Unloadable Computing Problem Based on Edge Distributed Computing

Xiaoliang He[1,†][a], Jiazhen Xu[2,‡,*][b] and Zhilin Yan[3,**][c]

[1]*College of Mathematics and Applied Mathematics, Guangdong University of Foreign and Studies, Guangzhou, China*
[2]*College of Civil Engineering, Inner Mongolia University of Technology, Huhehaote, China*
[3]*College of Data Science, City University of Macau, Macau, China*
† ‡

Keywords: Edge Distributed Computing, Computation Offloading, Task Offloading, Resource Allocation.

Abstract: Due to limitations in power, computing power, and storage, mobile devices struggle to meet the demands of rapidly developing applications. Offloading computing has emerged as a promising solution, becoming a research focus. Edge distributed systems address this by offloading tasks from mobile devices to nearby edge servers or networked devices. This paper focuses on edge distributed computing offloading and conducts the following research: (1) An overview of common MEC mechanisms is provided, covering key technologies like virtualization, SDN, CDN, SON, cloud computing, and collaborative computing. The characteristics of edge distributed systems, such as scalability, location relevance, diversity, randomness, time-varying nature, and autonomy, are discussed. Typical MEC implementation methods and future trends are explored. (2) A shared bandwidth allocation algorithm using blockchain smart contracts is proposed to address wireless resource scheduling challenges. This scheme eliminates the need for a central server, reducing latency and enhancing scalability. (3) An optimized mobile edge collaborative learning algorithm is proposed, which reduces data traffic and communication delays by shifting machine learning tasks to local devices. A compact parameter set replaces redundant models to minimize excessive transmission.

1 INTRODUCTION

The rise of the Internet of Things (IoT) has led to a surge in smart devices (Babatunde, Bodhaswar, 2016), accompanied by an increase in compute-intensive and latency-sensitive tasks. However, mobile devices face significant challenges in processing these tasks due to limitations in power consumption, computing capability, and storage capacity. Against this backdrop, edge computing, as a new computing paradigm, has emerged. By deploying computing resources at the network edge, it reduces task processing latency, lowers energy consumption, and enhances user experience. Computation offloading, as one of the key technologies of edge distributed computing, has become a current research hotspot.

Blockchain technology, with its characteristics of decentralization, immutability, and transparency, holds great potential in the field of edge distributed computing. It ensures task security and reliability through a distributed ledger and achieves automated management of computing tasks via smart contracts (Baranwal, Kumar, Vidyarthi, 2023). Although blockchain technology has been applied in task scheduling optimization, enhancement of node trustworthiness, and improvement of computing result reliability, its challenges in performance, scalability, and energy consumption limit its widespread application (Chen, Wang, Liu, 2021).

This paper delves into the key technologies of blockchain-based edge distributed computing offloading, including trust foundation, elastic offloading, fair scheduling, and security assurance. The goal is to improve computational efficiency, ensure security, and optimize user experience. The research outcomes include a multi-chain

[a] https://orcid.org/0009-0009-5025-2576
[b] https://orcid.org/0009-0006-3452-0110
[c] https://orcid.org/0009-0002-7818-9176
[*] Corresponding author

He, X., Xu, J. and Yan, Z.
Unloadable Computing Problem Based on Edge Distributed Computing.
DOI: 10.5220/0013703200004670

In *Proceedings of the 2nd International Conference on Data Science and Engineering (ICDSE 2025)*, pages 638-644
ISBN: 978-989-758-765-8

collaborative trustworthy computing offloading model that achieves data traceability, a collaborative computing offloading method that constructs standardized interaction processes, and a smart contract-driven adaptive offloading strategy. By transforming the task allocation problem into a stochastic optimization problem, the strategy uses stochastic optimization algorithms to reduce overall costs and increase task completion rates. The deployment of smart contracts with reward/punishment mechanisms incentivizes computing nodes to participate, ensuring successful task completion and enhancing system robustness and scheduling efficiency.

