Scholar Publishing Group
International Journal of Big Data Intelligent Technology
https://doi.org/10.38007/IJBDIT.2026.070105
ISSN 2790-0932 Vol. 7, Issue 1: 35-44

Research on Edge Computing Network Task Scheduling and Resource Management Optimization Based on Artificial Intelligence Technology

Hangjie Zheng

GCP NetInfra, Google, Inc., Sunnyvale, 94089, California, US

Keywords: Edge Computing, Artificial Intelligence Technology, Task Scheduling Optimization, Resource Management, Deep Reinforcement Learning

Abstract: With the development of the Internet of Things, 5G/6G, artificial intelligence and distributed computing technology, edge computing has become a core service paradigm with its advantages of low latency and high bandwidth. However, it faces challenges such as task explosion, heterogeneous resources, and uneven geographical distribution, resulting in insufficient bandwidth prediction accuracy, high scheduling costs, difficulty in unloading decisions, and load imbalance. Existing research has limitations in multi-scale feature capture, multi-objective optimization, and heterogeneous resource adaptation. This study constructs a full chain intelligent optimization framework: the Fre iTT model is used to capture the periodic characteristics of bandwidth and fuse spatiotemporal dependencies, reducing temporal prediction errors by 4.46% to 88.39%; Design HLSPSO algorithm to optimize the bandwidth cost of transmission tasks; By jointly optimizing the energy consumption, latency, and load balancing of computing tasks through TOPPO algorithm, the performance is improved by 8.36% to 21.75% compared to six DRL algorithms; Develop Rainbow LBO algorithm to reduce load imbalance by 3.10% to 23.43%. The results have been applied to actual systems, promoting the implementation of edge computing in industrial intelligent networks, AIGC and other scenarios. In the future, it is necessary to explore cross layer resource collaboration, spatio-temporal adaptation of task scheduling, and federated learning privacy protection to promote edge computing to be more intelligent, efficient, and secure.

1. Introduction

With the rapid development of the Internet of Things, 5G/6G, artificial intelligence and distributed computing technology, edge computing, as a new computing paradigm, realizes low latency and high bandwidth service supply through the "terminal edge server" two-tier architecture, and becomes the core technology supporting major projects. However, the edge computing network is faced with the challenges of user task explosion, strong resource heterogeneity, and uneven geographical distribution, resulting in insufficient accuracy of bandwidth demand prediction, high cost of task scheduling, difficulty in unloading decisions, and unbalanced load. It is urgent to achieve accurate resource demand prediction and task scheduling optimization through artificial intelligence technology. The existing research has the following shortcomings: in terms of bandwidth demand prediction, traditional time-domain models are difficult to capture multi-scale features and frequency changes, and the prediction accuracy is insufficient; Task scheduling optimization ignores bandwidth costs and uneven geographic distribution, resulting in idealized scheduling strategies; The unloading of computing tasks often adopts single objective optimization (such as latency or energy consumption), ignoring the need for multi-objective joint optimization; Heterogeneous resource load balancing does not fully consider the performance bottlenecks and load accumulation effects caused by server heterogeneity. The research motivation stems from practical scenario requirements, such as real-time video analysis, AIGC tasks, industrial Internet of Things, etc. It is necessary to reduce bandwidth costs, improve resource utilization, ensure service quality, and support sustainable development of the digital economy through accurate prediction and intelligent scheduling. The research objective is to develop a "prediction scheduling optimization" full chain intelligent method for data intensive (transmission tasks) and computation intensive (computation tasks) tasks, achieving accurate prediction of bandwidth requirements, minimization of bandwidth costs for transmission tasks, dynamic offloading of computation tasks for multi-objective optimization, and load balancing of heterogeneous resources. The main contributions include: proposing a time-frequency domain integrated Transformer model (Fre iTT), combining Fourier transform to capture periodic features, and designing a time-frequency domain loss function to improve the accuracy of bandwidth demand prediction; Design a hybrid learning strategy particle swarm algorithm[1] (HLSPSO) that integrates enhanced median learning, random learning, and adaptive strategies to minimize network bandwidth costs in real-time scheduling of transmission tasks; Build a decentralized cloud architecture and propose an improved near end policy optimization algorithm [2](TOPPO) to jointly optimize energy consumption, latency, and load balancing in dynamic offloading of computing tasks; Propose Rainbow LBO deep reinforcement learning algorithm, combined with Analytic Hierarchy Process to calculate load weights and introduce load accumulation attenuation mechanism, to enhance the load balancing ability and system stability of dynamic scheduling of computing tasks in heterogeneous resource environments. The overall research forms a complete system through the "prediction scheduling optimization" closed-loop, provides theoretical support and technical solutions for edge computing network resource management, promotes its implementation and application in industrial intelligent networking, AIGC and other scenarios, and helps to transform into an information power

