optimizes the system performance, and improves the response speed and throughput capacity. The problem of multi-vehicle competition for computing resources in the Internet of Vehicles is solved by combining the time-varying Markov decision model and the quantum-inspired deep reinforcement learning method [7], achieving intelligent task offloading in multiple scenarios. Meanwhile, blockchain technology is utilized to ensure the openness, transparency and security of the resource allocation process, thereby significantly improving the resource scheduling efficiency, flexibility and scalability of the system.

The integration of blockchain and edge intelligent systems not only solves the trust and security problems in traditional systems [8], but also promotes the improvement of resource collaboration and management efficiency through innovative mechanisms. Nevertheless, in the future, continuous in-depth research is still needed in aspects such as the improvement of privacy protection mechanisms, the lightweight design of consensus algorithms, and cross-platform collaboration.

3. Overview of System Architecture and Key Technologies

3.1. Intelligent Resource Scheduling Model Based on Deep Reinforcement Learning

In the constructed edge intelligent computing system, the overall architecture is composed of terminal nodes, edge nodes, distributed ledger modules, remote data centers and global scheduling controllers. The tasks generated by the terminal nodes can be executed locally, transmitted to the adjacent edge nodes via short-range wireless links, or further forwarded to the remote data center for processing via wired links. Each edge node not only has a certain computing capacity, but also integrates a ledger mechanism to record and verify the key information during the task offloading process, so as to enhance the credibility and security of the system.

In the system, it is set that the tasks generated by each terminal node have two main characteristics: data volume and computational complexity, which are represented by the number of bits and the required computing period respectively. For each task, its optional processing path is represented by three identification variables: if it is completed locally, it is executed locally; If transmitted to edge processing, it is marked as edge execution; If further uploaded to the data center, it will be marked as remote execution. These three states require that the task can only be accomplished by one of the paths. Formula (1) is as follows.

$$x_j^l + x_j^e + x_j^c = 1 \tag{1}$$

x_j^l、x_j^eandx_j^c respectively indicate whether the task is processed locally, at the edge, or remotely.

Each terminal node has a limited processing capacity and upper limit of energy consumption. When choosing the processing path for its tasks, it needs to balance the local resource constraints and the transmission energy consumption overhead. The computing resources of edge nodes need to simultaneously meet the dual allocation requirements of task computing and ledger consensus, while remote data centers undertake computing tasks that handle some highly complex tasks to make up for the insufficiency of the capabilities of edge nodes. The scheduling controller dynamically optimizes the task allocation strategy based on the resource status of each node and network conditions, with the goal of reducing the overall processing delay and communication cost.

The ledger module performs verification and accounting operations on all received tasks on the edge side. It screens trusted nodes through the consensus mechanism for packaging and recording, and writes the processing results into an unalterable ledger. This mechanism not only improves the auditability of the task scheduling path, but also effectively prevents the occurrence of behaviors such as data forgery and task tampering.

This system realizes an efficient, low-latency and verifiable task offloading process through a multi-layer collaborative computing structure and an embedded ledger mechanism, and is suitable for edge intelligent computing applications with high requirements for both security and response speed in resource-constrained scenarios.

In a multi-layer computing architecture, the tasks generated by the terminal can be processed locally, offloaded at the edge, or executed remotely in the cloud. If the task is completed locally at the terminal, the delay is determined by the amount of task computation and the local computing capacity, while the energy consumption is proportional to the square of the CPU frequency, demonstrating the efficiency advantage of local processing under low data volume and low computing intensity. In contrast, when offloading tasks to edge nodes, the upload delay of the wireless link and the processing capacity of edge computing resources need to be considered. The task upload rate depends on the channel bandwidth, transmission power, channel gain, background noise and interference power, which in turn affects the transmission delay and energy consumption.