In related research, Li Yun et al. proposed intelligent collaborative computing offloading and resource allocation algorithms (Li, Zhang, Yao, 2024), constructing a joint optimization problem to minimize system energy consumption while meeting user latency constraints. The Gat-HMARL algorithm was employed, and simulations showed performance improvements. In the joint optimization of intelligent computing offloading and service caching (Li, Nan, Yao, et al, 2025), a DAG task offloading and resource optimization problem was established, and the MADDPG algorithm was used to explore optimal strategies. Experiments demonstrated that the algorithm performed excellently in reducing energy consumption and improving cache hit rates. Lin Hongcai proposed the O2O-DRL and DR-DRL methods based on DRL (Lin, 2024), which addressed the cold start problem in reinforcement learning and improved task success rates. In another study with the same name, a solution for edge distributed computing offloading was proposed in response to the limitations of mobile devices. It introduced key technologies and proposed a blockchain-based shared bandwidth allocation algorithm driven by smart contracts to reduce latency and enhance system scalability. An optimized mobile edge collaborative learning algorithm was also proposed.

This paper reviews the key technologies of edge distributed computing offloading, including computation offloading algorithms, resource allocation strategies, the application of blockchain technology in resource scheduling, and the optimization of mobile edge collaborative learning algorithms. It aims to summarize the current research progress and challenges and to propose future research directions, with the expectation of further advancing the development of edge computing technology.

2 DATASETS

The data in this paper presents the architecture of the edge - distributed computing network, covering the connections and data flow paths among components such as edge devices, edge servers, and cloud computing centers. It also provides symbols and parameters related to computational offloading, such as task volume and computing power, laying the foundation for mathematical modeling. The experimental parameters are diverse, involving different computational tasks, network conditions, and device performance scenarios, which effectively verify the effectiveness and performance of the computational offloading method and comprehensively support the research work.

This paper trains Informer and double LSTM on the ETTh1, ETTm1, and ECL datasets. Informer is a prediction model adopting an encoder - decoder architecture and has 11,330,055 parameters; while the double - layer long short - term memory network (LSTM) contains 4,233,735 parameters. ETTh1 and ETTm1 represent two - year electricity data from two cities in China. ETTh1 is applicable to hourly readings, and ETTm1 is used for readings at 15 - minute intervals. ECL shows the hourly electricity consumption data of 321 customers in the United States over two years.

3 EXPERIMENTAL METHODS

3.1 Distributed Reinforcement Learning

In this paper, the task offloading method based on distributed reinforcement learning demonstrates unique research value and practical significance. It is reflected in the following aspects:

1.Data Quality Assessment (DQ) Phase: Since edge computing involves multi-source heterogeneous data, these data may have low-quality issues such as missing values and erroneous values due to device differences and network fluctuations. By assessing from multiple dimensions such as accuracy, completeness, consistency, and timeliness, a comprehensive understanding of the data status can be achieved. For example, in terms of accuracy, data verification algorithms can be used to compare with known standards or historical data; completeness assessment can check whether there is a lack of key information in the data; consistency is achieved by cross-checking the same type of data from different data sources; and timeliness is judged based on the data generation time and the time requirements of the application scenario. This step lays the foundation for subsequent processing and ensures the reliability of the data.

2.Data Repair (DR) Phase: The repair algorithm based on a new repair consensus mechanism plays a role, adopting corresponding technologies for different types of low-quality data. For example, for missing values, if the data has time series characteristics, linear interpolation or spline interpolation methods can be used; erroneous data can be corrected according to the data distribution law and business logic by setting thresholds or rules; incomplete data blocks can be rebuilt using data redundancy or backup. These means effectively improve data quality and reduce its negative impact on distributed computing.

3.Task Scheduling Distributed Reinforcement Learning (DELTA) Step: Here, the distributed reinforcement learning algorithm is used, regarding edge devices as agents. Each agent makes decisions based on its own computing resources, network connection status, and the data quality assessed and repaired, as well as the information obtained from the surrounding environment. Agents continuously interact with the environment during task offloading, taking actions, such as executing tasks, offloading to other devices or servers, and learn and optimize strategies based on reward feedback such as the timeliness of task completion and the degree of energy consumption reduction, thereby achieving efficient task offloading based on a new low-quality data distribution strategy and ensuring data privacy with the characteristics of blockchain.

