Advances in Computer, Signals and Systems (2025)
Clausius Scientific Press, Canada

DOI: 10.23977/acss.2025.090201
ISSN 2371-8838 Vol. 9 Num. 2

Design and implementation of a low-latency network scheduling algorithm for edge-oriented computing

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Keywords: Edge Computing, Low Latency, Network Scheduling Algorithm, Resource Allocation, Task Priority

Abstract: With the rapid development of the Internet of Things and real-time applications, the demand for low-latency network scheduling by edge computing is becoming increasingly urgent. However, traditional scheduling algorithms face the challenges of high latency and insufficient efficiency in dynamic task allocation, resource heterogeneity, and burst traffic scenarios. This paper designs and implements a low-latency network scheduling algorithm for edge computing. By building a hierarchical scheduling framework, combining dynamic task priority evaluation and resource pre-allocation mechanism, the collaboration efficiency between edge nodes is optimized. The algorithm adopts a distributed task queue management strategy, dynamically adjusts the task distribution weight, and introduces a lightweight feedback mechanism to correct scheduling decisions in real time. Experimental results show that in a simulated edge computing environment, compared with the classical scheduling algorithm, the algorithm in this paper reduces the average latency by 28.7%, the task completion rate increases by 19.4%, and can maintain a stable throughput in high concurrency scenarios. The research verifies the effectiveness of the proposed algorithm in reducing end-to-end latency and improving resource utilization, and provides new solutions for real-time service scheduling in edge computing scenarios.

1. Introduction

The rapid development of the Internet of Things, 5G, and AI technologies has driven the rise of edge computing, which sinks computing resources to the edge of the network, effectively reduces data transmission distance, reduces latency, and improves user experience. In areas such as autonomous driving, telemedicine, and the industrial Internet, millisecond-level delay differences in edge computing are critical to system reliability and safety. The wide application of edge computing also faces challenges, such as the limited resources of edge nodes and the complex network environment. Low-latency network scheduling, as the core, aims to optimize task allocation and resource scheduling to meet high real-time requirements. In the industrial Internet of Things, low-latency scheduling ensures real-time monitoring and rapid response of equipment status to avoid production accidents. Although researchers have made progress in low-latency network scheduling, such as on-board edge computing network load balancing strategy and multi-user edge computing task uninstallation scheduling algorithm, the existing studies focus on single target optimization and lack multi-target collaborative optimization. With the expansion of edge computing scale, efficient

low-latency scheduling in large-scale heterogeneous networks still needs to be explored. Therefore, the research of low-latency network scheduling algorithm for edge computing is of theoretical and practical significance, which can provide support for the design of edge computing system, promote technological development, improve the practical application performance by optimizing the network scheduling strategy, and provide technical support for innovation in smart medical and other fields. This paper aims to design a low delay network scheduling algorithm for edge computation, comprehensively considering task features, network states and resource constraints to achieve delay minimization. The research results will enrich the theoretical system of edge computing, and provide new ideas for the practical application performance optimization.

The existing research has both results and shortcomings, highlighting the importance and necessity of carrying out relevant research. The research objectives clearly aim to solve key problems, which is expected to promote the development of edge computing.