If the task is transferred to the cloud server for execution, in addition to the wireless transmission from the terminal to the base station, it also needs to go through the wired transmission from the base station to the cloud, and finally the task calculation is completed on the high-performance cloud platform. Although cloud resources are abundant and processing capabilities are strong, limited by the transmission efficiency and scheduling delay of network links, the overall processing delay and transmission energy consumption still need to be comprehensively evaluated. Therefore, different tasks need to dynamically select the optimal execution path based on their data scale, computing intensity and network conditions to achieve a balance between processing efficiency and energy consumption.

As shown in Figure 1, in this system, the task offloading requests submitted by users through terminal devices will be transmitted to a distributed network composed of base station edge servers, and these servers jointly build a decentralized verification and computing environment. The system selects the server with relatively abundant and stable resources as the master node, which is responsible for summarizing and scheduling task requests. Other nodes participate in verification to ensure the transparency and consistency of task information. Each task offloading is regarded as a transaction. Through a five-stage consensus process including request submission, node broadcasting, status confirmation, voting consistency, and feedback response, the system achieves efficient and fault-tolerant collaborative confirmation among nodes, ensuring the accuracy and security of records in the distributed ledger, thereby enhancing the credibility of task processing and the overall stability of the system.

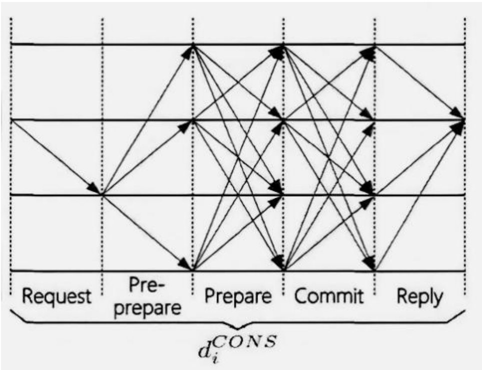

Figure 1. Blockchain consensus process

This paper adopts the deep reinforcement learning algorithm based on the double-delay deterministic strategy (TD3) to effectively find the approximate optimal solution through intelligent decision-making. The transmission power control subproblem P1 independently becomes a quasi-convex problem under the condition of fixed variables and can be efficiently solved by the fractional programming method. The overall problem is modeled as a Markov decision process, with actions covering task offloading, consensus and resource allocation, states including task quantity and channel gain, and the reward function guiding optimization with negative utility. The TD3 algorithm continuously optimizes the strategy through the actor-critic network structure, experience replay and soft update mechanism, achieving intelligent task scheduling and resource management, and improving the system performance.

3.2. Experiment and Analysis

In this paper, a double-delay deterministic strategy deep reinforcement learning model is constructed based on the PyTorch platform. A fully connected neural network with two hidden layers is adopted as the architecture of the actor and critic networks. The ReLU activation function is used to handle the neurons in the hidden layers. The output layers apply Softmax and linear activation respectively to adapt to the mixed action space. During the training process, the model updated its parameters through experience replay and the Adam optimizer. Eventually, it achieved stable convergence in 50,000 rounds of training, and the reward function gradually stabilized during approximately 140 to 350 rounds of training.

With the advancement of training, the model effectively adjusted the task offloading strategy, gradually reducing the number of locally processed tasks and increasing the proportion of offloaded tasks at the edge and in the cloud accordingly. Eventually, the proportion of tasks among the three tended to be balanced, and the task processing delay and terminal energy consumption of the overall system were significantly reduced.

This paper also designs three control schemes: Fixed Computing Resource Allocation (FCRCP), Disabled Dynamic Resource Allocation (CRAD), and Shut down Transmission Power Control (TPCD). Through comparative analysis, the proposed schemes are superior to the control schemes in multiple performance indicators, showing an efficiency improvement of up to 18% to 24%. Moreover, it still maintains good adaptability and resource utilization when the amount of task computation and data increases. However, the performance degradation of the control scheme is more obvious due to fixed resource allocation or strategy limitations, especially showing a significant disadvantage in scenarios with increased loads. The intelligent resource scheduling method proposed in this paper effectively improves the processing efficiency and energy consumption performance of the system by coordinating computing resources and power control, demonstrating strong practical value and promotion potential.

