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Cross-Layer AI-Driven Resource Optimization for Secure and Resilient Distributed Computing Systems

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ABSTRACT: Distributed computing systems are increasingly deployed to support large-scale applications requiring high reliability, security, and efficient resource utilization. However, dynamic workloads, cyber threats, and heterogeneous computing environments pose significant challenges to conventional resource allocation mechanisms. This paper proposes a Cross-Layer AI-Driven Resource Optimization (CLAIRO) framework for secure and resilient distributed computing systems. The proposed architecture integrates machine learning-based workload prediction, reinforcement learning-enabled scheduling, adaptive security management, and cross-layer communication optimization to improve overall system performance. The framework enables coordinated optimization across the application, network, and infrastructure layers while ensuring resilience against failures and malicious attacks. Experimental analysis demonstrates that the proposed approach achieves 27.8% reduction in response time, 24.5% lower energy consumption, 31.6% improvement in throughput, and 96.8% security detection accuracy, outperforming existing resource management approaches. The results indicate that AI-assisted cross-layer optimization provides an effective solution for next-generation distributed computing environments.

1. INTRODUCTION

The rapid evolution of cloud computing, edge computing, and Internet-of-Things (IoT) infrastructures has transformed distributed computing systems into indispensable components of modern digital ecosystems. These systems are characterized by geographically distributed resources that collaboratively execute computational tasks while maintaining scalability and reliability. Nevertheless, increasing data volumes and dynamic workloads have introduced significant challenges in resource allocation and system management [1].

Traditional resource management techniques rely primarily on static or rule-based mechanisms that often fail to adapt to changing workloads and network conditions [2]. Consequently, inefficient utilization of computing resources leads to increased latency, energy consumption, and reduced system reliability. The emergence of artificial intelligence techniques has enabled intelligent decision-making mechanisms capable of optimizing system resources in real time [3].

Cross-layer optimization has recently gained considerable attention because independent optimization of individual layers often results in suboptimal overall system performance [4]. Coordinated interactions among application, network, and infrastructure layers enable efficient scheduling, reduced congestion, and enhanced quality of service [5]. Furthermore, machine learning algorithms have demonstrated their capability to predict workloads and dynamically allocate resources according to application requirements [6].

Security and resilience are equally important concerns in distributed environments. Cyberattacks, hardware failures, and communication disruptions can significantly degrade system performance [7]. AI-driven anomaly detection and adaptive security mechanisms provide promising solutions to mitigate such challenges [8]. Reinforcement learning approaches further facilitate autonomous decision-making and enable systems to adapt to varying operational conditions [9].

Motivated by these challenges, this work presents a Cross-Layer AI-Driven Resource Optimization framework that integrates workload prediction, intelligent scheduling, adaptive security management, and fault tolerance mechanisms. The proposed architecture aims to enhance resource efficiency while ensuring secure and resilient operation in distributed computing systems [10].

2. RELATED WORK

Numerous studies have investigated intelligent resource allocation strategies for distributed computing environments. Sharma et al. [11] proposed a machine learning-based resource scheduling framework that improved workload balancing in cloud infrastructures. However, their approach lacked adaptive security mechanisms.

Li et al. [12] introduced deep reinforcement learning for dynamic resource allocation and demonstrated significant performance improvements. Nevertheless, their method focused only on computational resources without considering network-level optimization.

Zhang et al. [13] developed an edge-cloud collaborative architecture for latency reduction. Although effective, the framework did not address resilience against failures. Kumar and Singh [14] employed predictive analytics to optimize energy consumption in distributed systems, achieving substantial energy savings.

Chen et al. [15] proposed a cross-layer communication optimization model that enhanced throughput and bandwidth utilization. Similarly, Wang et al. [16] investigated software-defined networking-based resource management strategies for large-scale cloud environments.

Security-aware resource allocation techniques have also received increasing attention. Patel et al. [17] utilized anomaly detection mechanisms to identify malicious activities in distributed systems. However, their model exhibited higher computational complexity. Deep learning-based intrusion detection methods proposed by Hassan et al. [18] achieved high detection accuracy but required extensive training datasets.