2. Related technology and research status

Edge computing migrates computing, storage, and network resources to the edge of the network to reduce the physical distance between data processing and users, reduce latency, and improve the response speed. It is closer to data sources and terminal devices, and can process large amounts of data locally and reduce reliance on the core network. In the Industrial Internet of Things, edge computing can process sensor data in real time to avoid latency problems. Edge computing features include low latency, high bandwidth utilization, and localization power. Low latency is critical in real-time applications, such as autonomous driving. High bandwidth utilization reduces data transmission volume and avoids network congestion. Localization power enables edge computing to operate in disconnected or unstable situations. The edge computing architecture is divided into three layers: the terminal device layer, the edge layer, and the cloud layer. The terminal device layer is responsible for data acquisition and generation; the edge layer is responsible for data preprocessing and storage; the cloud provides large-scale computing and storage resources for complex tasks. This hierarchical architecture enables edge computing to respond flexibly to different task requirements. Edge computing works by "processing data nearby". When the terminal device generates the data, the edge server decides to process it locally or upload it to the cloud. For example, in the video surveillance system, the edge server analyzes the video stream in real time and only uploads the keyframes to the cloud, reducing the network pressure. The requirements of network scheduling for edge computing include an efficient resource scheduling algorithm, a low-latency communication mechanism, and energy consumption optimization. The computing power of the edge server should be reasonably allocated in multi-user scenarios. In the industrial Internet, the task scheduling algorithm needs to consider the real-time state of the equipment and the network bandwidth changes. On resource-limited edge devices, ensuring performance and reducing energy consumption are challenging. Edge computing sinks to the edge of the network through resources to improve data processing efficiency and response speed. Its success depends on an efficient network scheduling algorithm. In the future, to design the intelligent and flexible scheduling mechanism will be the research focus.

2.1 Research status of low-latency network scheduling

The applicability of the low-latency network scheduling algorithm in edge computing varies significantly. Li et al proposed a hybrid heuristic based on dynamic prioritization that effectively reduced the end-to-end delay to below 12ms, but did not consider the effect of network topology changes on task synchronization [1]. In the Industrial Internet of Things, the deterministic scheduling framework achieves the task response within 8ms through the two-queue structure, but

the model parameter update is limited by the offline training [2]. The Gupta team's hierarchical scheduling framework adopts a real-time energy-aware strategy, which reduces low energy consumption by 18% under the 30ms delay constraint, but the cross-layer communication overhead limits its scalability [5]. Mathematical models are generally used to describe the coupling relationship of task scheduling and resource allocation. The matching degree model established by Chen et al. realizes the dynamic mapping of the task and the edge nodes through multidimensional weight calculation, reducing the average delay fluctuation by 23% [8]. In the serverless architecture, the event-triggered based load scheduling mechanism reduces the cold start delay to less than 50ms by pre-allocating container resources, but may cause resource fragmentation problems [9]. The deep reinforcement learning method divides the state space into three dimensions, which improves the convergence speed by 1.7 times. However, the state space dimension problem still faces [4] when the large scale nodes are deployed. Table 1 shows the comparison of the core indicators of typical algorithms, revealing the characteristic differences of different technical routes in delay optimization. The evolutionary multi-task optimization method has an average delay of 9.2ms at the 5-node scale, but the delay increases to 82ms when the node size increases to 50, and the algorithm complexity grows nonlinearly with the scale [10]. The deterministic scheduling framework achieves 8ms hard real-time guarantee in industrial scenarios, but the fixed time window mechanism is difficult to adapt to the dynamic channel conditions, and the task discard rate can reach up to 17%. The optimization objective function is used to balance computational latency with transmission latency, but the multi-objective conflict problem is not resolved by [7]. Existing studies have weaknesses in dynamic environment adaptability. About 68% of the algorithms rely on the static network topology assumption, and the performance decay by more than 40% [3] when the node movement speed exceeds 30 km/h. The hybrid distributed fault-tolerant method reduces the task interruption rate to 0.3% by synchronizing the primary and standby nodes, but the redundant communication overhead leads to a 19% reduction in effective bandwidth utilization [11]. The heterogeneous characteristics of edge nodes are generally ignored in the algorithm design. Under the homogeneous node assumption, the average algorithm performance index is about 28% .

3. Design of the low-latency network scheduling algorithm

3.1 Algorithm design objectives and principles

In the edge computing scenario, the network scheduling algorithm aims to build a distributed decision framework to ensure the determination delay and meet the real-time requirements of 5G on-board network. The algorithm is based on the hierarchical control architecture, optimizing the computing and network resources, and the theoretical basis is the mixed integer programming model of the wireless networked control system.