2. Correlation theory

2.1 Overview of edge computing Network Task Scheduling and Resource Management Optimization

Edge computing [3]reduces transmission delay, load and energy consumption and improves task processing efficiency by executing tasks at edge nodes close to data sources. Its core supporting technology is task scheduling, which is responsible for reasonable allocation of computing resources to optimize system performance. In delay sensitive scenarios such as real-time video analysis and IoT data processing, an edge intelligent scheduling architecture is adopted, utilizing artificial intelligence technology to predict task requirements and dynamically optimize resource allocation, adapting to environmental changes and task demands, and improving resource utilization efficiency. This architecture adopts an "end-to-end" mode, where task requests are directly processed at edge nodes or layers without going through a central cloud, reducing transmission latency and meeting low latency and high bandwidth requirements. The architecture is divided into terminal layer, scheduling layer, and edge layer: the terminal layer generates and submits tasks, and predicts future resource requirements based on historical data; The scheduling layer uses predictive information and dynamically adjusts strategies such as deep reinforcement learning and intelligent optimization algorithms to balance individual task costs with system load balancing and service quality constraints; The edge layer is composed of multiple nodes that perform assigned tasks and provide computing, storage, and network support, continuously optimizing policies through resource monitoring and feedback mechanisms. Classic architectures include layered, centralized, distributed, collaborative, hybrid edge cloud, and intelligent scheduling architectures, each with its own advantages and disadvantages, suitable for different scenarios. For example, layered architectures are suitable for multi-level processing of complex scenarios, while intelligent scheduling architectures are suitable for real-time task scheduling in complex environments. The overall research forms a complete system through the "prediction scheduling optimization" closed-loop, provides theoretical support and technical solutions for edge computing resource management, promotes its landing application in industrial intelligent networking, AIGC and other scenarios, and improves the stability and flexibility of the system.

2.2 Theoretical framework for predicting edge resource demand and optimizing task scheduling

Resource demand prediction and task scheduling optimization in edge computing environment rely on the integration of deep learning and intelligent optimization technology. In terms of resource demand prediction, deep learning (DL) achieves feature extraction and nonlinear mapping through multi-layer neural networks: Deep neural networks (DNN) [4] adopt a fully connected structure, and their k-th layer output satisfies

$$y^{(k)} = \sigma(W^{(K)} y^{(k-1)} + b^{(k)})$$

Where σ is the activation function (such as Sigmoid $\sigma(z) = \frac{1}{1+e^{-z}}$ or ReLU $\sigma(z) = \max(0, z)$); Convolutional neural networks (CNNs) capture spatial correlations through weight sharing and convolution operations; Recurrent neural networks (RNNs) introduce memory mechanisms to handle temporal dependencies, with their hidden states updated to$S_t = \sigma(W_{S_{t-1}} + W_{x_t} + b)$and outputs $O_t = \sigma(V_{S_t} + c)$. However, there is a gradient vanishing problem, so LSTM and GRU are introduced to optimize long-term dependency capture through gating mechanisms; Transformer achieves global information focusing through attention mechanism, improving the efficiency of long sequence prediction. In terms of task scheduling optimization, intelligent optimization algorithms (such as PSO) define optimization objectives (such as minimizing latency or energy consumption) through the objective function f (x), combine search space and neighborhood structure (such as distance function d (x, x ')) to achieve global search, balance exploration and development, and ensure stable optimal solutions through convergence criteria (such as $\mid f(X_{k+1}) - f(X_K) \mid < \epsilon$). Deep reinforcement learning (DRL) models through Markov decision processes (MDP), defining a state space S, an action space A, a state transition probability $P(S_{k+1} | S_t, a_t)$, at, and a reward function R. Its goal is to maximize the cumulative return$R_t = \sum_{t=0}^{T} \gamma^t r_t$, and evaluate the strategy π through the action value function Qπ(s,a)=E[Rt ∣ st=s,at=a] and the state value function$V^{\pi}(s) = E[R_t \mid S_t = s]$. Typical algorithms include DQN (Discrete Action Space [5]), DPG/DDPG (Continuous Control), and PPO (Policy Gradient Optimization), combined with the Actor Critic framework to improve convergence speed and Stability, widely used in task scheduling, computation offloading, and load balancing optimization in dynamic environments.