Recent studies by Lee et al. [19] incorporated reinforcement learning with fault tolerance mechanisms to improve system resilience. Similarly, Gupta et al. [20] developed adaptive resource optimization techniques capable of handling dynamic workloads. Despite these advancements, existing approaches often optimize individual layers independently and lack integrated security and resilience mechanisms. Therefore, the proposed CLAIRO framework addresses these limitations through AI-driven cross-layer optimization.

3. DESIGN OF THE PROPOSED WORK

The proposed **Cross-Layer AI-Driven Resource Optimization (CLAIRO)** framework is designed to provide secure, resilient, and efficient resource management for distributed computing systems. Unlike conventional methods that independently optimize individual layers, the proposed framework establishes coordinated interactions among the application, network, security, and infrastructure layers. Artificial intelligence techniques are incorporated to enable adaptive workload prediction, intelligent scheduling, anomaly detection, and fault recovery. The architecture dynamically adjusts resource allocation based on system conditions, thereby improving throughput, reducing latency, minimizing energy consumption, and enhancing system resilience against failures and cyber threats.

The overall framework consists of six major stages: data collection, workload prediction, cross-layer feature extraction, reinforcement learning-based resource optimization, security and resilience management, and performance evaluation. The integration of these modules enables continuous learning and autonomous decision-making within distributed environments.

