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Enhanced efficiency and security in cross-chain transmission of blockchain internet of ports through multi-feature-based joint learning

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The rapid development of Blockchain Internet of Things (IoT) has intensified the need for efficient and secure cross-chain transmission across heterogeneous systems. However, traditional cross-chain methods, such as hash time-locked contracts and relay chains, focus primarily on security and correctness while neglecting performance optimization. This limitation is particularly pronounced in high-dynamic environments like port areas, where network congestion, high latency, and uneven resource utilization are prevalent challenges. To address these gaps, this study proposes a novel load-adaptive cross-chain control method tailored for Blockchain IoT systems in port areas. The proposed method integrates multi-feature joint learning with adaptive multi-channel joint bus control, enabling dynamic resource allocation and interference suppression for enhanced transmission efficiency. Furthermore, a distributed intelligent scheduling mechanism is introduced to improve scalability and stability under high-concurrency conditions by decentralizing task coordination across blockchain nodes. Additionally, federated learning is employed to optimize cross-chain communication while preserving data privacy, ensuring secure and collaborative optimization in multi-party environments. Extensive simulations validate the effectiveness of the proposed approach, demonstrating significant improvements in throughput, latency, and packet loss rate compared to traditional centralized methods. The results highlight the method's ability to balance dynamic network loads, minimize interference, and adapt to real-time conditions. This work bridges the gap between performance-oriented optimizations and privacy-preserving mechanisms, offering a scalable and secure solution for Blockchain IoT systems in complex and dynamic environments.

The rapid growth of Blockchain Internet of Things (IoT) has introduced unprecedented opportunities for secure and decentralized data exchange across heterogeneous systems. Cross-chain transmission (CCT) is fundamental to enabling interoperability among diverse blockchain networks[1]. This is particularly crucial in dynamic environments such as port areas, where network congestion, high transaction loads, and latency variability are prevalent challenges[2]. However, existing cross-chain solutions, including hash time-locked contracts (HTLC) and relay chains, are primarily designed to ensure transactional security and correctness[3,4]. While effective in static scenarios, these methods fall short of addressing the performance and scalability requirements necessary for high-demand environments like Blockchain IoT networks[5]

Recent advancements in cross-chain technologies, such as multi-feature joint learning (MFJL)[6,7], have demonstrated the potential to enhance resource utilization and reduce latency in CCT systems[8]. However, centralized scheduling mechanisms remain the norm[9], wherein a single control node governs task allocation and resource management[10]. This approach introduces significant limitations, including scalability bottlenecks and single-point failures[11], which restrict their applicability in large-scale Blockchain IoT environments[12]. Additionally, the collaborative nature of Blockchain IoT applications amplifies privacy concerns[13], as sensitive data may be exposed during optimization processes[14,15].

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To address these critical challenges, this study introduces a novel load-adaptive cross-chain control framework with the following contributions:

- Centralized scheduling methods often fail to meet the demands of high-concurrency environments. To overcome this, the proposed distributed scheduling mechanism decentralizes task coordination by leveraging blockchain nodes for collaborative load distribution. By integrating Graph Neural Networks (GNN) and on-chain smart contracts, the method enhances scalability and fault tolerance, ensuring stable performance under dynamic conditions.
- The increasing complexity and collaborative nature of Blockchain IoT systems necessitate privacy-preserving optimization techniques. Federated learning (FL) enables individual blockchain nodes to train local optimization models while sharing only model parameters, safeguarding sensitive data. This innovation provides real-time adjustments for priority scheduling and resource allocation without compromising privacy.
- Building on previous research, this study refines MFJL to optimize multi-channel joint bus control and suppress interference. The enhanced MFJL ensures balanced resource allocation and significant improvements in throughput, latency, and reliability in Blockchain IoT systems.These contributions address key gaps in existing cross-chain solutions by integrating decentralized scheduling, privacy-preserving optimization, and advanced learning techniques. Extensive simulations validate the proposed framework, demonstrating substantial improvements in throughput, latency, and packet loss rate compared to traditional methods. This work offers a robust, scalable, and privacy-focused solution for complex and dynamic Blockchain IoT environments, particularly in port systems.

Related work

Blockchain interoperability has become a critical area of research due to the increasing demand for seamless communication across heterogeneous blockchain systems. Existing cross-chain technologies, such as hash time-locked contracts (HTLC)[1] and relay chains[5], primarily ensure transactional security and correctness but often lack performance optimization. For example, Polkadot[16] utilizes a relay chain mechanism for secure cross-chain communication, and Cosmos[17] employs the Inter-Blockchain Communication (IBC) protocol. While these methods address security and compatibility, they typically rely on static configurations and single-channel communication, leading to suboptimal performance in dynamic and high-throughput environments.

Traditional cross-chain methods often lack dynamic load balancing and real-time scheduling mechanisms. This results in network congestion, high latency, and uneven resource utilization[18]. Existing approaches such as IoTChain[19] and WaltonChain[20] focus on blockchain integration for IoT applications but fail to optimize transmission performance under varying network loads. These limitations highlight the need for adaptive mechanisms in cross-chain systems.

In related domains, load balancing and adaptive scheduling have been widely studied for performance optimization[21,22]. For instance, dynamic task scheduling in edge computing[23] and multi-channel communication in distributed systems[24] have demonstrated significant improvements in throughput and latency. However, their application in cross-chain transmission remains limited, with few studies addressing the challenges of real-time load balancing and multi-channel optimization in blockchain systems.

Multi-channel transmission has shown promise in improving network throughput and reducing latency[25]. Techniques like channel multiplexing are commonly used in traditional networks but are rarely adopted in blockchain systems due to their complexity. Existing cross-chain solutions either neglect multi-channel optimization or fail to integrate it with adaptive load balancing and scheduling strategies, limiting their applicability in dynamic environments.

To overcome these limitations, decentralized scheduling and privacy-preserving optimization techniques have emerged as promising alternatives. Distributed intelligent scheduling mechanisms decentralize task allocation by leveraging collaborative decision-making among blockchain nodes, significantly improving scalability and fault tolerance[7,11]. For example, recent work highlights the integration of Graph Neural Networks (GNN) with on-chain smart contracts for dynamic load distribution, enabling decentralized systems to handle high-concurrency conditions more effectively. Additionally, federated learning (FL) has gained traction as a privacy-preserving optimization framework, enabling collaborative optimization of parameters across multiple blockchain nodes without exposing sensitive data[13,14]. FL has been effectively applied in IoT and cybersecurity contexts, showcasing its potential to address privacy concerns in collaborative environments[21].

These gaps in existing research underscore the need for a comprehensive solution that integrates load balancing, adaptive scheduling, and multi-channel transmission. This study addresses these gaps by proposing a load-adaptive cross-chain control method, designed to enhance transmission efficiency and reliability in Blockchain IoT systems.

Materials and methods

CCT link model of blockchain Internet of Things in port area

To realize the CCT control of the blockchain Internet of Things in the port area based on load adaptation, it is necessary first to construct the balanced configuration model of the CCT link of the blockchain Internet of Things in the port area and adopt the method of load balanced scheduling[24] to realize the compensation and adjustment of the joint autocorrelation dynamic characteristic parameters of the CCT link of the blockchain Internet of Things in the port area. The method of fuzzy link balanced adjustment[22] and distributed integration of characteristics is adopted by calculating the spatial characteristic parameters of the CCT link of the blockchain Internet of Things in the port area. The link equilibrium and amplitude response model of the CCT of the blockchain Internet of Things in the port area is constructed.

Combined with the method of adaptive equilibrium scheduling[26], the interference characteristics of the CCT of the blockchain Internet of Things in the port area are analyzed, and bit sequence scheduling is adopted to realize the optimal control of network transmission. The link model obtained is shown in Fig. 1.