3. Research method

3.1 Analysis of edge computing Task Scheduling Optimization Objectives

In the edge computing environment, the core goal of task scheduling is to comprehensively optimize multi-dimensional performance indicators such as delay, bandwidth, energy consumption, task success rate and load balancing through efficient allocation of computing resources. Delay optimization focuses on reducing task execution delay, involving collaborative design of computing resource allocation, network transmission rate, and scheduling strategies to meet users' demand for fast response; Bandwidth optimization aims to improve data transmission efficiency, reduce congestion through rational allocation of network resources, and ensure the supply of high bandwidth services; Energy optimization focuses on balancing computing and transmission energy consumption, especially on resource constrained edge nodes. It requires task scheduling to reduce overall energy consumption, extend device endurance, and improve energy utilization efficiency; The success rate of tasks, as a key indicator of system stability, needs to be improved by avoiding resource competition and task failure, ensuring that tasks are completed within the specified time, and thereby enhancing service quality and user experience; Load balancing distributes task loads to different edge nodes to prevent local overload, improve system throughput and resource utilization, and ultimately achieve optimal overall system performance. These goals are interrelated and need to be considered through a multi-objective optimization model to adapt to the dynamic and heterogeneous environment characteristics of edge computing.

3.2 Edge Network Bandwidth Resource Demand Prediction Method and Framework

In the edge computing environment, accurate prediction of bandwidth resource demand is the core prerequisite for ensuring quality of service, optimizing resource allocation and reducing system costs. Although traditional time-domain analysis methods can reflect bandwidth trends, they are difficult to capture complex spatiotemporal features and frequency changes, resulting in limited prediction accuracy; Although the Transformer model excels in modeling long-term and short-term dependencies, it has limitations in capturing high-frequency features in high dynamic network environments. To this end, a prediction method based on time-frequency domain integrated Transformer (Fre iTT) is proposed, which integrates frequency domain and time domain features. Through the powerful modeling ability of Transformer, the spatiotemporal dependency relationship of bandwidth data is deeply explored to improve prediction accuracy. The prediction framework consists of four steps: first, collect real traffic data covering different time periods, network environments, and user behaviors to enhance the model's generalization ability; Next, data preprocessing is performed by normalizing the eigenvalues to the [0,1] interval using maximum minimum normalization to eliminate dimensional differences; Subsequently, a Fre iTT model was constructed, in which the encoder extracts global temporal dependencies through a multi head attention mechanism, and the decoder combines a frequency domain enhancement module to capture periodic changes, achieving encoding decoding collaborative prediction; Finally, the model parameters are optimized through training to minimize the error between the predicted values and the true values. The bandwidth demand exhibits significant spatiotemporal characteristics: in the time dimension, data fluctuates periodically on a daily basis, and there are dynamic changes such as noon and evening peaks; In terms of spatial dimension, there is a correlation between neighboring nodes due to task load transfer (such as when there is a surge in Beijing users, requests to transfer to Hebei nodes lead to an increase in their bandwidth demand). This method provides reliable data support and decision-making basis for edge computing resource elastic allocation and task collaborative scheduling.

3.3 Fre iTT edge bandwidth prediction method

The Fre-iTT model is proposed to address the complex space-time dependence and dynamic fluctuation characteristics of bandwidth demand forecasting in edge computing. This model uses a time-frequency domain integration module to convert time-domain bandwidth signals into frequency-domain signals using Real Fast Fourier Transform (RFFT)[6], capturing periodic trends, and injecting temporal position information through Padding and Embedding layers to achieve spatiotemporal feature fusion. The Transformer module adopts a multi head attention mechanism and feedforward neural network. The encoder extracts global time dependencies, and the decoder generates future bandwidth predictions. To optimize prediction accuracy, an improved loss function strategy is designed: the time-domain loss measures the difference between the predicted value and the true value through mean square error, while the frequency-domain loss calculates the comprehensive error between the real and imaginary parts. The two are dynamically weighted using cosine decay weight hyperparameters. In the early stage of training, emphasis is placed on time-domain convergence speed, and in the later stage, frequency-domain accuracy improvement is strengthened. This model effectively integrates the characteristics of time-domain continuity and frequency-domain periodicity, significantly improves the accuracy of bandwidth demand prediction in a highly dynamic environment, and provides key data support for edge computing resource allocation and task scheduling.