From the perspective of theoretical basis, distributed reinforcement learning fits the distributed architecture characteristics of edge computing. Edge devices have dispersed and limited resources, and traditional centralized algorithms are powerless in this environment. Distributed reinforcement learning endows each edge device with the ability to learn and make decisions independently, and continuously optimizes system performance through interaction and collaboration between devices. The data quality assessment and repair phase directly hit the core of the multi-source heterogeneous data problem, effectively avoiding the disadvantages of computing convergence delay and result deviation caused by low-quality data, and laying a solid foundation for accurate task offloading. The integration of blockchain technology is the icing on the cake. Its decentralized and tamper-proof attributes consolidate the data security line of defense, effectively resist malicious intrusion and data tampering, and effectively ensure data privacy and the cornerstone of system trust.

In the experimental design dimension, a simulated edge computing scenario covering multiple edge devices and servers is constructed, and variables such as task types, data quality levels, and network conditions are set multidimensionally. Key indicators such as task completion time, system energy consumption, data quality improvement, and privacy protection effectiveness are comprehensively considered to accurately judge the advantages and disadvantages of this method compared with other strategies. The experimental results show its significant effectiveness. In terms of task completion time, the offloading strategy that intelligently adapts to data and network conditions can flexibly allocate tasks to suitable devices or servers, greatly reducing processing time. System energy consumption is effectively controlled due to the reasonable task allocation mechanism, avoiding device overload, and distributed reinforcement learning continuously optimizes strategies to achieve energy consumption minimization. Data quality is significantly improved after assessment and repair, effectively ensuring the accuracy of application d computational resources, and performance may be limited in complex edge scenarios and large-scale task offloading. The accuracy and efficiency of data quality assessment and repair algorithms also need to be improved.

Compared with other related research, such as the D2HM algorithm in "Distributed Heterogeneous Task Offloading Algorithm in Mobile Edge Computing," which uses distributed game theory and Lyapunov optimization to achieve differentiated control of heterogeneous tasks and elastic resource allocation, reducing average delay; and the JORA method in "JORA: Blockchain-based efficient joint computing offloading and resource allocation for edge video streaming systems," which uses blockchain smart contract incentive mechanisms to solve joint offloading, allocation, and video compression optimization problems, achieving efficient resource utilization and energy consumption - accuracy balance. These achievements have opened up new ideas for the research of blockchain-based edge distributed computing offloading, and the task offloading method based on distributed reinforcement learning is expected to continuously iterate and optimize in the process of integrating its own advantages and drawing on the strengths of others, deeply promoting the development of edge computing offloading technology, and improving the system's comprehensive performance and application efficiency.

3.2 Test

3.2.1 Identity Information Encryption Test

In this study, in order to deeply evaluate the performance of algorithms related to identity information encryption, plaintext identity information data in the range of ((0, 10]MB) was specifically generated as the test dataset. The AES algorithm, ECDH key agreement encryption and decryption scheme, and ECIES scheme were implemented using the BouncyCastle library in C# for encryption and decryption performance testing. At the same time, development packages such as BitcoinSVCryptor and BsvSimpleLibrary were used to better interact with the Bitcoin network.

3.2.2 Zero-Knowledge Identity Authentication Test

Programming was carried out on two parts of the crowdsourcing logistics platform: generating zero - knowledge questions and verifying zero - knowledge proofs. In the test, 1 to 250 users were simulated to simultaneously initiate zero - knowledge authentication challenges to the crowdsourcing logistics platform.

3.3 Experimental design

In the algorithm comparison experiment of edge distributed computing, in order to simulate the large-scale multi-access edge computing (MEC) scenario, the experimental environment is set to contain multiple mobile devices (MD) and multiple edge servers (ES). The amount of MD and ES can be adjusted according to the specific needs of the experiment. At the beginning of each time slot, each MD randomly generates tasks of different sizes according to the Bernoulli distribution, and the size of the tasks is expressed in data volume (unit: Mbit). In the experimental environment of this paper, several algorithms are compared to evaluate their performance in dealing with MEC task unloading.