The change in the transmission rate from the base station to the cloud server significantly affects the overall performance of the system. When the transmission delay increases nearly twice from the default level, the performance of all schemes decreases to varying degrees. The reason is that the speed of data upload by the base station slows down, resulting in a significant increase in task processing delay. The performance gap between the scheme in this paper and the Fixed Resource Allocation Scheme (FCRCP) gradually widens with the increase of transmission delay. This is because the lack of dynamic computing resource allocation forces more tasks to be unloaded to the edge server, thereby causing the tension of computing resources. Meanwhile, the performance gap between the scheme in this paper and the Disabled Transmission Power Control Scheme (TPCD) gradually narrowing as the transmission rate decreases. The reason is that the increase in the load of edge servers leads to an increase in the proportion of local task processing. Although it improves the processing efficiency of some tasks, it also causes waste of computing resources and affects the overall performance of the system.

With the improvement of computing resources of edge servers, the performance of each scheme of the system has been effectively enhanced. This is mainly because the increased computing power reduces the task processing delay. The performance gap between the scheme proposed in this paper and the Fixed Resource Allocation Scheme (FCRCP) and the Disabled Resource Allocation Scheme (CRAD) significantly Narrows when edge computing resources are sufficient, indicating that the negative impact of fixed computing resource occupation and insufficient resource allocation on system performance is mitigated. In contrast, the scheme proposed in this paper shows greater advantages when compared with the Disabled Transmission Power Control Scheme (TPCD), which is attributed to the reasonable task offloading strategy that improves the overall utilization rate of resources.