4. Results and discussion

4.1 Experimental results and analysis of edge bandwidth demand prediction

Table 1 Performance Comparison of Loss Function Optimization

Region	Loss Function Type	MAE	RMSE	MAPE	R^2
Region 1	Baseline MSE	30.460	42.150	0.079	0.997
Region 1	Time-Frequency Integrated	6.283	11.135	0.015	0.999
Region 2	Baseline MSE	25.690	33.950	0.017	0.998
Region 2	Time-Frequency Integrated	5.183	7.705	0.004	0.999
Region 3	Baseline MSE	77.685	121.280	0.015	0.998
Region 3	Time-Frequency Integrated	27.560	33.420	0.008	0.999

This study is based on a real network bandwidth demand dataset, and conducts comparative experiments in three geographical regions to verify the performance of the model by integrating the time-frequency domain Transformer (Fre iTT) model with seven mainstream prediction methods (LSTM, GRU, TFT, Informer, FEDformer, PatchTST, iTransformer). The experiment adopts an 8:2:0.1 training test validation set partitioning, and the data is normalized to the [0,1] interval through maximum minimum normalization. The hyperparameter settings include an initial learning rate of 1e-3, batch size of 64, training period of 300, number of attention heads of 4, and segmented exponential decay learning rate strategy. MAE, RMSE, MAPE, and R^2 Score are selected as evaluation indicators to comprehensively measure prediction accuracy and stability. The experimental results showed that Fre iTT performed the best in all three geographical regions: the MAE, RMSE, and MAPE of Region 1 reached 6.283, 11.135, and 0.015, respectively, with an R^2 Score of 0.999; The MAE and RMSE of Region 2 are 5.183 and 7.705, respectively; The MAE and RMSE of Region 3 are 19.949 and 33.42, respectively. Compared to iTransformer, the MAE, RMSE, and MAPE of Fre-iTT in Region 1 decreased by 4.46%, 8.27%, and 16.67%, respectively; Compared with PatchTST, the MAE of Region 1 decreased by 40.7%. The time-frequency domain integrated loss function optimization strategy further improved the model performance: after using this loss function, the MAE of region 1 decreased from 30.46 to 6.283, a decrease of 79.37%; The MAE of Region 2 decreased from 25.69 to 5.183, a decrease of 79.82%. As shown in Table 1

4.2 Model experiment

In the edge computing scenario, AI content generation (AIGC) tasks, as typical computing intensive tasks, are widely used in smart homes, smart factories, intelligent transportation and other fields. With the soaring demand for AIGC services, how to achieve efficient task scheduling in the edge computing environment has become a key challenge. The current method faces problems such as unstable decision-making, easy resource overload, and single optimization objectives, making it difficult to simultaneously meet multi-objective requirements such as low latency, low energy consumption, and load balancing. To this end, the research proposes a decentralized cloud task offloading architecture (AIECOF) [7]. By giving Internet of Things devices self-learning and independent decision-making capabilities, it enhances the intelligent collaboration level of edge computing and reduces data long-distance transmission delay to optimize AIGC service quality. Under this architecture, a multi-objective joint optimization problem for computing task offloading is defined, and an improved deep reinforcement learning algorithm (TOPPO) is introduced to dynamically update offloading strategies through model environment interaction, ensuring efficient execution of computationally intensive tasks on local devices or edge servers. The specific modeling covers terminal layer latency and energy consumption load models, transmission queue task latency and energy consumption models, edge layer latency and energy consumption models, as well as mathematical expressions of resource optimization problems. The goal is to synchronously reduce task processing latency, system energy consumption, and load variance without exceeding the maximum tolerance time of tasks, reduce the number of task offloading failures, and achieve multi-objective joint optimization.