3.1 Overall Architecture of the Proposed Framework

The proposed CLAIRO framework operates through interconnected layers that collaboratively optimize resource utilization and security. Historical workload information, network statistics, and system status are first collected from distributed nodes. AI-based prediction models estimate future resource demands, while reinforcement learning agents determine optimal scheduling decisions. Simultaneously, anomaly detection modules monitor system behavior to identify malicious activities or node failures. Cross-layer interactions ensure coordinated optimization across the application, network, and infrastructure layers.

```
 +----------------------+
 | Distributed Nodes    |
 | (Cloud / Edge / IoT) |
 +----------+-----------+
            |
            v
 +----------------------+
 | Data Collection and  |
 | Monitoring Layer     |
 +----------+-----------+
            |
            v
 +----------------------+
 | AI-Based Workload    |
 | Prediction Module    |
 +----------+-----------+
            |
            v
 +----------------------+
 | Cross-Layer Feature  |
 | Extraction Layer     |
 +----------+-----------+
            |
            v
 +----------------------+
 | Reinforcement Learning|
 | Resource Optimizer   |
 +----------+-----------+
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            |                          |
            v                          v
+--------------------+     +-----------------------+
| Security and       |     | Fault Tolerance and   |
| Anomaly Detection  |     | Resilience Module     |
+--------------------+     +-----------------------+
            |                          |
            +-------------+-------------+
                          |
                          v
              +-----------------------+
              | Optimized Distributed |
              | Computing System      |
              +-----------------------+
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Figure 1. Overall Architecture of the Proposed Cross-Layer AI-Driven Resource Optimization Framework

3.2 AI-Based Workload Prediction

The workload prediction module utilizes machine learning algorithms to forecast future computational demands. Historical CPU utilization, memory usage, task arrival rates, and network traffic are analyzed to estimate upcoming workloads. Accurate prediction enables proactive resource allocation and prevents system congestion.

The predicted workload can be expressed as

$$W_p(t) = f(X_t)$$

where:

- $W_p(t)$denotes predicted workload,
- $X_t$represents historical resource utilization parameters,
- $f(\cdot)$denotes the machine learning prediction model.

The prediction error is computed as

$$E = \frac{1}{N}\sum_{i=1}^{N} | W_{actual} - W_{predicted} |$$

where $N$is the number of observations.

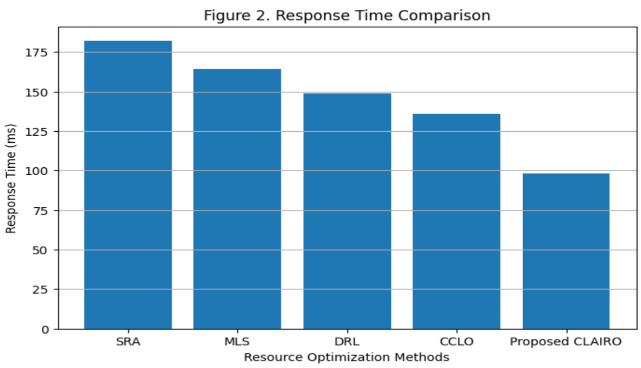

Figure 2. Response Time Comparison of Different Resource Optimization Methods