In the CCT link model of the port blockchain IoT shown in Fig. 1, the CCT model of the port blockchain IoT is constructed by code function conversion, and the continuous domain matching function of the CCT of the port blockchain IoT is obtained:

$$P_{dec} = decode(C, k) \tag{1}$$

Wherein k is the time slice size associated with the CCT of the blockchain IoT in the port area, C is the time interval sequence of the CCT of the blockchain IoT in the port area, and P_{dec} is the block matching parameter of the power distribution and the CCT of the blockchain IoT in the resource port area. According to the above analysis, the RF unit of the CCT of the blockchain IoT in the port area is as follows:

$$decode(C, k) = \begin{cases} 0 & C = k - 1 \\ \sum\limits_{p=1}^{n-1} 2^{k-2-\sum\limits_{q=1}^{p} i_q} & \end{cases} \tag{2}$$

Wherein k is the cross-chain allocation parameter of blockchain Internet of Things in the port area, adopting the method of hybrid, multiple access[25], n is the total equidistant discretization is necessary to reduce the influence of extreme values and outliers of Things in the port area, and the symbol sequence P_{dec} transmitted by blockchain Internet of Things in the port area is converted into a binary sequence of $k-2$ bits, which is the privacy protection information P of high-speed transmission of the CCT business of blockchain Internet of Things in the port area. According to the prior parameter estimation result, the dynamic allocation parameter $P_{sec} = 10$ for the CCT of the port blockchain Internet of Things is obtained, and then $P = 10$. During RF processing, get the analysis of the delay bandwidth for the port blockchain IoT's CCT and the delay tolerance in the cross-chain high-dimensional state space of the port blockchain IoT as follows:

$$x = [x_1, \cdots x_i \cdots x_j^i \cdots]^T \in R^{nN} \tag{3}$$

Wherein $x_1, \cdots x_i \cdots x_j^i$ is the semantic feature attribute set, and R^{nN} is the real number field. Discretization[27] can divide continuous data into several "segments." The principles of segmentation are equidistant, equal frequency, optimization, or according to the data characteristics. Discretization can effectively overcome the hidden defects in data and make the model results more stable. The extreme value of data is an important factor affecting the model effect. Extreme values cause model parameters to be too high or too low. Therefore, it is necessary to reduce the influence of extreme values and outliers by equidistant discretization. By discrete processing, the fairness transmission factor of the port blockchain IoT CCT is the dynamic characteristic parameter, and m is the spatial parameter. By similarity measurement, the signal received in the slot is $H \in [0, 2^m - 1]$, where M is the link bandwidth agreed by both parties of the port blockchain IoT CCT communication, obtained the coding function for the delay of the port's blockchain IoT CCT:

$$H = \sum_{i=0}^{m-1} P_i 2^i \tag{4}$$

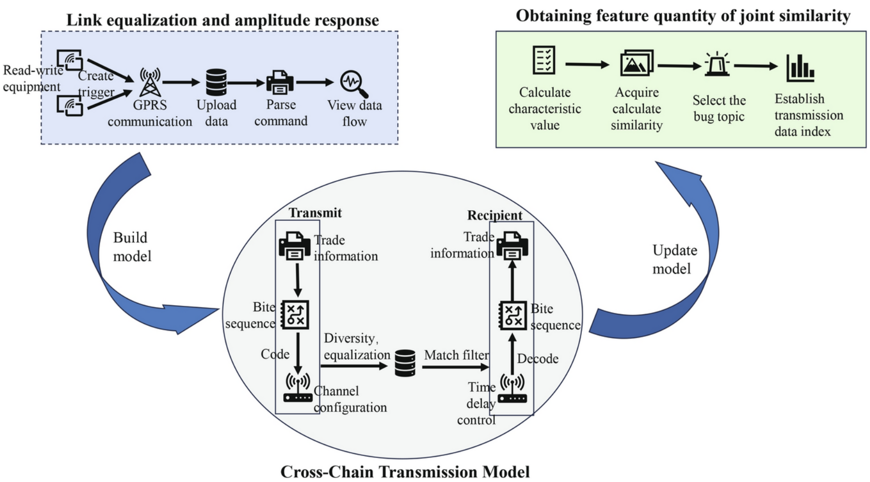

Figure 1. The overall architecture of CCT model of Things in Port.

Wherein P is the discrete characteristic series of the code sequence length m of the CCT of the blockchain Internet of Things in the port area, and the signal-to-noise ratio of the CCT of the blockchain Internet of Things in the port area in the t time slot is obtained. The following describes the dynamic Doppler spectrum[28] of the blockchain Internet of Things in the port area:

$$C_{T'}(f)\,Y_{T'}(f)=C_{T'}(f)\sum_{n}x\left(f-\frac{n}{T'}\right)e^{2\pi\left(f-\frac{n}{T'}\right)\tau 0}=C_{T'}(f)\,X(f)\,e^{2\pi f\tau 0} \tag{5}$$

Wherein $|f|\leq\frac{1}{T'}$,$X(f)$ are the response strength of the cross-chain of the blockchain Internet of Things in the port area, to construct the transmission equilibrium scheduling model of the cross-chain of the blockchain Internet of Things in the port area.

Cross-chain link balance design of blockchain IoT in port area

This paper analyzes the characteristic quantity of correlation constraint parameters of the CCT control of the blockchain IoT in the port area. It adopts the method of parameter estimation and priority scheduling of the blockchain IoT CCT link to obtain the difference function. It is concluded that the time interval *Si* of the CCT of the blockchain IoT in port area is a random variable, where $S_i\left(\mu_i,\sigma_i^2\right)$ indicates that the CCT delay of the blockchain IoT in port area satisfies the normal distribution.

*S*1 and *M*1 represent the joint similarity characteristic quantity of the CCT of the blockchain Internet of Things in the port area. Construct the link model of the cross-chain network in the port area's blockchain Internet of Things, and we obtain the fuzzy parameters between the transmission delay *D* and *Si* as follows:

$$d=60-\sum_{i=1}^{H}S_i \tag{6}$$

Where S_i is the ambiguity, *h* is the information entropy, and the multipath delay bandwidth of the cross-chain nodes of the port blockchain IOT is:

$$Cap_{adj}=60-\mu-\sum_{i=2}^{H}\mu_i \tag{7}$$

Where μ is the propagation loss, and μ_i is the relationship between distance and propagation time. Adaptive weighted control[29] is adopted to carry out fuzzy matching on the links across the chain of the Internet of Things in the port area.

By comparing the joint distribution features between *M*1 and *M*2, Obtain the iterative formula of link balance in selecting the forward transmission network:

$$f(k+1)=f(k)-\mu\cdot\rho\cdot e_{MDMMA}(k)y^{*}(k) \tag{8}$$

$$e_{MDMMA}(k)=c[|P|^2-e_{MDMMA}(k)] \tag{9}$$

Wherein ρ is the similarity coefficient of the CCT of the port blockchain IoT, and the signal-to-noise ratio of the t slot is calculated to obtain the decision function[30] of the long-distance cross-chain coverage of the port blockchain IoT as follows:

$$f_F(k+1)=|P|^2-\mu\cdot\rho\cdot e_{MDMMA}(k) \tag{10}$$

Among them, the energy consumption of the cross-chain network of the blockchain Internet of Things in the port area is:

$$e_{MDMMA}(k)=f_F(k+1)-e_{MDMMA}(k) \tag{11}$$

According to the above analysis, Construct the load estimation model of the port area's blockchain IoT CCT using the parameter estimation method and priority scheduling. *M*4 represents the load parameter, and the energy consumption factor $2m-1$ is obtained. The coding function of business data transmitted to users is:

$$C=encode(P,k) \tag{12}$$

Wherein *P* is the joint characteristic distribution information of the CCT of the blockchain Internet of Things in the port area, and its length is $(k+2m-2)$, and *k* is the size of the time slice. The delay of the cross-chain information scheduling of the block-chain Internet of Things in the port area is:

$$U=\{H_1+1,I,H_k+1\} \tag{13}$$

H_1 is a recursive algorithm to evaluate the channel characteristics, and H_k is a spread spectrum parameter. Hence, we construct a load estimation model for the port area's blockchain Internet of Things CCT, and the interference suppression of the CCT of the blockchain Internet of Things in the port area is realized according to the MFJL algorithm.