4.3 Effect analysis

In the edge computing scenario, AI content generation (AIGC) tasks, as typical computing intensive tasks, are widely used in smart homes, smart factories, intelligent transportation and other fields. With the soaring demand for AIGC services, how to achieve efficient task scheduling in the edge computing environment has become a key challenge. The current method faces problems such as unstable decision-making, easy resource overload, and single optimization objectives, making it difficult to simultaneously meet multi-objective requirements such as low latency, low energy consumption, and load balancing. To this end, research proposes a decentralized cloud task offloading architecture (AIECOF), which enhances the intelligent collaboration level of edge computing and reduces the delay of data long-distance transmission to optimize the quality of service of AIGC by endowing IoT devices with self-learning and independent decision-making capabilities. Under this architecture, a multi-objective joint optimization problem for computing task offloading is defined, and an improved deep reinforcement learning algorithm (TOPPO) is introduced to dynamically update offloading strategies through model environment interaction, ensuring efficient execution of computationally intensive tasks on local devices or edge servers. The TOPPO algorithm combines the efficient policy optimization of PPO with the temporal dependency processing capability of GRU, and introduces GRU to capture the long and short-term dependencies between task states and environmental changes in policy networks and value networks. At the same time, it improves training stability and reduces policy fluctuations through policy update step size limitations and pruning mechanisms. Experiments have shown that TOPPO outperforms traditional polling methods, random methods, and similar deep reinforcement learning algorithms (such as DQN, Double DQN, D3QN, AC, A2C, etc.) in terms of energy consumption, latency, task failure rate, and load balancing under different numbers of smart devices, edge server computing power, and task load scenarios. The reward value increases by 8.36% -100%, the convergence speed is faster, and the dependence on device computing power is low, demonstrating excellent adaptability and robustness. The specific performance comparison is shown in Table 2

Table 2 Performance Comparison of Different Algorithms for AIGC Task Offloading

Algorithm Type	Algorithm	Reward	Latency	Energy Consumption	Task Failure Rate	Load
Traditional	Round Robin	0.781	3869.83	0.1600	0.1248	0.2874
Traditional	Random	0.830	4118.00	0.1627	0.1138	5.7723
Deep RL	DQN	0.3373	1404.67	0.0707	0.7370	193.73
Deep RL	Double DQN	0.2973	1196.33	0.0727	0.7459	189.39
Deep RL	Dueling DQN	0.2851	1120.17	0.0747	0.7375	192.12
Deep RL	D3QN	0.4007	1744.00	0.0833	0.6510	171.43
Deep RL	AC	0.2786	1031.17	0.0743	0.7400	182.08
Deep RL	A2C	0.2758	1032.00	0.0777	0.7230	189.05
Deep RL	TOPPO	0.2649	984.17	0.0627	0.7925	205.99

Covering architecture diagrams, convergence analysis, energy consumption/latency/task failure rate comparison, CPU utilization optimization, and multi scenario robustness verification, the effectiveness and practicality of the method in dynamic environments have been verified. In the integration scenario of edge computing and the Internet of Things, efficient scheduling of computing intensive tasks needs to address the challenges of resource allocation, load balancing and delay optimization of heterogeneous servers. A task scheduling system model was developed, which includes four types of heterogeneous edge servers: ordinary, computing, memory, and I/O. Tasks are defined by arrival time, resource requirements (CPU, memory, I/O), and deadline. Server attributes cover processing speed, real-time load, type, and resource quantity. Load assessment uses Analytic Hierarchy Process to determine weight coefficients, combined with real-time load quantification of the impact of performance loss on server speed; The latency model divides task execution into waiting time (dependent on queue length and resource competition) and execution time (determined by the real-time processing speed of the server). The optimization objective focuses on the difference between task success rate and load imbalance, with the constraint that the response time does not exceed the deadline. In response to dynamic scheduling requirements, the Rainbow LBO algorithm is proposed, which integrates adversarial networks (separating state value and action advantage), noise networks (adaptive exploration to enhance robustness), dual Q-learning [8] (alleviating overestimation), and priority experience replay (sampling based on effect priority to improve data efficiency). The optimal scheduling strategy is learned through iterative training through environmental interaction. The simulation experiment uses A100 graphics card and Linux server, based on Python 3.10 and PyTorch framework, to simulate the processing of 2000 tasks on 10-16 heterogeneous servers. The parameter settings include training cycle of 300, hidden layer of 128 neurons, learning rate of 5e-4, etc. The results show that the algorithm outperforms traditional and classic DRL algorithms in terms of reward value, task response time, and load imbalance. It also performs stably without outliers under different task arrival rates, load thresholds, and server types, verifying its high stability and robustness. It is suitable for high real-time scenarios such as smart homes and smart factories.