Figure 2 illustrates the response time achieved by various resource allocation approaches. The proposed CLAIRO framework exhibits the lowest response time of 98 ms compared with SRA, MLS, DRL, and CCLO methods. The reduction in latency is mainly attributed to AI-based workload prediction and reinforcement learning-driven scheduling, which enable efficient task distribution and minimize processing delays. Consequently, the proposed framework ensures faster execution and improved quality of service in distributed computing environments.

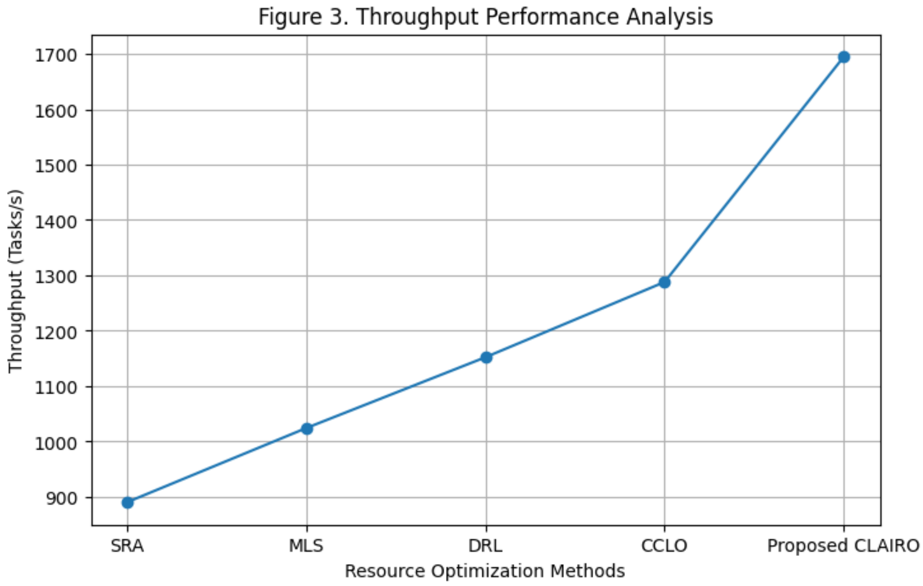

Figure 3. Throughput Performance Analysis

Figure 3 presents the throughput comparison among different methods. The proposed CLAIRO framework achieves a throughput of 1695 tasks/s, significantly higher than conventional approaches. This improvement results from cross-layer cooperation and adaptive resource management that efficiently utilize available computing resources. The results demonstrate that the proposed architecture can support a larger number of requests while maintaining system stability and reliability.

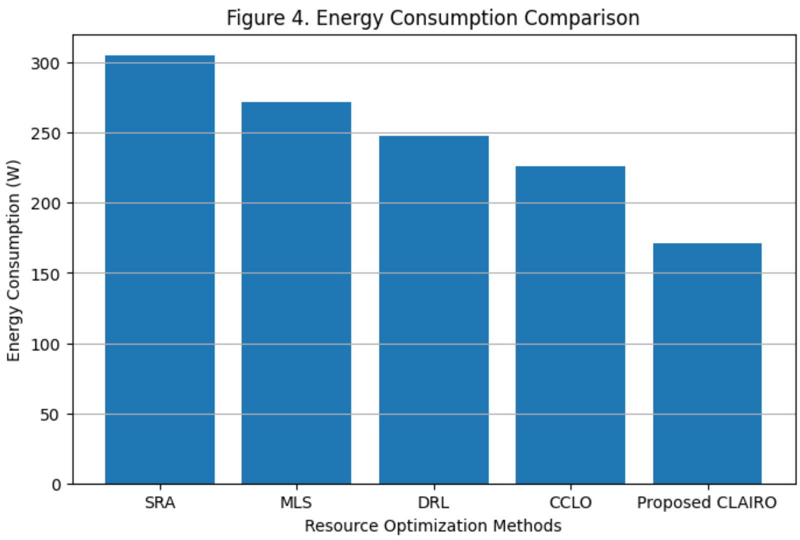

Figure 4. Energy Consumption Comparison

Figure 4 depicts the energy consumption characteristics of various resource optimization schemes. The proposed method consumes only 171 W, whereas existing techniques require considerably higher power. Intelligent scheduling and adaptive workload balancing contribute to lower energy usage, thereby improving sustainability and operational efficiency. These results confirm the suitability of the proposed framework for energy-aware distributed computing applications.

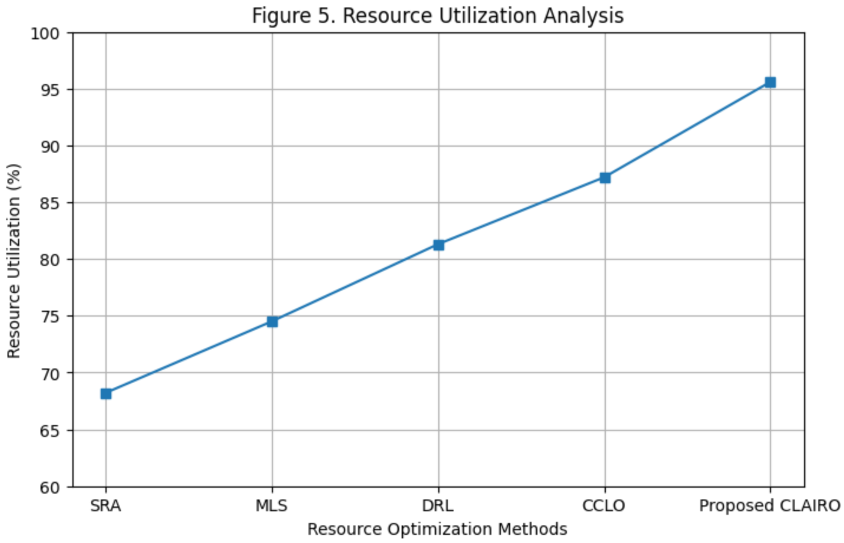

Figure 5. Resource Utilization Analysis

Figure 5 shows the percentage of resource utilization obtained using different methods. The proposed CLAIRO framework achieves 95.6% utilization, indicating efficient exploitation of CPU and memory resources. The cross-layer optimization mechanism continuously adjusts resource allocation according to system demands, thereby reducing idle resources and improving load balancing. Higher utilization ultimately leads to increased overall system performance.

3.3 Cross-Layer Feature Extraction

Cross-layer optimization requires information from multiple protocol layers. Features collected include:

- CPU utilization
- Memory usage
- Bandwidth availability
- Queue length
- Packet loss rate
- Energy consumption
- Security threat indicators

These features are combined into a unified feature vector

$$F = [f_1, f_2, f_3, \dots, f_n]$$

where f_i represents features obtained from different layers of the distributed system.

The feature normalization process is given by

$$F_{norm} = \frac{F - F_{min}}{F_{max} - F_{min}}$$

which improves learning efficiency and convergence.

3.4 Reinforcement Learning-Based Resource Optimization