Distributed intelligent scheduling mechanism

To overcome the limitations of centralized scheduling by decentralizing task allocation and improving system scalability and fault tolerance. The distributed intelligent scheduling mechanism combines Graph Neural Networks (GNN) for network topology analysis and smart contracts for autonomous task coordination.

Network State Collection: Each node broadcasts its current state information, CPU utilization (u_i), Bandwidth availability (b_i), Storage availability (s_i). Nodes receive these broadcasts and update their adjacency matrix A and state vector $h_i = [u_i, b_i, s_i]$.

GNN-based modeling: Using A and h_i, GNN computes the optimal load distribution. Node states are updated iteratively:

$$h_i^{(t+1)} = \sigma\Big(\sum_{j \in N(i)} A_{ij} W^{(t)} h_j^{(t)} + b^{(t)}\Big) \tag{14}$$

where $N(i)$ represents the neighbors of node i, and σ is an activation function such as ReLU.

Task distribution strategy: Nodes calculate the task transfer matrix T based on GNN predictions:

$$T_{ij} = \alpha \cdot \max(h_i - \theta, 0) \tag{15}$$

Where θ is the load threshold and α is a scaling factor.

Execution via smart contracts: Smart contracts execute the task distribution plan T, ensuring that overloaded nodes offload tasks to their neighbors efficiently.

Monitoring and feedback: Nodes continuously monitor their load status and feed updates back into the GNN model to adapt to dynamic changes.

Network transmission adaptive multi-channel joint bus control optimization

Matched filtering and interference suppression

According to the MFJL algorithm, the interference suppression of the CCT of the blockchain IoT in the port area is realized, and the different characteristic components of the cross-chain switching channels of the blockchain IoT are analyzed. By adopting the methods of load balancing grid scheduling parameter fusion[23] and packet switching[9], the joint queue length of the CCT of the blockchain IoT in the port area is $R_{MDMMA\_i}(i = 1, \cdots, N)$. In the forward link model of the blockchain IoT in the port area, the time delay difference when the cross-chain base station of the blockchain IoT interacts with the wireless network is satisfied:

$$abs[|P|^2 - e_{MDMMA}(k)] = \min_i abs[|P|^2 - e_{MDMMA}(k)] \tag{16}$$

Wherein ρ represents the joint characteristic quantity of cross-chain resource allocation of blockchain IoT in port area $0 \leq \rho \leq 1$, the delay distinct wireless amount of resource allocation through blockchain IoT in the port area, combined with the balanced control of blockchain IoT in the port area.

Adopts dynamic compensation[31] technology to carry out symbol sampling processing of blockchain IoT in the port area to obtain distributed integration and scheduling of characteristics and brings the delay expansion process of blockchain IoT in the port area as follows:

$$a(\theta_0) = [1, \exp(-\varphi_1), \ldots, \exp(-(M-1)\varphi_2)]^T \tag{17}$$

Wherein φ_1 and φ_2 represent training sequence and recursive analysis parameters, respectively. Using low-dimensional and discrete link space estimation and load balancing scheduling, Obtain the corresponding load of cross-chain resource allocation for the blockchain Internet of Things in the port area:

$$b(\theta) = \frac{1}{2}[a(\theta_0)] \tag{18}$$

Combined with the cross-chain multipath feature matching method and load optimization configuration of port blockchain IoT, the decision function relationship between transmission and link classification selection in the cross-chain packet switching network of the port's blockchain IoT is obtained.

$$w_{BLCMV} = R^{nN}[a(\theta_0), b(\theta)]([a(\theta_0), b(\theta)]^H \tag{19}$$

Based on the adaptive weighted control method, the joint probability density feature estimation of the blockchain Internet of Things cross-chain in the port area is carried out. Obtain the link resource allocation output under the optimal decision of the optimization objective:

$$\tilde{y}(t)(t) = \int_{-\infty}^{\infty} \tilde{c}(H;t) \left\{ \sum_{n=-\infty}^{\infty} \tilde{s}(t-nT) \frac{\sin(2\pi(H-nT))}{2\pi(H-nT)} \right\} d\tau \tag{20}$$

Wherein the load overhead of the cross-chain resource allocation link of the blockchain Internet of Things in $W(e_s)$ port area is:

$$W(e_S) = \tilde{y}(t) \times X(f) \tag{21}$$

Through the above processing, combined with the MFJL method, the cross-chain interference suppression of the blockchain Internet of Things in the port area is realized, obtaining the detector structure model, as shown in Fig. 2.

Enhanced multi-feature joint learning

To optimize multi-channel control and suppress cross-chain interference for efficient transaction processing. MFJL dynamically extracts transaction features, detects interference, and adjusts channel allocation.

Feature data collection: Each transaction T_i is characterized Priority (P_i), Expected latency (d_i), Resource demand (r_i). Nodes aggregate transaction features into a feature set $T = \{x_1, x_2, \cdots, x_n\}$.

Interference detection and mitigation: Interference between transactions *i* and *j* is measured by:

$$I_{ij} = corr(x_i, x_j) \tag{22}$$

where *corr* is the correlation coefficient. Transactions with high I_{ij} are assigned to separate channels.

Dynamic channel allocation: Channels are allocated to minimize the overall latency function:

$$F = \sum_{i=1}^{n} \frac{w_i}{\sum_{j=1}^{m} a_{ij}} \cdot d_i \tag{23}$$

Where w_i is the transaction weight, and a_{ij} is a binary variable indicating whether T_i is assigned to channel *j*.

Execution and adjustment: High-priority transactions are allocated to low-latency channels. Channel allocations are adjusted iteratively based on feedback from interference detection.

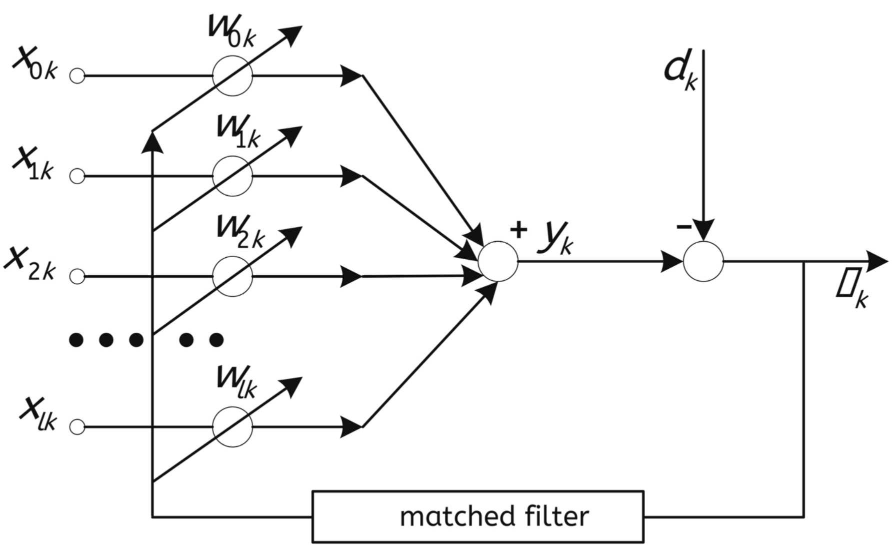

Figure 2. Detector design of CCT link of blockchain internet of things in port area.