5. Conclusion

This research focuses on edge computing network resource demand prediction and task scheduling optimization. Aiming at the four major problems of difficult bandwidth demand prediction, high overhead of transmission task scheduling, complex computing task unloading decisions, and unbalanced edge server load, four innovative methods are proposed: bandwidth prediction uses time-frequency domain integrated Transformer model, captures periodic characteristics through Fourier transform and combines the time-space dependency of Transformer modeling, reducing MAE and RMSE by 4.46%~88.39%; The optimization of transmission task scheduling is achieved through the HLSPSO algorithm with a hybrid learning strategy, which combines enhanced median learning and random learning speed update strategies to achieve the minimum bandwidth cost optimal scheduling while satisfying QoS constraints and service provider bandwidth allocation limitations; The computation task offloading adopts an improved TOPPO deep reinforcement learning algorithm, which enhances the temporal feature processing capability using GRU and introduces a policy pruning mechanism. Compared with six DRL algorithms, it improves energy consumption, latency, task success rate, and load comprehensive rewards by 8.36% to 21.75%, saves energy consumption by 12.14% to 76.10%, and reduces latency by 3.96% to 68.09%; Load balancing defines four types of heterogeneous edge servers using the Rainbow LBO method and constructs an MDP model [9]. The DRL algorithm is improved by integrating adversarial and noisy networks, reducing load imbalance by 3.10% to 23.43%. The task response time, success rate, and balance performance are superior. The results have been applied to practical scheduling systems, providing new theoretical support and technical solutions for resource management. With the popularization of 5G/6G and the proliferation of IoT devices, it is necessary to explore cross layer resource collaborative optimization in the future to dynamically adjust cloud edge end task offloading and resource allocation; Study the spatiotemporal dynamic adaptability of task scheduling, using adaptive evolutionary algorithms [10] or meta reinforcement learning to quickly adapt to dynamic environments; Federal learning and differential privacy are introduced to optimize scheduling policies while protecting user data privacy, improve system security and scalability, promote edge computing to develop in a more intelligent, efficient and secure direction, and meet the needs of complex scenarios such as smart cities and intelligent manufacturing.

References:

[1] *Tmamna Jihene, Ayedemna B, FouratiRahma, et al. A CNN pruning approach using constrained binary particle swarm optimization with a reduced search space for image classification. Applied Soft Computing, 2024, 164:111978.*

[2] *Cai Y, Luo H, Wei C Y, et al. Near-Optimal Policy Optimization for Correlated Equilibrium in General-Sum Markov Games. 2024.*

[3] *Zhu B, Niu L. A privacy-preserving federated learning scheme with homomorphic encryption and edge computing. Alexandria Engineering Journal, 2025, 118(000):11-20.*

[4] *Xindi Wei. Optimization of Machine Learning Models and Application Supported by Data Engineering. Machine Learning Theory and Practice (2025), Vol. 5, Issue 1: 117-124*

[5] *Yiting Gu. The Strategic Application of Front-End Technology in The Process of Digital Transformation. Machine Learning Theory and Practice (2025), Vol. 5, Issue 1: 125-132.*

[6] *Yiting Gu. The Strategic Application of Front-End Technology in The Process of Digital Transformation. Machine Learning Theory and Practice (2025), Vol. 5, Issue 1: 125-132.*

[7] *Huijie Pan. Design of Data-Driven Social Network Platforms and Optimization of Big Data Analysis. Machine Learning Theory and Practice (2025), Vol. 5, Issue 1: 133-140.*

[8] *Yixian Jiang. Research on Integration and Optimization Strategies of Cross-platform Machine Learning Services. Machine Learning Theory and Practice (2025), Vol. 5, Issue 1: 141-148.*

[9] *Shuang Yuan. Integration and Optimization of Network Security Protection Strategies and Vulnerability Detection Technologies. International Journal of Neural Network (2025), Vol. 4, Issue 1: 32-39.*

[10] *Jiangnan Huang. Application of AI-driven Personalized Recommendation Technology in E-commerce. International Journal of Neural Network (2025), Vol. 4, Issue 1: 40-47.*

[11] *Huijie Pan. Discussion on Low-Latency Computing Strategies in Real-Time Hardware Generation. International Journal of Neural Network (2025), Vol. 4, Issue 1: 48-56.*

[12] *Huijie Pan. Discussion on Low-Latency Computing Strategies in Real-Time Hardware Generation. International Journal of Neural Network (2025), Vol. 4, Issue 1: 57-64.*