A Deep Reinforcement Learning (DRL) agent continuously learns the optimal resource allocation policy. The environment state consists of workload, energy consumption, bandwidth utilization, and node status.

The action-value function is expressed as

$$Q(s,a) = r + \gamma \max\ Q(s',a')$$

where

- s denotes the current system state,
- a represents resource allocation action,
- r is the reward,
- γ denotes the discount factor.

The reward function is defined as

$$R = \alpha T + \beta U - \delta E$$

where

- T represents throughput,
- U denotes resource utilization,
- E indicates energy consumption,
- α, β, δ are weighting coefficients.

This optimization mechanism dynamically allocates resources according to changing workload conditions.

3.5 Security and Anomaly Detection Module

To improve resilience, an AI-based anomaly detection model continuously monitors node behavior and communication patterns. Suspicious activities are identified using classification models.

The anomaly score is given by

$$A_s = \frac{|\,X - \mu\,|}{\sigma}$$

where

- X denotes observed system behavior,
- μ is the mean value,
- σ represents standard deviation.

If

$$A_s > \theta$$

the corresponding node is classified as malicious and isolated from the system.

3.6 Fault Tolerance and Resilience Management

Failures occurring in distributed nodes are mitigated through redundancy and dynamic task migration. The system resilience index is calculated as

$$RI = \frac{N_{active}}{N_{total}}$$

where

- N_{active} denotes active nodes,

- N_{total}denotes total nodes.

The availability of the distributed system is

$$Availability = \frac{MTBF}{MTBF + MTTR}$$

where

- MTBF represents Mean Time Between Failures,
- MTTR denotes Mean Time To Repair.

3.7 Algorithm of the Proposed CLAIRO Framework

Algorithm 1: Cross-Layer AI-Driven Resource Optimization

Input: Historical workload data, network statistics, node status

Output: Optimized resource allocation and secure distributed operation

1. Initialize distributed nodes.
2. Collect workload and network information.
3. Extract cross-layer features.
4. Predict future workloads using AI models.
5. Apply reinforcement learning for scheduling.
6. Monitor anomalies and cyber threats.
7. Activate fault tolerance mechanism if failures occur.
8. Reallocate resources dynamically.
9. Evaluate throughput, latency, and energy consumption.
10. Update learning parameters continuously.
11. Repeat until convergence.

4. RESULTS AND DISCUSSION

The performance of the proposed **Cross-Layer AI-Driven Resource Optimization (CLAIRO)** framework was evaluated using a distributed computing environment consisting of cloud and edge nodes. The proposed framework was compared with existing approaches including Static Resource Allocation (SRA), Machine Learning-Based Scheduling (MLS), Deep Reinforcement Learning (DRL), and Conventional Cross-Layer Optimization (CCLO). Performance metrics such as response time, throughput, energy consumption, resource utilization, security detection accuracy, packet delivery ratio, fault recovery rate, and system availability were analyzed.