Network transmission delay equalization

This paper analyzes the different characteristic components of the cross-chain switching channels of the blockchain IoT and constructs a joint control model for the transmission of the CCT link of the blockchain IoT in the port area by adopting the method of cross-chain load balancing and grid scheduling and parameter fusion, and obtains the maximum allowable delay:

$$L = \mu\sqrt{\sum_{i=1}^{n}\frac{(W(e_S))^2}{H}} \tag{24}$$

Considering the parameter estimation of the non-ideal blockchain IoT CCT link, obtain the achievable theoretical rate of the CCT link in the port's blockchain IoT.

$$\theta = L\sum_{i=1}^{n} R_{MDMMA\_i} \times \beta \tag{25}$$

According to the above delay estimation results, the optimized iterative transfer function for the delay transmission control of the CCT link in the blockchain Internet of Things is obtained.

$$d_n = \{^{+1, a_n = c_n}_{-1, a_n \neq c_n}, (n-1)T_c \leq t \leq nT_c \tag{26}$$

According to the above design, the cross-chain load balancing grid scheduling and parameter fusion methods are adopted to realize the CCT adaptive multi-channel joint bus control and link balancing design of the port blockchain IoT and to improve the balance and real-time performance of the CCT of the port blockchain IoT.

Federated learning-based optimization and security

To ensure privacy-preserving optimization in collaborative Blockchain IoT environments by training local models and aggregating them securely. Federated learning allows nodes to collaboratively optimize global parameters without sharing raw data.

Local model training: Each node *i* trains a local optimization model f_w using its private dataset D_i:

$$L_i(w) = \frac{1}{|D_i|}\sum_{x \in D_i} l(f_w(x), y) \tag{27}$$

Where *l* is the loss function.

Parameter encryption and upload: Before uploading, nodes encrypt their model parameters w_i by adding Gaussian noise:

$$w_i' = w_i + N(0, \sigma^2) \tag{28}$$

Where $N(0, \sigma^2)$ ensures differential privacy.

Global model aggregation: The federated server aggregates the received parameters to compute the global model:

$$w^{(t+1)} = \sum_{i=1}^{N}\frac{|D_i|}{\sum_{j=1}^{N}|D_j|}w_i^{(t)} \tag{29}$$

Redistribution and local adaptation: The updated global model $w^{(t+1)}$ is distributed to nodes, where further local training ensures adaptation to node-specific conditions.

Privacy validation: The aggregated parameters are validated for privacy compliance by checking the variance introduced by $N(0, \sigma^2)$.

Experimental setup and test results

Materials and Methods

To evaluate the performance of the proposed load-adaptive cross-chain control method for Blockchain IoT, we conducted a series of simulations using the NS-3[32] network simulator. The network environment was designed to emulate cross-chain transmission (CCT) scenarios, incorporating load balancing and adaptive scheduling mechanisms.

Network topology and configuration

The simulated network consisted of 8 nodes, including two blockchain nodes (source and destination) and intermediate relay nodes representing cross-chain communication links. Each link was configured with a bandwidth of 1Gbps and a delay of 2ms. Packet sizes were set to 1024 bytes, and transmission intervals were configured at 50ms to mimic real-world blockchain transaction patterns.

Evaluation metrics and comparison baselines

To assess the performance, the following key metrics were employed: Throughput (Mbps): Total data successfully transmitted per unit time. Latency (ms): Average time taken for data packets to travel from source to destination. Packet Loss Rate: The proportion of data packets lost during transmission.

The proposed method was compared against a traditional cross-chain transmission approach without load balancing[21] or adaptive scheduling[22]. This baseline represents the commonly used methods in current Blockchain IoT systems.

The simulation results demonstrate the advantages of the proposed method in terms of throughput, latency, and packet loss rate. Table1 summarizes the throughput performance under varying data loads. The proposed method achieves significantly higher throughput compared to the baseline, particularly under high-load conditions. At a data load of 300 packets per second, the proposed method improves throughput by 15.8%, highlighting its effectiveness in mitigating network congestion. The latency results under different link delays are presented in Table1. The proposed method consistently reduces latency across all conditions. For instance, at a link delay of 10ms, the latency is reduced by 25.2% compared to the baseline, showcasing its suitability for real-time Blockchain IoT applications. The packet loss rate results are displayed in Table1. The proposed method achieves significantly lower packet loss rates under all conditions, indicating improved robustness and reliability of data transmission.

The experimental results confirm the effectiveness of the proposed load-adaptive cross-chain control method in improving transmission performance for Blockchain IoT systems. The enhanced throughput demonstrates the method's ability to handle high data loads effectively, making it suitable for scenarios with high transaction volumes. The latency reduction results further validate the effectiveness of the adaptive scheduling mechanism, especially in high-delay environments. This characteristic is critical for real-time applications, where minimizing delays is essential. Additionally, the lower packet loss rates highlight the robustness of the proposed method, ensuring reliable data transmission even under challenging network conditions. These findings are consistent with the design goals of reducing network congestion and improving cross-chain transmission efficiency.

Load balancing and recovery time of distributed intelligent scheduling

This experiment aims to validate the effectiveness of distributed intelligent scheduling in improving load balancing and recovery time under various failure rates. The hypothesis is that distributed scheduling can achieve better load distribution and faster recovery through node collaboration.

Environment: Constructed a blockchain network with 10 nodes using the NS-3 simulator to simulate cross-chain transmission scenarios. Link configuration: bandwidth of 1 Gbps, latency of 2 ms. Controlled Variables: Failure rate varied from 10% to 70%, with a fixed transaction load of 300 transactions per second. The distributed intelligent scheduling mechanism is mainly compared with the centralized scheduling method[9], focusing on verifying its improvements in load balancing and fault recovery time.

Figures 3 and 4 present the experimental results: Load Balancing: Distributed scheduling consistently achieved lower load variance than centralized scheduling under different failure rates. For instance, at a failure rate of 50%, distributed scheduling achieved a load variance of 0.4 compared to 0.75 for centralized scheduling, a 46.7% reduction. Recovery Time: Distributed scheduling significantly reduced recovery time compared to centralized scheduling. At a failure rate of 50%, distributed scheduling achieved a recovery time of 12 seconds, compared to 22 seconds for centralized scheduling, a 45.5% reduction.

Privacy protection and model performance of federated learning

This experiment evaluates whether the federated learning framework can maintain high model performance while preserving data privacy, compared to centralized optimization without privacy protection.

Environment: Simulated a network of five blockchains, each training a local optimization model. The model used is a multi-layer perceptron, with input data including transaction latency, throughput, etc. Controlled Variables: Number of nodes increased from 1 to 7. The model performance of federated learning under privacy protection is compared with the traditional centralized optimization method[7] without privacy protection.

Figures 5 and 6 present the experimental results: Model Accuracy: Federated learning achieved slightly lower accuracy than the non-privacy baseline, with a difference of less than 2%. For instance, at five nodes, federated

	Throughput (Mbps)		Latency (ms)		Packet Loss Rate (%)	
Data Load (packets/s)	Baseline	Proposed	Baseline	Proposed	Baseline	Proposed
100	8.5	9.2	5.2	4.8	0.8	0.4
200	15.7	17.4	9.4	7.5	1.5	0.7
300	22.1	25.6	16.3	12.2	3.1	1.4

Table 1. Comparison of Throughput, Latency, and Packet Loss Rate in Cross-Chain Transmission.

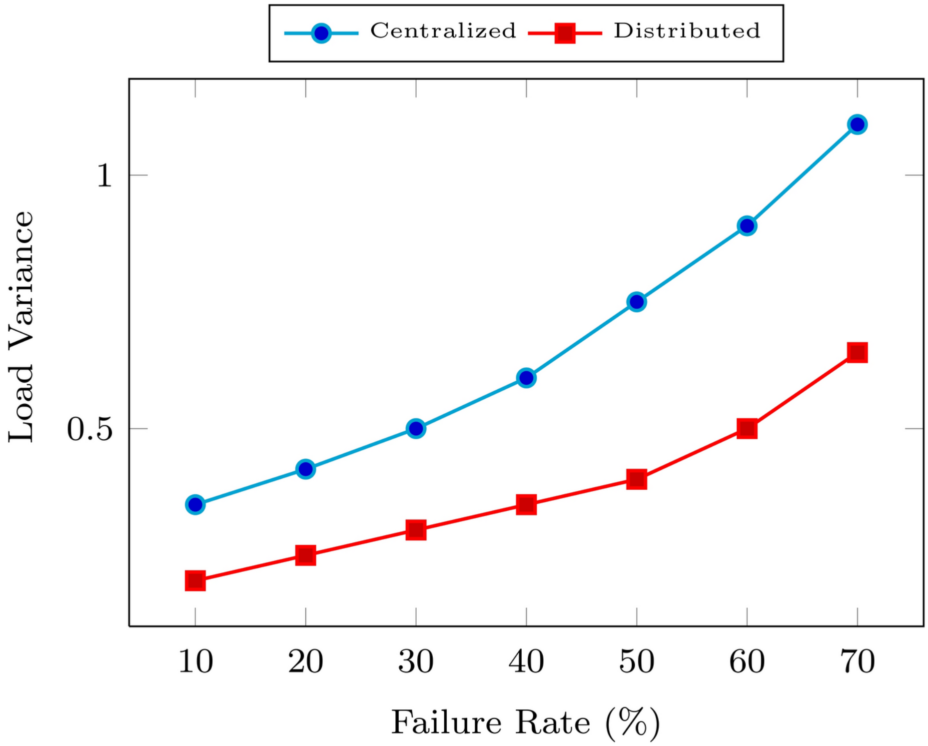

Figure 3. Load balancing comparison.