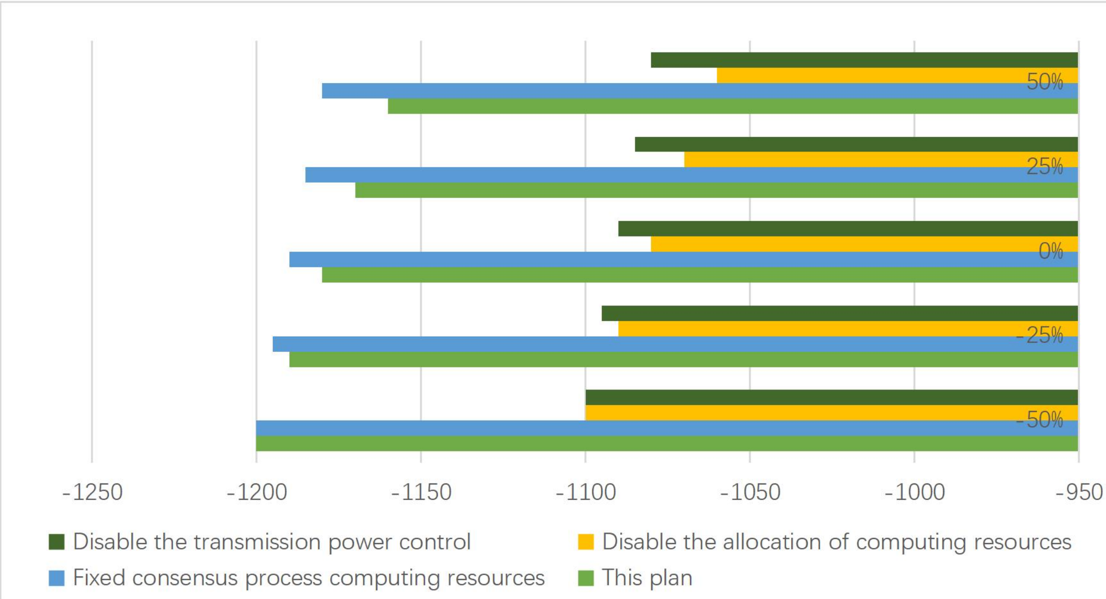

Figure 2. The influence of channel bandwidth on performance

As shown in Figure 2, the expansion of channel bandwidth directly promotes the improvement of system performance. The reason is that the wider bandwidth reduces the delay of task upload, enabling the network controller to offload tasks from terminal devices to base stations more actively. However, at the same time, due to the increase in upload tasks, the computing resources that the blockchain consensus can allocate decrease. The waste of computing resources in the scheme of disabling the transmission power control exacerbates this situation, resulting in a further widening of the performance gap between the scheme in this paper and other schemes when the bandwidth increases.

The three key factors, namely the transmission rate from the base station to the cloud server, the computing capacity of the edge server, and the channel bandwidth, jointly determine the efficiency of the system. Only through scientific and reasonable resource allocation and management can the system performance be maximized and the waste of computing resources be reduced.

4. Design of Intelligent Edge Block Fusion Architecture and Scheduling Optimization Method

4.1. Construction Scheme of Multi-task Collaborative Reasoning and Block Verification System

This study constructs an intelligent task processing architecture that integrates edge computing and blockchain mechanisms. The system consists of multiple base stations, each of which is equipped with an edge server and is responsible for managing the machine learning tasks generated by multiple sensors within its coverage area. After the sensor generates the task locally, it can choose local inference or offload the task to the edge server of the corresponding base station through a wireless link based on the current resource status. If the edge resources are insufficient, the task will be further transmitted to the remote cloud server through a wired connection. The system flexibly manages the task scheduling path through control variables and controls the data scale by adjusting the image acquisition resolution, thereby ensuring the controllability of task processing and the balance of resource usage. Since the structure of the reasoning model is fixed, the computing load will not fluctuate due to input changes, which is convenient for the system to conduct unified scheduling under the condition of concurrent multiple tasks.

On the edge side, each server needs to perform inference computing and blockchain mining tasks simultaneously. The system ensures the parallel processing of the two types of tasks by rationally allocating computing resources and reduces the total processing delay. The blockchain module records the information of all offloaded tasks and generates new blocks by using consensus mechanisms such as proof of work to ensure the security and credibility of task data. As a high-performance computing support node, the cloud server undertakes task processing when the edge computing capacity is insufficient, and conducts scheduling and resource allocation through a unified network controller. The controller coordinates the transmission power of sensors, the allocation of computing resources and the selection of task paths to achieve a multi-layer collaborative and efficient intelligent computing system, thereby constructing a distributed reasoning and management platform with credibility, low latency and high scalability.

With the continuous increase in the complexity of machine learning inference tasks, the system introduces Gpus with high parallel processing capabilities to replace traditional cpus, significantly improving processing speed and meeting the dual computing requirements of blockchain mining and intelligent inference. The system flexibly selects the reasoning operation to be completed locally by the sensor, at the edge node or in the cloud according to the source of the task and the computing intensity, thereby achieving the optimal balance of latency and resource utilization in different scenarios. Among them, if the task is executed locally, it only involves inference delay. If it is processed by the edge server, the transmission and processing time consumption needs to be calculated. And when uploaded to the cloud, the impact of remote communication needs to be further considered. In the communication design of the system, the frequency division access mechanism is adopted. Interference is effectively isolated through independent subcarrier division, and the uplink rate is dynamically calculated based on link parameters and channel states to ensure the stability and efficiency of data transmission.

In terms of reasoning accuracy modeling, the system divides the reasoning strategies into lightweight and high-precision modes based on the amount of task data and the complexity of the model, and establishes the functional relationship between the two by using the regression results of existing experiments to achieve the controllable scheduling of reasoning quality. To complete task offloading and block verification, the edge server participates in the transaction construction and block broadcasting processes while completing the allocation of inference tasks. Meanwhile, the system formulates the optimal resource allocation scheme through a unified scheduling model, comprehensively considering the weighted indicators inversely proportional to processing delay, energy consumption and accuracy. Based on the constraints of computing resources, power limitations and task paths, So as to achieve the collaborative operation of efficient reasoning and secure verification in a multi-source heterogeneous environment.