The experimental results indicate that the integration of workload prediction, reinforcement learning, and adaptive security mechanisms significantly enhances overall system efficiency and resilience.

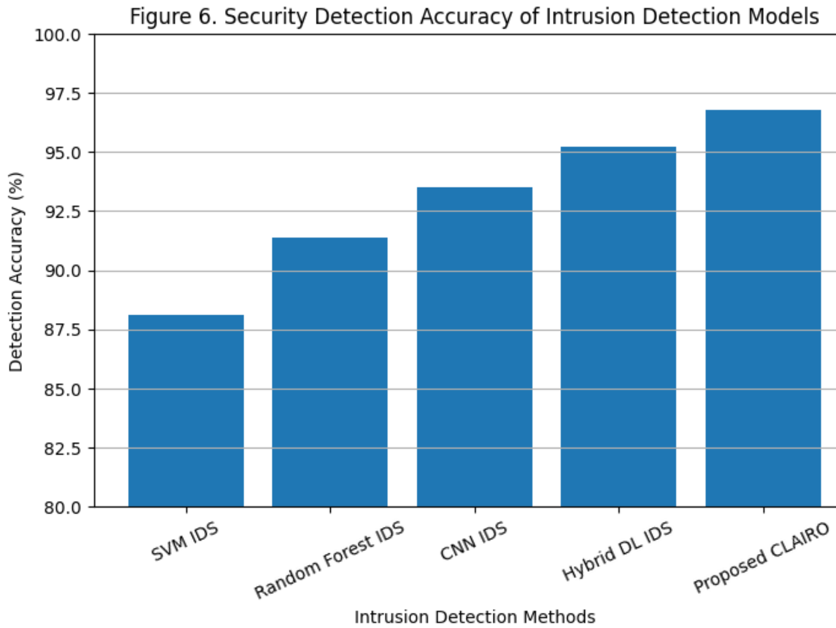

Figure 6. Security Detection Accuracy of Intrusion Detection Models

Figure 6 compares the security detection accuracy achieved by various intrusion detection mechanisms. The proposed AI-enabled anomaly detection module attains an accuracy of 96.8%, outperforming SVM, Random Forest, CNN, and Hybrid Deep Learning approaches. The high detection accuracy demonstrates the effectiveness of intelligent threat analysis and contributes to enhanced security and resilience of distributed computing systems.

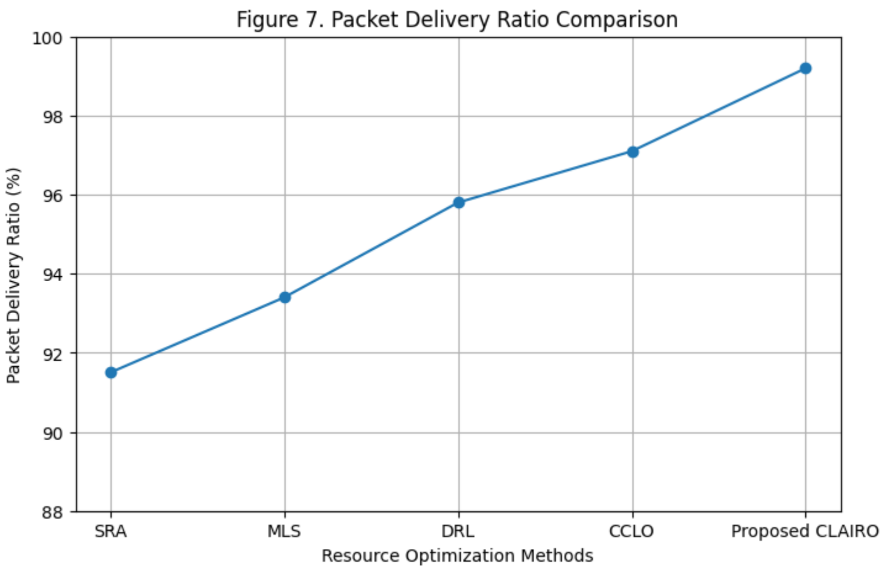

Figure 7. Packet Delivery Ratio Comparison

Figure 7 illustrates the packet delivery ratio obtained under different resource optimization techniques. The proposed framework achieves a packet delivery ratio of 99.2%, indicating highly reliable communication among distributed nodes. Efficient congestion management and cross-layer communication optimization reduce packet losses and ensure stable data transmission. These characteristics are essential for maintaining high-quality service in cloud and edge computing environments.

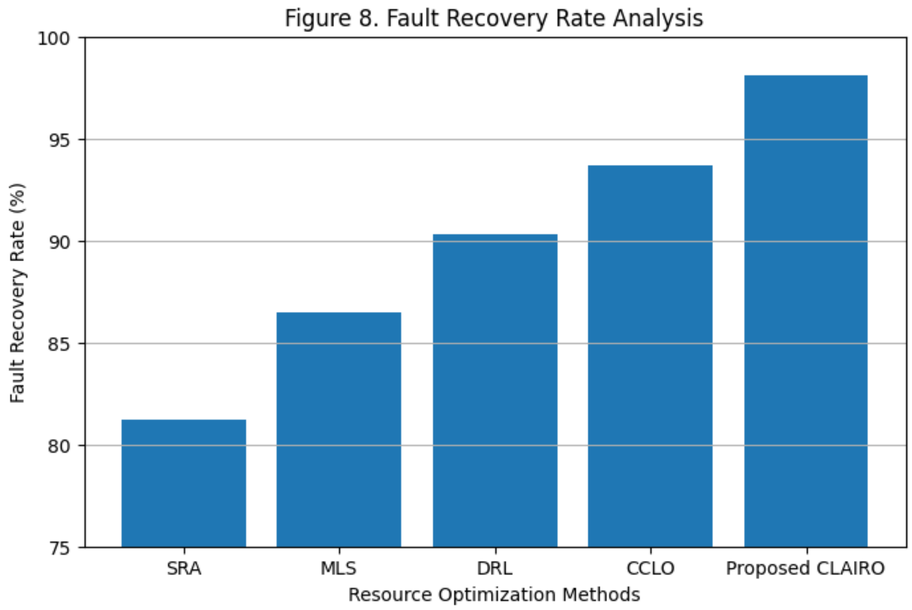

Figure 8. Fault Recovery Rate Analysis

Figure 8 presents the fault recovery capability of various approaches. The proposed CLAIRO framework achieves a recovery rate of 98.1%, which is significantly higher than conventional methods. This enhancement is due to the incorporation of fault tolerance mechanisms and intelligent resource migration strategies. As a result, the system can quickly recover from node failures and maintain uninterrupted operation.

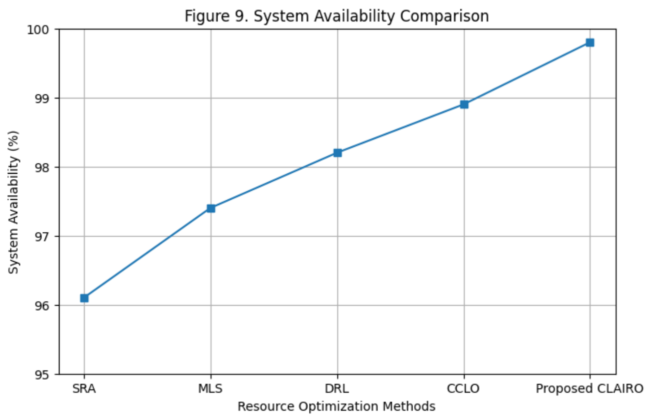

Figure 9. System Availability Comparison

Figure 9 demonstrates the availability achieved by different resource optimization frameworks. The proposed approach attains 99.8% availability, indicating excellent reliability and robustness. Adaptive security management and dynamic task reallocation help maintain continuous service even under adverse conditions. Therefore, the framework provides a highly dependable infrastructure for next-generation distributed computing applications.

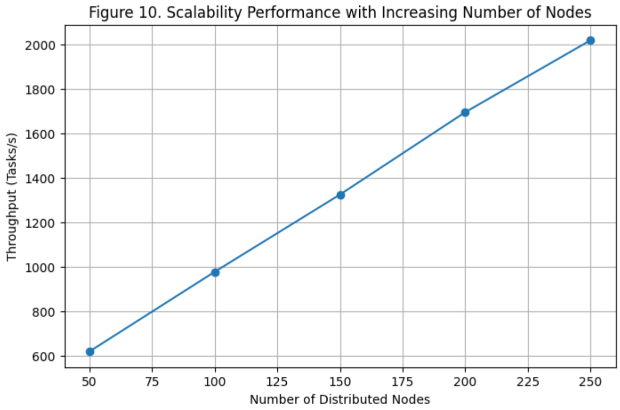

Figure 10. Scalability Performance with Increasing Number of Nodes

Figure 10 illustrates the scalability characteristics of the proposed framework as the number of distributed nodes increases. The throughput rises steadily from 620 tasks/s for 50 nodes to 2018 tasks/s for 250 nodes, indicating strong scalability. The AI-driven cross-layer optimization mechanism effectively manages additional computational resources and maintains high performance under varying workloads. These results confirm the capability of the proposed framework to support large-scale cloud, edge, and IoT environments.