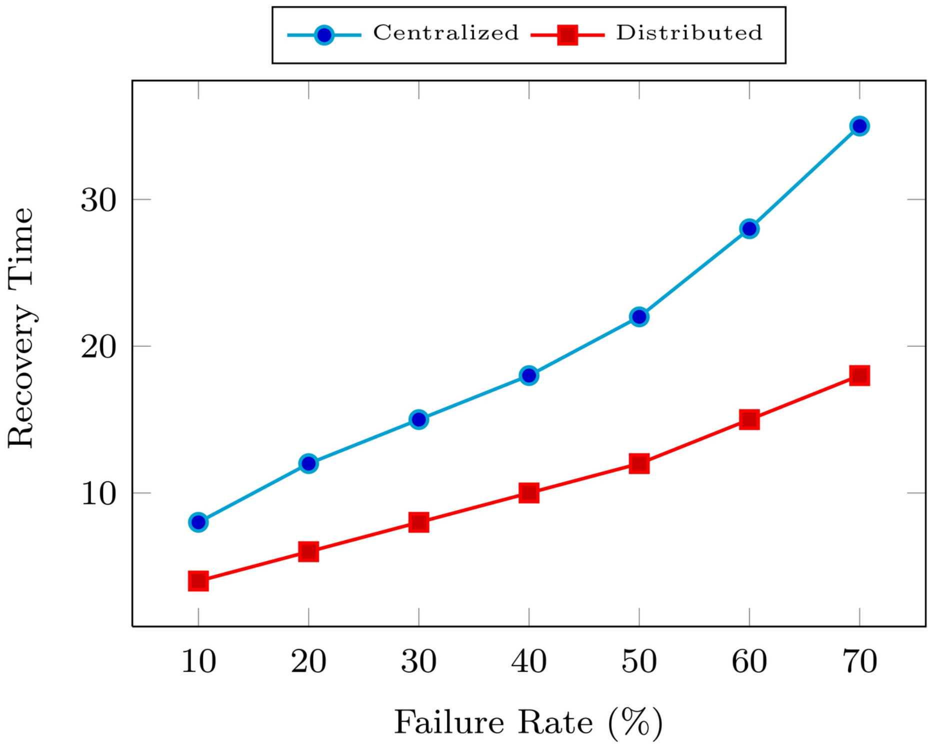

Figure 4. Fault recovery time comparison.

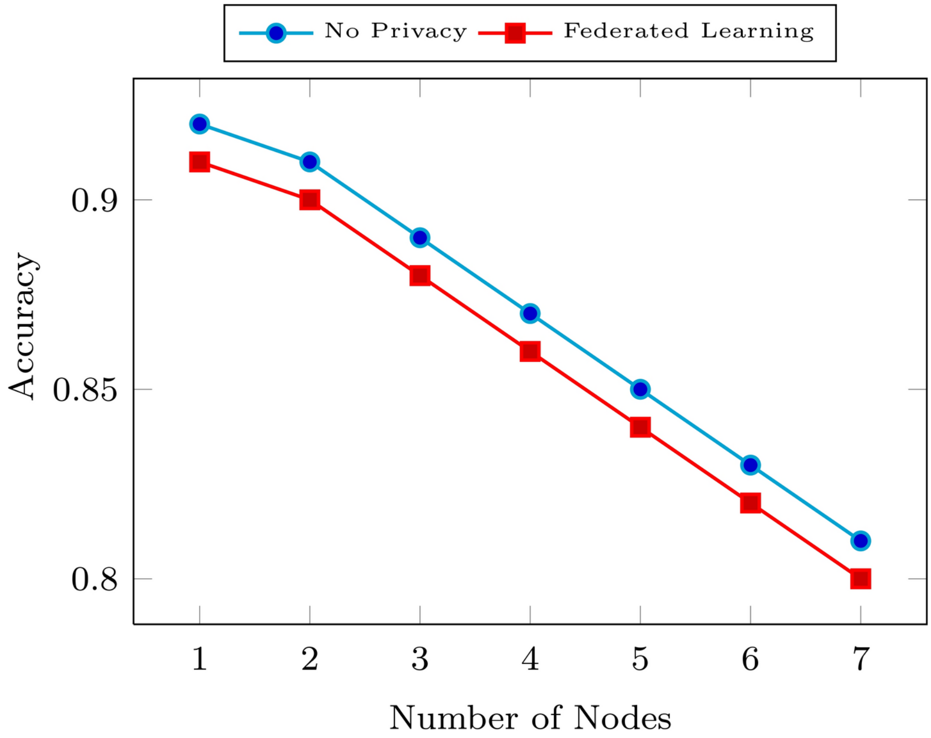

Figure 5. Model accuracy comparison.

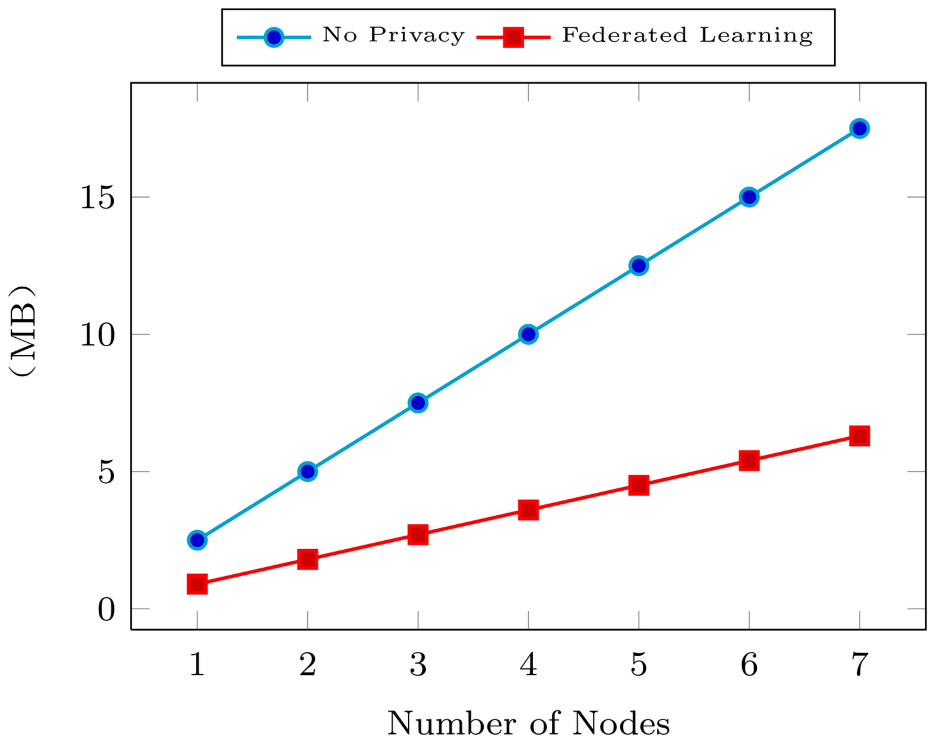

Figure 6. Communication overhead comparison.

learning achieved an accuracy of 84%, compared to 85% for the baseline. Communication Overhead: Federated learning significantly reduced communication overhead. For instance, at five nodes, federated learning required 4.5 MB, compared to 12.5 MB for the baseline.