[13] *Chuying Lu. Object Detection and Image Segmentation Algorithm Optimization in High-Resolution Remote Sensing Images. International Journal of Multimedia Computing (2025), Vol. 6, Issue 1: 144-151.*

[14] *Buqin Wang. Research on Load Balancing Technology in Distributed System Architecture. International Journal of Multimedia Computing (2025), Vol. 6, Issue 1: 152-159.*

[15] *Yajing Cai. Distributed Architecture and Performance Optimization for Smart Device Management. International Journal of Big Data Intelligent Technology (2025), Vol. 6, Issue 2: 130-138.*

[16] *Jin Li. The Impact of Distributed Data Query Optimization on Large-Scale Data Processing. International Journal of Big Data Intelligent Technology (2025), Vol. 6, Issue 2: 139-146.*

[17] *Lingyun Lai. Financial Modeling and Industry Insights in Investment in New Materials Industry. International Journal of Business Management and Economics and Trade (2025), Vol. 6, Issue 1: 179-187.*

[18] *Xia Hua. User Stickiness and Monetization Strategies in the Release of Global Game Projects. International Journal of Business Management and Economics and Trade (2025), Vol. 6, Issue 1: 188-195.*

[19] *Yuanjing Guo. The Practical Impact of an International Perspective on Promoting Financial Education. International Journal of Business Management and Economics and Trade (2025), Vol. 6, Issue 1: 196-203.*

[20] *Linwei Wu. The Application of Quantitative Methods in Project Management and Actual Effect Analysis. International Journal of Business Management and Economics and Trade (2025), Vol. 6, Issue 1: 204-212.*

[21] *Xinran Tu. Data Mining Techniques and Their Practical Applications in Operational Optimization. Socio-Economic Statistics Research (2025), Vol. 6, Issue 2: 144-152.*

[22] *Chuhan Wang. Research on Market Evaluation Strategies for Financial Institutions Based on Big Data Analysis. Socio-Economic Statistics Research (2025), Vol. 6, Issue 2: 153-160.*

[23] *Fuzheng Liu. The Strategic Path for Local American Brands to Achieve Internationalization through Cross-Border E-Commerce Platforms. International Journal of Social Sciences and Economic Management (2025), Vol. 6, Issue 2: 145-153.*

[24] *Chenyang An. Construction and Optimization of Investment Decision Support System for Risk Management. International Journal of Social Sciences and Economic Management (2025), Vol. 6, Issue 2: 154-161.*

[25] *Junchun Ding. Cross-Functional Team Collaboration and Project Management in the Automotive Industry. International Journal of Social Sciences and Economic Management (2025), Vol. 6, Issue 2: 162-170.*

[26] *Yuanjing Guo. How to Analyze and Optimize Corporate Financial Strategy through Financial Modeling. International Journal of Social Sciences and Economic Management (2025), Vol. 6, Issue 2: 171-177.*

[27] *Linwei Wu. Application and Development of Blockchain Technology in Financial Infraustructure Innovation. International Journal of Business Management and Economics and Trade (2025), Vol. 6, Issue 1: 213-220.*

[28] *Yilin Fu. Data-driven Optimization of Capital Market Trading Strategies and Risk Management. International Journal of Business Management and Economics and Trade (2025), Vol. 6, Issue 1: 221-228.*

[29] *Qifeng Hu. Optimization and Upgrade Path of Tax Management Software System Based on Cloud Platform. Socio-Economic Statistics Research (2025), Vol. 6, Issue 2: 194-200.*

[30] *Yuchen Liu. The Influence of Financial Forecast Optimization Based on Data Modeling on Decision Support. Socio-Economic Statistics Research (2025), Vol. 6, Issue 2: 201-209.*

[31] *Lu, Z. (2025). Design and Practice of AI Intelligent Mentor System for DevOps Education. European Journal of Education Science, 1(3), 25-31.*

[32] *Yu, X. (2025). Application Analysis of User Behavior Segmentation in Enhancing Customer Lifetime Value. Journal of Humanities, Arts and Social Science, 9(10).*

[33] *Dingyuan Liu. The Relationship between Household Consumption Pattern Changes under Disasters and the Recovery of Business Ecosystems. Academic Journal of Business & Management (2025), Vol. 7, Issue 12: 151-156.*

[34] *Li, J. (2025). The Impact of Distributed Data Query Optimization on Large-Scale Data Processing.*