MADDPG algorithm is a multi-agent depth deterministic strategy gradient algorithm, which is a classical algorithm to solve MEC task unloading problem. The algorithm can deal with the cooperation and competition between multiple agents, but the computational complexity is high in large-scale scenarios. In the experiment, MADDPG algorithm is used as one of the comparison algorithms to evaluate the performance of MF-MATO algorithm. DDPG algorithm is a distributed single-agent algorithm, which can not deal with the interaction between agents and partial observability. Due to the partial observability of MEC environments, the performance of DDPG algorithms may be limited. In the experiment, DDPG algorithm is used as one of the comparison algorithms to highlight the advantages of MF-MATO algorithm in dealing with partially observable problems. LSTM-DQN algorithm introduces LSTM network into DQN to solve part of the observable problem, but it is still a single-agent algorithm. The algorithm can deal with the partially observable problem of a single agent, but it cannot deal with the cooperative relationship between multiple agents. In the experiment, LSTM-DQN algorithm is used as one of the comparison algorithms to evaluate the performance of MF-MATO algorithm in collaborative task unloading. The Random algorithm is a simple uninstall strategy in which MD randomly generates uninstall decisions. The algorithm does not rely on any optimization algorithm or model, so it can be used as a benchmark comparison algorithm to evaluate the performance improvement of other algorithms. Then the MADDPG, DDPG, LSTM-DQN and Random experimental results were compared and analysed. The performance of different algorithms is evaluated by comparing the average delay and average task dropout rate.

4 ANALYSIS OF EXPERIMENTAL RESULTS

4.1 Distributed Reinforcement Learning Analysis

In terms of task completion time, the experimental results show that the method performs excellently. Due to its ability to intelligently select task offloading strategies based on data quality and network conditions, for example, when a certain edge device has limited resources or data processing capabilities, it can quickly transfer tasks to other devices or servers with sufficient resources. This allows tasks to be processed in a more suitable environment, effectively avoiding processing delays caused by device performance bottlenecks or data issues, thereby significantly reducing task completion time and improving the system's overall response speed, which is crucial for edge computing application scenarios with high real-time requirements.

From the perspective of system energy consumption, the method has also achieved good results. Through a reasonable task allocation mechanism, it avoids the situation where some devices are overloaded and consume too much energy. The distributed reinforcement learning algorithm continuously learns and optimizes task offloading strategies, enabling tasks to be executed on devices or servers with lower energy consumption, achieving the minimization of system energy consumption. In edge computing environments, devices usually rely on limited energy supplies (such as battery-powered mobile edge devices), and reducing energy consumption helps to extend the device's endurance time and improve the system's sustainable operation capability.

Regarding the degree of data quality improvement, after the data quality assessment and repair steps, the reliability and availability of the data are significantly enhanced. Experimental results show that low-quality data repaired can produce more accurate results in subsequent task offloading and processing processes. In application fields with strict data quality requirements, such as the Industrial Internet of Things and the Energy Internet, accurate data processing results are the key to ensuring the normal operation of the system and the scientific nature of decision-making. For example, in the monitoring and control of industrial production processes, high-quality data can ensure the precise operation of equipment and timely warning of failures, avoiding production accidents or efficiency losses caused by data errors.

In terms of privacy protection effects, the introduction of blockchain technology provides a solid guarantee for data privacy. Experimental results have confirmed that the task offloading framework based on blockchain effectively prevents data leakage and tampering. In edge computing environments, data may be transmitted and processed between multiple devices and servers, facing many security risks. The decentralized and tamper-proof characteristics of blockchain ensure the security and integrity of data throughout the computing offloading process, protecting user privacy and enhancing user trust in edge computing systems.

However, the experimental results also reveal some limitations of the method. For example, the training and convergence of distributed reinforcement learning algorithms may require a longer time and more computational resources. In edge computing environments, the computing power of edge devices is relatively weak, which may affect the deployment and performance of the method in practical applications. Especially in complex edge computing environments and large-scale task offloading scenarios, with a large number of devices and complex task types, the difficulty of algorithm training and convergence may further increase, thereby limiting the application scope and effectiveness of the method. In addition, the accuracy and efficiency of data quality assessment and repair algorithms still need to be further improved to better cope with the complex and changing data quality issues in edge computing.