Optimization of multi-feature joint learning (MFJL) for interference mitigation

This experiment validates the effectiveness of MFJL in optimizing resource utilization and reducing transaction latency under high interference, compared to traditional methods without interference optimization.

Environment: Simulated a multi-channel transmission environment with a fixed transaction load of 300 transactions per second. Different interference levels (0.2 to 1.0) were set. Controlled Variables: Interference levels were represented by the correlation I_{ij} between transactions. The effect of MFJL on interference suppression of cross-chain transactions is compared with the baseline method[15] (cross-chain transmission scheme without interference optimization).

Figures 7 and 8 present the experimental results: Resource Utilization: MFJL significantly improved resource utilization in high interference scenarios. For example, at an interference level of 1.0, MFJL achieved a utilization rate of 60%, compared to 45% for the baseline, a 33.3% improvement. Transaction Latency: MFJL significantly reduced transaction latency. For instance, at an interference level of 1.0, MFJL achieved a latency of 18 ms, compared to 22 ms for the baseline, a reduction of 18.2%.

Comprehensive energy efficiency

This experiment validates the energy efficiency of the proposed method under high transaction loads compared to methods without energy optimization.

Environment: Simulated transaction loads ranging from 50 to 500 transactions per second. Energy consumption data were collected using an energy model. Controlled Variables: Transaction load was the only variable. The energy efficiency experiments are compared with the baseline method[33] (cross-chain transfer framework without energy optimization).

Figures 9 and 10 present the experimental results: Total Energy Consumption: The proposed method significantly reduced energy consumption under high load scenarios. For example, at 500 transactions per second, the proposed method consumed 90 J, compared to 110 J for the baseline, an 18.2% reduction. Energy per Throughput: The proposed method also significantly improved energy efficiency. For instance, at 500 transactions per second, the proposed method achieved an energy efficiency of 4.0 J/Mbps, compared to 5.5 J/Mbps for the baseline.

Conduct an experimental test to verify the application performance of this method in achieving CCT balance and adaptive multi-channel joint bus control of the blockchain Internet of Things in the port area. Under the environment of Matlab R2019b, simulate the corresponding program using the Matlab coding algorithm in the background with a central frequency 1.

The symbol bandwidth of the CCT of the port blockchain IoT is 120Bps, the length of symbol sequence sampling is 1024, the iteration time interval of the cross-chain test sequence of the port blockchain IoT is

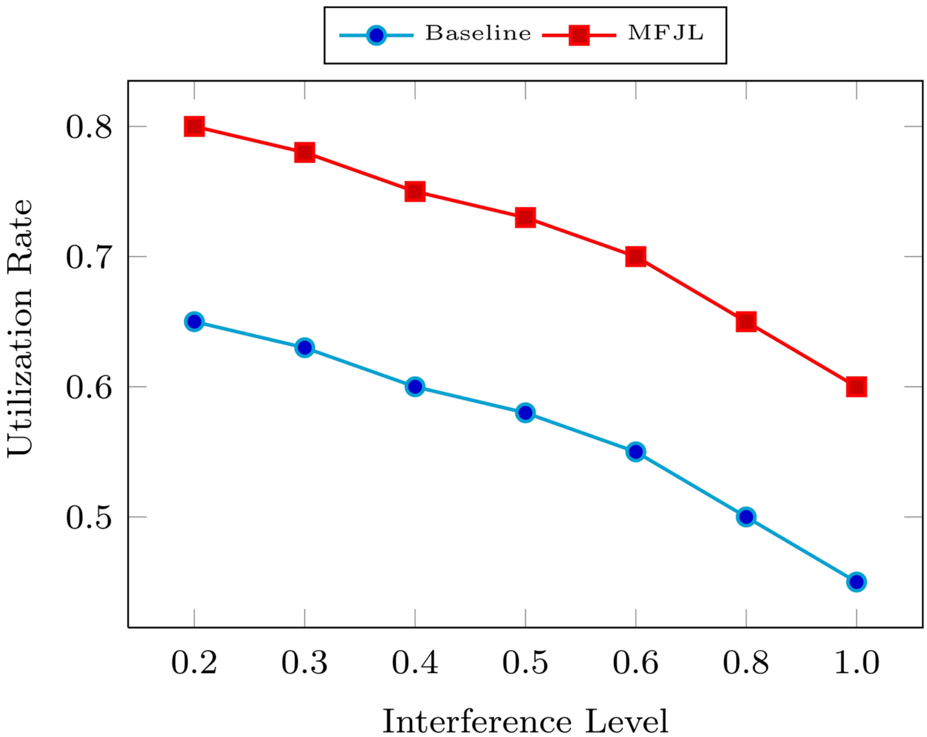

Figure 7. Resource utilization comparison.

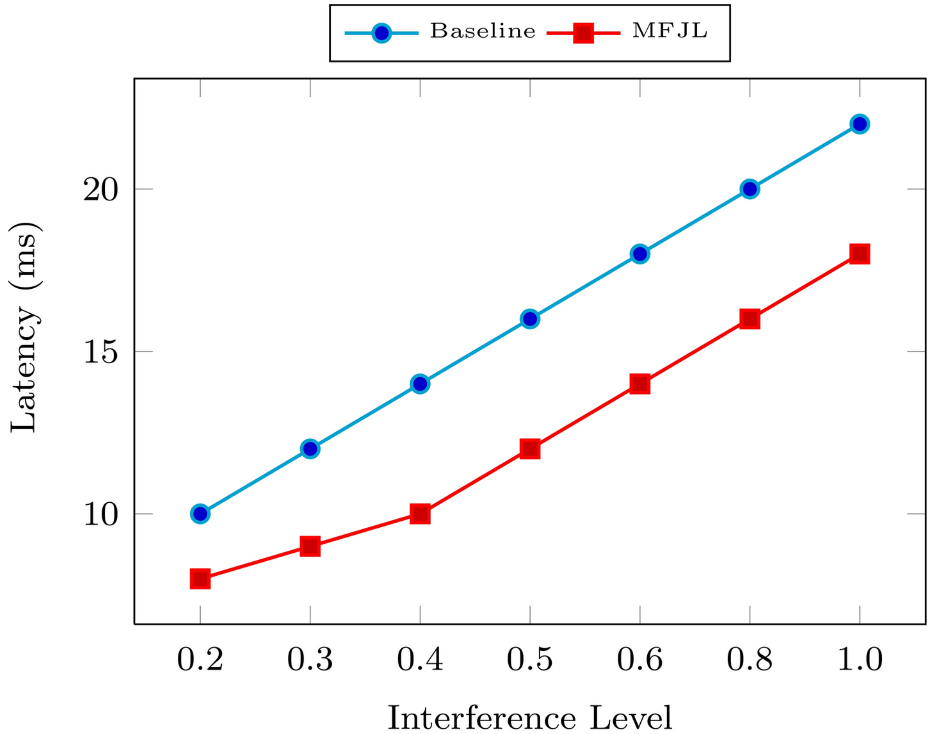

Figure 8. Transaction latency comparison.