To efficiently solve optimization problems with mixed variables and non-convex, this paper proposes a deep reinforcement learning algorithm that integrates a double-delay mechanism and a deterministic strategy. This algorithm incorporates decisions such as task offloading, computing resource allocation, and blockchain mining into a unified action space by constructing a Markov decision process, and the strategy network generates scheduling schemes based on the current state. Meanwhile, the evaluation network makes a value judgment on the strategy.

To reduce the training complexity, in this paper, a fast numerical method is introduced as an embedded module in the power control subproblem, enabling the algorithm to efficiently approach the optimal solution during the iterative process. In terms of network deployment, the system continuously collects status information through the edge controller and issues the optimized control parameters to the edge nodes and the cloud for execution, achieving dynamic coordination of tasks and fine allocation of resources. Ultimately, it realizes lower online computing overhead and good engineering adaptability while maintaining system performance.

4.2. Analysis of Experimental Results

The deep reinforcement learning algorithm based on the double-delay and double-deterministic strategy proposed in this paper is developed using the PyTorch platform, and the experimental environment is built on the hardware facilities that support GPU virtualization, providing strong computational support for model training. Through multiple experimental tests, the research team systematically screened and determined the hyperparameter Settings with the best performance in the algorithm. Among them, both the main actor network and the critic network adopted a fully connected structure with two hidden layers, which contained 2048 and 1024 neurons respectively. The activation function selected was ReLU to enhance the nonlinear expression ability. The output layer is activated respectively through the Softmax function and the linear function to ensure the effective output of discrete and continuous actions.

As the amount of task computation increased from 50% to 150%, all schemes showed performance degradation. The reason was that the increase in computing requirements led to higher processing delay, while the TDCD scheme, due to the lack of a data volume adjustment mechanism, further exacerbated the transmission delay and the performance gap gradually widened. The FTP scheme limits the transmission efficiency due to the fixed transmission power, which makes the edge and cloud resources unable to be fully utilized. The inference delay increases significantly with the increase of tasks. The FCRBM scheme is also affected by the unreasonable allocation of computing resources, and the delay of reasoning tasks increases significantly.

When the amount of task data increases, the transmission delay of all schemes rises. The TDCD scheme cannot flexibly adjust the amount of data, and the transmission delay aggravates under the condition of large data volume, affecting the overall performance of the system. The FTP scheme has a large increase in transmission delay due to the fixed transmission power, further reducing the efficiency. The performance gap of the FCRBM scheme Narrows when the amount of data increases. This is because the increase in data transmission delay alleviates the pressure caused by the occupation of fixed mining resources.

The increase of channel bandwidth promotes the performance improvement of each scheme. The increase of communication resources reduces the transmission delay. The gap between the TDCD scheme and this method narrates due to the increase of bandwidth. The FTP scheme is limited by the insufficient task offloading capacity caused by the fixed transmission power, and its performance disadvantage intensifies with the increase of bandwidth. The performance gap of the FCRBM scheme gradually expands with the increase of bandwidth. Because fixed mining resources have become the bottleneck of the system.

The improvement of the transmission rate between base stations alleviates the latency of blockchain propagation and mining. Due to the lack of task offloading adjustment ability in the TDCD and FTP schemes, edge computing resources are not fully utilized, and the gap with this method widens as the rate increases. The increase in the transmission rate from the base station to the cloud also enhances performance. However, the TDCD solution has a fixed data volume, resulting in significant transmission delay. The FTP solution has a fixed transmission power limit for task offloading, leading to low resource utilization. The FCRBM solution reduces the performance gap. Due to the increase in task offloading to the cloud, the reliance on edge server mining resources is decreased.