4.2 Distributed Reinforcement Learning Analysis

The ECDH key agreement scheme takes longer than the AES algorithm. This is because it not only needs to derive the shared key but also has to use the shared key to derive the symmetric key for encryption and decryption operations. The encryption and decryption time of the ECDH key agreement encryption and decryption scheme is shorter than that of the ECIES scheme. This is because the identity information in this paper is stored in Bitcoin SV (BSV) blockchain transactions. During the process of uploading to the blockchain, the trader signs the transaction with OP_RETURN, which eliminates the computational overhead of the MAC verification algorithm in the ECIES scheme. Although the encryption and decryption efficiency of the ECDH key agreement scheme is lower compared to the AES algorithm, the blockchain - based identity information encryption and decryption scheme implemented in this study still has a relatively fast encryption and decryption speed and strong practicality.

As the number of users increases, when the number of users is the same, the authentication delay of the scheme proposed in this paper is shorter than that of the SHAO scheme, and the authentication speed is faster. Under the condition of an equal number of users, the transaction - processing ability of the scheme proposed in this paper is better than that of the SHAO scheme. The scheme proposed in this paper has significantly improved the authentication delay and authentication efficiency of the crowdsourcing logistics platform, effectively enhancing the authentication performance of the system.

4.3 Algorithm analysis

In Figure 1, the MF-MATO algorithm shows good performance stability and optimization ability in dealing with multi-agent cooperation problem and partially observable problem. MADDPG algorithm also shows some advantages in dealing with multi-agent cooperation problem, but its performance fluctuates greatly. As a single-agent algorithm, DDPG algorithm may not be as effective as MADDPG and MF-MATO in dealing with multi-agent cooperation problems. LSTM-DQN algorithm has some limitations in dealing with partially observable problems, but its performance is relatively stable (Lu, Li, 2024).

In Figure 2, two algorithms, MF-MATO and LSTM-DQN, are selected for comparison. MF-MATO may be an algorithm for multi-agent or edge computing, while LSTM-DQN introduces LSTM (Long short-term memory) networks in DQN (deep Q network) to handle partially observable problems. MF-MATO algorithm may have better performance stability and optimization ability when dealing with multi-agent or edge computing tasks. LSTM-DQN algorithm is sensitive to the state transition mode when dealing with partially observable problems, so it needs to be carefully considered in specific applications. Increasing the number of MD may affect the performance of the algorithm, depending on factors such as the algorithm type, state transition method, and metrics. The average delay and MDR are used as effective tools to evaluate the performance of the algorithm (Lu, Li, 2024).

Finally, it is verified that MF-MATO algorithm and MADDPG algorithm can make MD cooperative decision in the system, and the utilization rate of computing resources is higher.

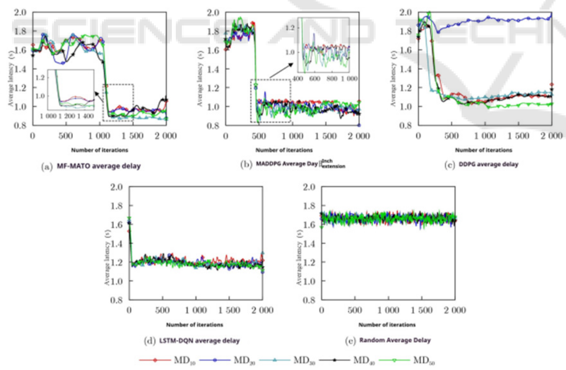

Figure 3: Average latency curve of different algorithms (Lu, Li, 2024).

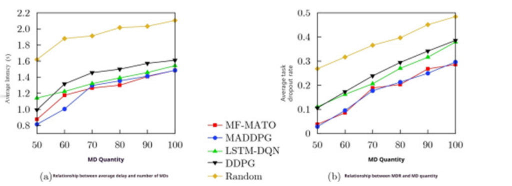

Figure 4: Average latency and MDR vary with the number of MDs (Lu, Li, 2024).