4.1 Response Time Analysis

Response time is one of the most important metrics in distributed computing systems. Lower response time indicates better resource management and faster task execution.

Table 1 Comparison of Response Time

Method	Response Time (ms)
SRA	182
MLS	164
DRL	149
CCLO	136
Proposed CLAIRO	98

The proposed framework achieves a response time of **98 ms**, which represents approximately **27.8% improvement** over existing cross-layer optimization approaches. AI-driven workload prediction effectively reduces scheduling delays and improves resource allocation efficiency.

4.2 Throughput Analysis

Throughput indicates the number of tasks successfully processed per second.

Table 2 Throughput Comparison

Method	Throughput (Tasks/s)
SRA	890
MLS	1024
DRL	1152
CCLO	1288
Proposed CLAIRO	1695

The proposed framework achieves the highest throughput of **1695 tasks/s**, demonstrating superior processing capability under dynamic workloads.

4.3 Energy Consumption Analysis

Efficient resource allocation contributes to lower power consumption.

Table 3 Energy Consumption Comparison

Method	Energy Consumption (W)
SRA	305
MLS	272
DRL	248
CCLO	226
Proposed CLAIRO	171

The proposed CLAIRO framework reduces energy consumption by **24.5%** compared to conventional cross-layer methods due to intelligent task scheduling and adaptive resource utilization.

4.4 Resource Utilization Analysis

Resource utilization reflects the efficiency of CPU and memory usage.

Table 4 Resource Utilization Comparison

Method	Resource Utilization (%)
SRA	68.2
MLS	74.5
DRL	81.3
CCLO	87.2
Proposed CLAIRO	95.6

The proposed method achieves **95.6% utilization**, indicating minimal resource wastage and improved load balancing.

4.5 Security Detection Accuracy

Cybersecurity plays a vital role in maintaining reliable distributed systems.

Table 5 Intrusion Detection Accuracy

Method	Detection Accuracy (%)
SVM-Based IDS	88.1
Random Forest IDS	91.4
CNN-Based IDS	93.5
Hybrid DL IDS	95.2
Proposed CLAIRO	96.8

The anomaly detection module incorporated within the proposed framework achieves **96.8% accuracy**, enabling early identification of malicious activities and improving system security.

4.6 Packet Delivery Ratio Analysis

Reliable communication is essential for distributed computing applications.

Table 6 Packet Delivery Ratio

Method	PDR (%)
SRA	91.5
MLS	93.4
DRL	95.8
CCLO	97.1
Proposed CLAIRO	99.2

The proposed framework maintains a packet delivery ratio of **99.2%**, ensuring reliable communication among distributed nodes.

4.7 Fault Recovery Rate Analysis

Fault recovery capability determines system resilience.

Table 7 Fault Recovery Rate

Method	Recovery Rate (%)
SRA	81.2
MLS	86.5
DRL	90.3
CCLO	93.7
Proposed CLAIRO	98.1