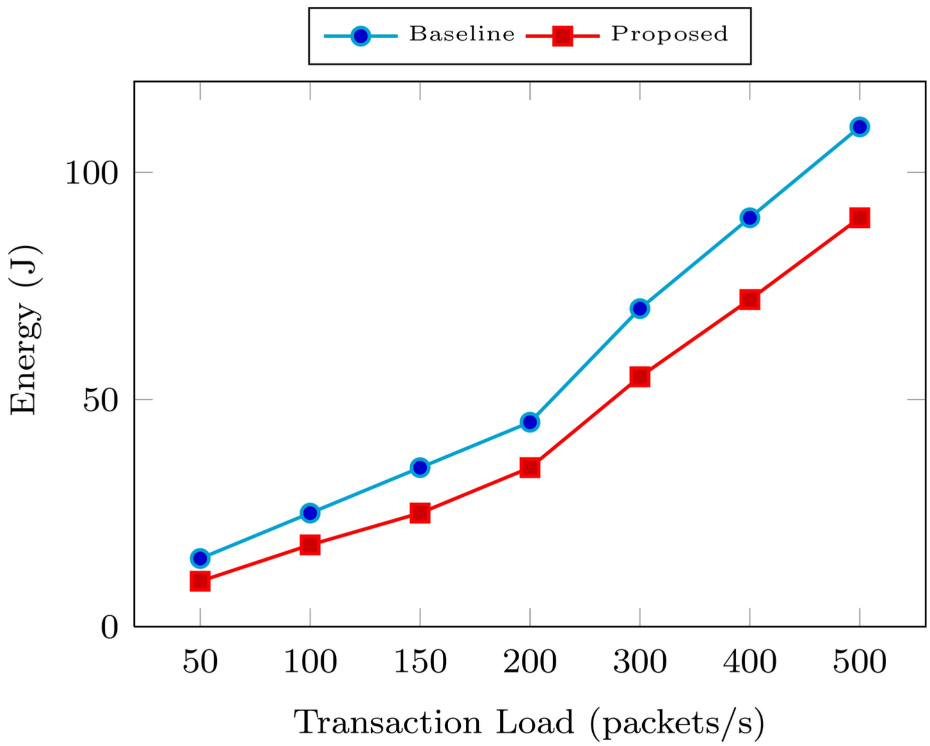

Figure 9. Energy efficiency comparison.

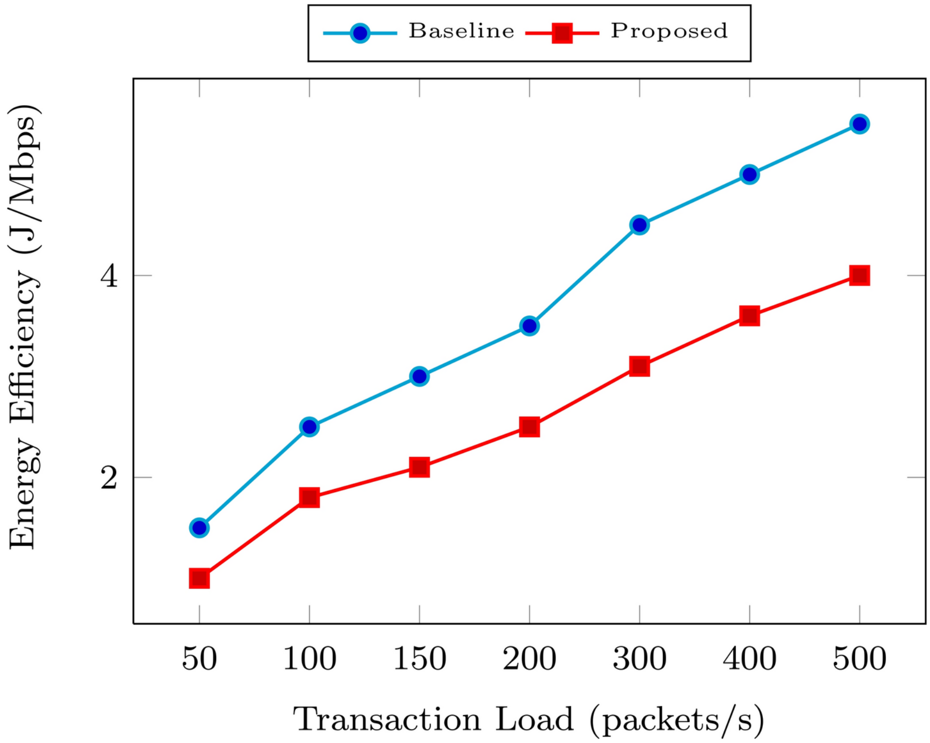

Figure 10. Comparison of energy consumption per unit throughput.

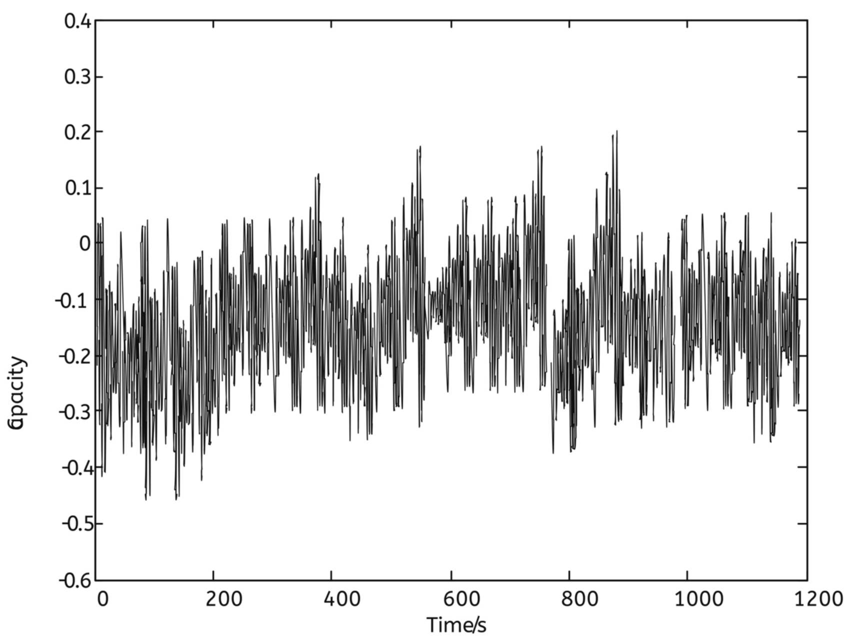

Figure 11. Relationship between the capacity of CCT of blockchain Internet of Things in the port area and the size of the time slice.

2.4ms, and the spatial link equilibrium parameters of the port blockchain IoT cross-chain are $\alpha = 0.37$ and $\beta = 2.5 \times 10^{-5}$. According to the parameter setting, the relationship between the capacity of the CCT of the port blockchain IoT and the size of the time slice is shown in Fig. 11.

According to the analysis of Fig. 11, through the time delay balance control of the cross-chain of the blockchain IoT in the port area, the capacity output balance of the CCT of the blockchain IoT in the port area is good. Set the number of subcarriers of the cross-chain network of the blockchain IoT in the port area to 120 and obtain the energy efficiency of the blockchain IoT in the port area, as shown in Figs. 12 and 13.

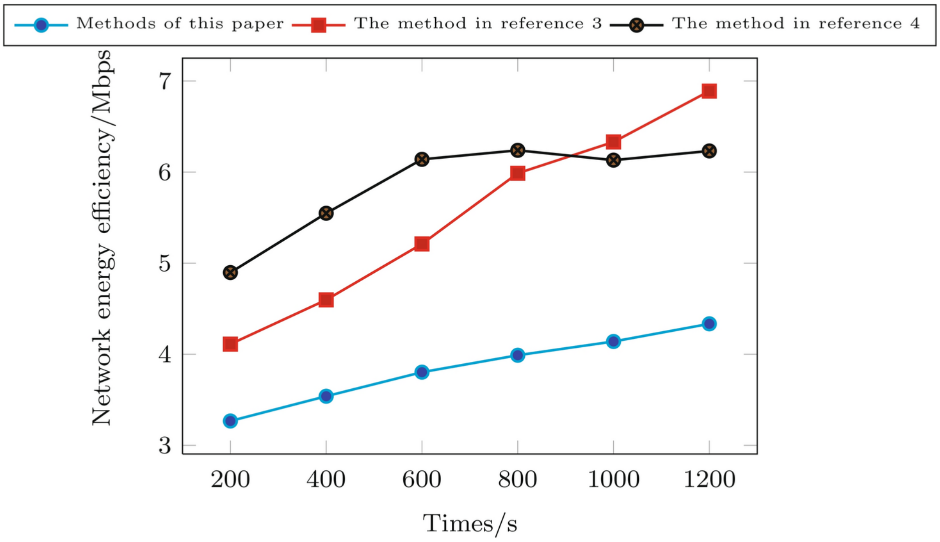

Figure 12. Energy efficiency distribution of cross-chain network of blockchain Internet of Things in port area—Cross-chain energy efficiency input of port blockchain Internet of Things.