5 CONCLUSIONS

With the rise of Internet of Things (IoT) technology, the number of smart devices has surged, and the number of computing-intensive and latency-sensitive tasks has gradually increased. Due to the limitations of power consumption, computing power and storage capacity, mobile devices face huge challenges in processing these tasks. Edge distributed computing offloading technology, as a solution, reduces task processing latency and energy consumption by deploying computing resources at the network edge.

Scalability, location correlation, diversity, randomness, time variability and autonomy are the characteristics of edge distributed systems, which make edge distributed systems flexibly applied in different scenarios. The application of blockchain technology includes the use of the decentralization, immutable and transparent characteristics of blockchain technology to ensure the safety and reliability of tasks in edge distributed computing, and the automated management of computing tasks through smart contracts. The paper proposes a smart contract-based shared bandwidth allocation algorithm combined with blockchain technology to reduce delay and improve system scalability, optimize the mobile edge collaborative learning algorithm, and improve task unloading efficiency and system performance. This paper verifies the effectiveness and performance of the algorithm through experiments, including task completion time, system energy consumption, data quality improvement and privacy protection effect.

The experimental results show that the proposed method can significantly reduce the task completion time, improve the overall response speed of the system, reduce energy consumption and extend the battery life of the equipment. Compared with other research results such as D2HM algorithm and JORA method, this paper shows the unique advantages of the proposed method in task unloading, resource allocation and system performance optimization.

In conclusion, this paper explores the key technologies of blockchain-based edge distributed computing offloading, proposes the optimization algorithm method, and verifies its performance. However, there are still some limitations and challenges that need to be further explored and addressed by future research.

AUTHORS CONTRIBUTION

All the authors contributed equally and their names were listed in alphabetical order.

REFERENCES

Babatunde, S., Bodhaswar, T. J., Attahiru, S. 2016. Solving resource allocation problems in cognitive radio networks: a survey. EURASIP J. Wireless Comm. and Networking. Volume 2016 , Issue 1. PP 1-14.

Baranwal, G., Kumar, D., Vidyarthi, D. P. 2023. Blockchain based resource allocation in cloud and distributed edge computing: A survey. Computer Communications. Volume 209, Issue. PP 469-498.

Chen, J., Wang, Y. L., Liu, T. 2021. A proactive resource allocation method based on adaptive prediction of resource requests in cloud computing. EURASIP Journal on Wireless Communications and Networking. Volume 2021, Issue 1.

Hisham, M. A. 2025. UAV-assisted mobile edge computing model for cognitive radio-based IoT networks. *Computer Communications* 108071-108071.

Gao, R. L., Zhang, W. Z., Mao, W. Y., Tan, J. J., Zhang, J., Huang, H. Y., ... & Huang, F. Y. 2025. Method towards collaborative cloud and edge computing via RBC for joint communication and computation resource allocation. *Journal of Industrial Information Integration* 100776-100776.

Li, Y., Nan, Z. Y., Yao, Z. X., et al. 2025. Distributed intelligent computing offloading and service caching joint optimization for DAG tasks. Journal of Sun Yat-sen University (Natural Science Edition in Chinese and English), 64(1): 71-82.

Li, Y., Zhang, J. X., Yao, Z. X., et al. 2024. Neighborhood-aware distributed intelligent edge computing offloading and resource allocation algorithm. Science China: Information Sciences, 54: 413–429, doi: 10.1360/SSI-2023-0177

Li, Z. Y., Wu, Y., Zhang, W. W., Li, Y. G. 2022. A Trusted Identity Authentication Model for Crowdsourcing Logistics Based on the UTXO - Model Blockchain. Journal of Jiangsu University.

Lin, H. C., 2024. Research on distributed task offloading technology under edge computing. Computer Science, 51(6): 1-10.

Lu, X. L. & Li, D. K. 2024. Task unloading algorithm for large-scale multi-access edge computing scenarios. Journal of Electronics and Information. 1-11.