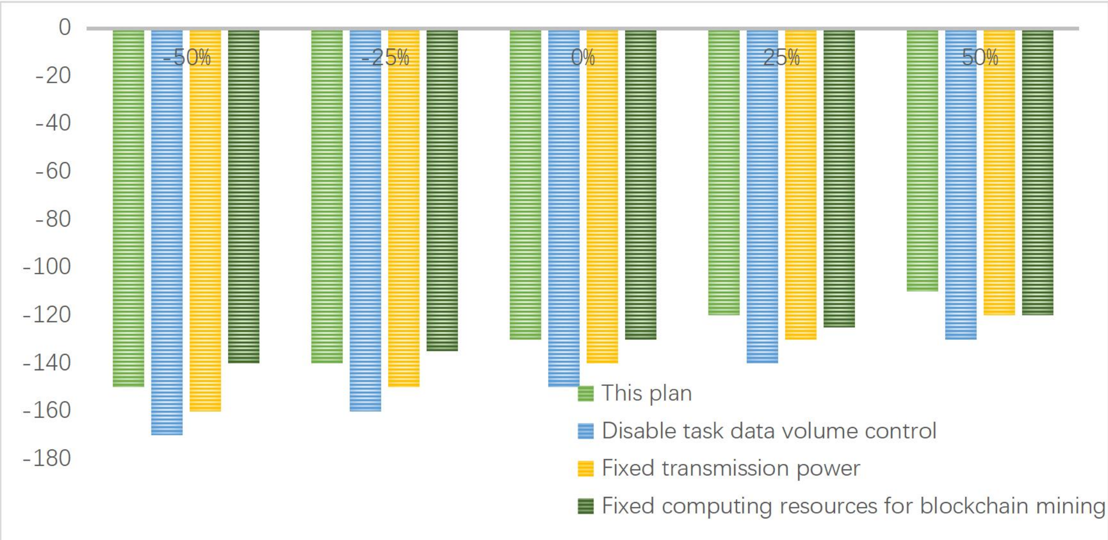

Figure 3. Impact of Changes in computing Resources of edge servers

As shown in Figure 3,When the computing resources of edge servers are enhanced, all schemes achieve performance improvement. The enhancement of computing power shortens the inference delay. However, under this condition, the TDCD scheme leads to an increase in transmission delay due to the fixed amount of task data, and the performance gap increases. Under the fixed transmission power limit of the FTP scheme, the increase in task offloading aggravates the transmission delay and reduces the system efficiency. The performance gap of the FCRBM scheme has narrowed, and the proportion of fixed mining resources has weakened its overall impact.

The method proposed in this paper coordinates communication and computing resources by dynamically adjusting the task data volume, transmission power and computing resource allocation, significantly reduces inference delay, improves energy efficiency and accuracy, and performs better than the three schemes of disabling data volume control, fixed transmission power and fixed mining resource allocation.

5. Conclusions and Prospects

This paper focuses on the joint optimization problem of task offloading and computing resource allocation in the blockchain-assisted edge computing environment and proposes an algorithm based on the double-delay deep deterministic policy gradient. This algorithm realizes the efficient matching of the blockchain consensus process and edge computing tasks by coordinating the offloading decision, transmission power control and computing resource allocation of terminal devices. It significantly reduces the overall processing delay of the task and the terminal energy consumption, while improving the reasoning accuracy and stability of the system. The research verified through multi-scenario simulation that this method exhibits superior adaptability and performance advantages under different computing requirements, data scales and network conditions, surpassing the traditional single optimization strategy. However, the scheme designed in this paper still needs to be further expanded to deal with the complex dynamic tasks and diverse communication models in the real environment. Future work will focus on improving the long-term optimization mechanism, enriching the diversity of transmission models, and constructing a multi-task and multi-model collaborative framework to enhance the application effect and wide applicability of the algorithm in actual edge intelligent scenarios.

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