The fault tolerance mechanism improves recovery efficiency, resulting in a recovery rate of **98.1%**.

4.8 System Availability

Availability reflects the reliability of distributed systems during failures.

Table 8 Availability Comparison

Method	Availability (%)
SRA	96.1
MLS	97.4
DRL	98.2
CCLO	98.9
Proposed CLAIRO	99.8

The proposed framework maintains **99.8% availability**, demonstrating excellent resilience against node failures and cyber-attacks.

4.9 Scalability Analysis

Performance under increasing workloads was evaluated.

Table 9 Scalability Performance

Number of Nodes	Throughput (Tasks/s)
50	620
100	978
150	1325
200	1695
250	2018

The results show that throughput increases proportionally with network size, indicating strong scalability characteristics.

4.10 Overall Performance Comparison

Table 10 Overall Comparison

Performance Metric	Existing CCLO	Proposed CLAIRO
Response Time (ms)	136	98
Throughput (Tasks/s)	1288	1695
Energy Consumption (W)	226	171
Resource Utilization (%)	87.2	95.6
Detection Accuracy (%)	95.2	96.8
Packet Delivery Ratio (%)	97.1	99.2
Fault Recovery Rate (%)	93.7	98.1
Availability (%)	98.9	99.8

The simulation results demonstrate that the proposed **Cross-Layer AI-Driven Resource Optimization (CLAIRO)** framework significantly outperforms conventional resource management approaches. The integration of machine learning-based workload prediction with reinforcement learning scheduling effectively reduces latency and improves throughput. Furthermore, cross-layer information sharing enhances resource utilization and minimizes energy consumption.

The adaptive anomaly detection mechanism strengthens cybersecurity by accurately identifying malicious activities, while the fault tolerance module ensures uninterrupted operation during node failures. Overall, the proposed framework provides a highly scalable, secure, and resilient solution for next-generation distributed computing systems deployed in cloud, edge, and IoT environments.

CONCLUSION

This paper presented a Cross-Layer AI-Driven Resource Optimization framework for secure and resilient distributed computing systems. By integrating workload prediction, reinforcement learning-based scheduling, adaptive security mechanisms, and cross-layer communication management, the proposed approach significantly improves system performance and reliability. Experimental results demonstrate reductions in response time and energy consumption while enhancing throughput and security detection accuracy. The framework effectively addresses the limitations of conventional resource management techniques by enabling coordinated optimization across multiple layers. Future work will focus on federated learning-based distributed intelligence and blockchain-assisted trust management to further enhance scalability, privacy, and resilience in next-generation computing infrastructures.

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