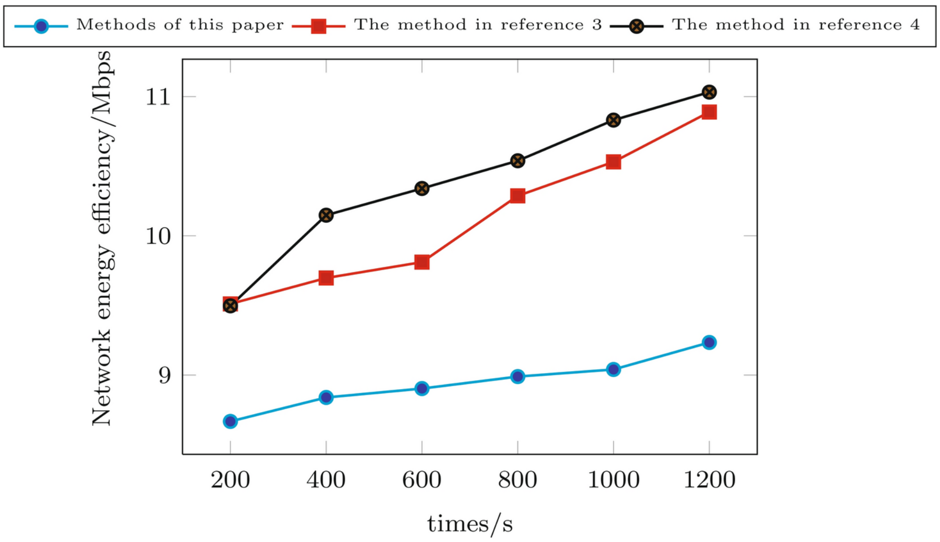

Figure 13. Energy efficiency distribution of cross-chain network of blockchain Internet of Things in port area—Cross-chain Energy Efficiency Output of Blockchain Internet of Things in Port Area.

According to the analysis of Figs. 12 and 13, through the adaptive multi-channel joint bus control, the energy efficiency overhead of the cross-chain network of the blockchain IoT in the port area is effectively restrained. In this paper, the average value of the cross-chain energy efficiency input of the blockchain Internet of Things in the port area is 5Mbps, that of the reference[34] method is 6.1Mbps, and that of the method in reference[35] is 5.8Mbps. This is because the method in this paper adopts load balancing scheduling to realize the compensation and adjustment of the joint autocorrelation dynamic characteristic parameters of the blockchain Internet of Things in the port area to improve the energy efficiency input effect. The maximum value of the cross-chain energy efficiency output of the Internet of Things in the port blockchain is 9Mbps, which is 10.2Mbps in the method of reference[34] and 10.9Mbps in the method of reference[35]. This is because the method in this paper realizes the interference suppression of the CCT of the Internet of Things in port blockchain according to the MFJL algorithm and effectively reduces the energy efficiency output.

By testing the network's average queue length and energy consumption overhead, the comparison result of the CCT efficiency of the blockchain IoT in the port area is shown in Figs. 14 and 15.

By analyzing Figures 14 and 15, it can be seen that through the balanced design of the CCT of the blockchain IoT in the port area, the average queue length of the cross-chain network of the blockchain IoT in the port area is higher, the energy consumption overhead is lower, and the reliability of network output is improved.

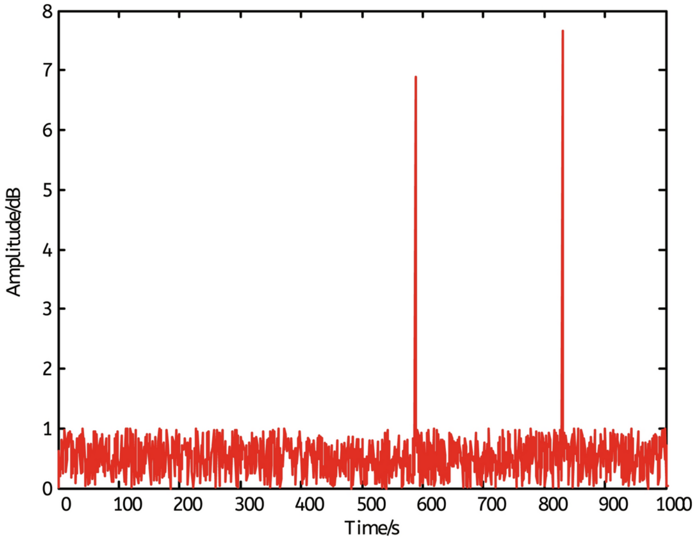

Figure 14. Average queue length of CCT of blockchain Internet of Things in the port area.

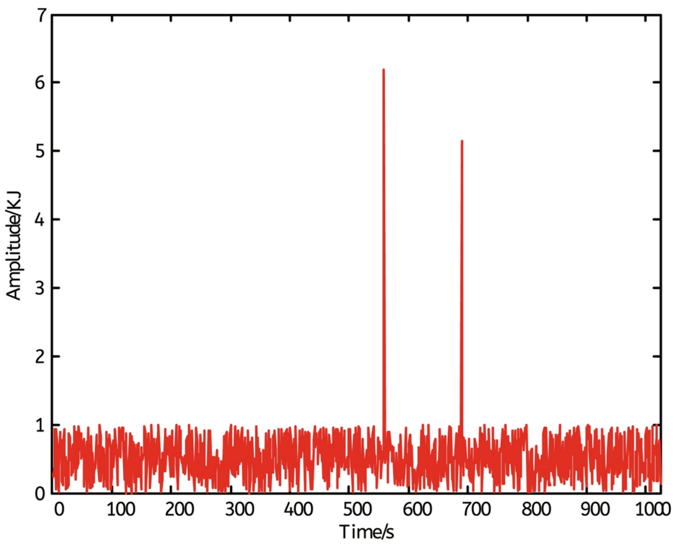

Figure 15. Energy consumption of the Internet of Things in the port area across the chain.

Conclusions

This study presents a load-adaptive cross-chain control framework for Blockchain IoT systems, designed to enhance efficiency, scalability, and security in dynamic environments like ports. Key findings include, Enhanced Load Balancing and Fault Tolerance, Distributed intelligent scheduling reduced load variance by 46.7% and improved fault recovery times by 45.5%, outperforming centralized methods. Privacy-Preserving Optimization, Federated learning safeguarded data privacy while achieving high model accuracy (within 2% of baseline) and reducing communication overhead by 60%. Improved Resource Utilization with MFJL, Multi-feature joint learning increased resource utilization by 33.3% and reduced transaction latency by 18.2%, even in high-interference scenarios. Energy Efficiency, The proposed method lowered energy consumption by 18.2% and improved energy efficiency per throughput by 27.3%. Scalability and Real-Time Adaptation, The framework demonstrated robust performance under high transaction loads and dynamic conditions, making it suitable for real-time Blockchain IoT applications. Future work will focus on real-world deployment and integrating reinforcement learning and advanced cryptographic methods for enhanced adaptability and security. This research provides a comprehensive and practical solution to the challenges of Blockchain IoT cross-chain transmission, bridging gaps in efficiency, scalability, and privacy.

Data availability
The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

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Author contributions
Z.X. conceived and designed the study. Z.X. and X.Z. collected the data and performed the experiments. Z.X. and X.L. analyzed the data and interpreted the results. Z.X. drafted the manuscript. All authors revised the manuscript critically for important intellectual content, and approved the final version of the manuscript for

publication.

Additional information

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