The design criteria include: in resource efficiency, dynamic resource allocation based on Lyapunov optimization is adopted to realize Pareto optimization of service response and energy consumption; in fairness, the weighted polling strategy of time-varying weight is designed to ensure that the deviation rate of business flow bandwidth allocation is less than 12%; in scalability, modular micro-service architecture is adopted to support dynamic expansion of nodes, and the scheduling delay increases moderately with the increase of node scale.

3.2 Overall architecture of the algorithm

The algorithm architecture is designed for the low latency requirements of edge computing environments, covering input, core scheduling, resource allocation and output modules. The input module receives task requests and network states, and the core scheduling module makes task

sorting and scheduling decisions based on task dependency and resource availability. The resource allocation module allocates computing and transfers resources according to the scheduling decision, considering the network structure and link state to reduce latency. The output module feeds back the scheduling results to the edge nodes and the user equipment, adopts a lightweight messaging protocol to improve the real-time performance, and supports the dynamic adjustment.

The core scheduling module uses an improved greedy algorithm for dynamic ordering by combining task cutoffs and computational complexity. Tasks with high urgency prioritize computing resources, and tasks with low computing complexity prioritize transmission resources to reduce latency.

The resource allocation module adopts a hierarchical strategy, prioritizing allocating resources within edge nodes, and coordinating edge cloud and central cloud resources when insufficient. Considering the network topology and link state, we adjust the transmission path dynamically, and preferentially select low-latency MM-wave links in order to avoid the congested subchannel.

The output module uses a lightweight protocol to quickly transfer scheduling results and supports dynamic adjustment to respond to changes in network state or task requirements.

Module interaction: the input module receives information and transmits it to the core scheduling module; the core scheduling module generates decisions and transmits them to the resource allocation module; the resource allocation module allocates resources and feeds back to the core scheduling and output module; the output module feeds the results to the edge nodes and user equipment. Modular design improves algorithm scalability and adaptability.

3.3 Key technologies and strategies

Mind mapping takes the algorithm to achieve the low latency goal as the core, starting from the technical framework, respectively expand load prediction, task scheduling strategy, resource allocation, network delay optimization and burst traffic processing. Each part shows the specific method, formula, experimental data and code implementation in detail, clearly presents the overall architecture and key points of the algorithm, and contributes to a comprehensive understanding of the design and implementation of the algorithm. This algorithm adopts the technical framework combining dynamic priority task scheduling and multi-dimensional resource vector matching to achieve low latency goals.

4. Algorithm implementation details

The flowchart shows a three-stage processing process based on scheduling framework based on a dynamic priority queue. First, the algorithm running environment is initialized, the key matrix and tensor are built, and then the node status is obtained through resource monitoring. Finally, the core scheduler performs task assignment modeling and solution. The code implementation demonstrates the hierarchical architecture and core module functions, including task priority computing, resource allocation, scheduling execution, and exception handling. The whole process is logically coherent, from theoretical modeling to code implementation and test results, demonstrating how the scheduling framework achieves the low latency goal.

The proposed scheduling framework achieves the low-latency goals through a three-stage process. In the initialization stage, the task feature matrix and resource state tensor are constructed. The resource monitoring module collects the node CPU utilization, memory surplus and network bandwidth to constitute the resource state vector, and the update period is 200ms. The core scheduler uses mixed integer programming to model task assignment problems, and the objective functions and constraints are clearly defined. The code implementation builds a hierarchical architecture, and the core module includes the task queue manager, resource evaluator, and

scheduling decision maker. The task priority calculation function adopts the dynamic weight adjustment mechanism, the resource allocation module introduces the sliding window mechanism, the unlocked ring buffer design adopts the scheduling execution stage, and the exception processing module integrates the fault-tolerant strategy based on reinforcement learning. The test results show that this implementation can significantly reduce the end-to-end delay standard deviation and meet the deterministic delay requirements of industrial IoT scenarios.

4.1 Algorithm optimization measures

Analysis: The mind map takes "algorithm optimization and resource management" as the core, and clearly divides the content into three main branches: algorithm complexity optimization, resource utilization optimization and dynamic priority adjustment. Each branch further subdivided specific strategies, models, formulas and experimental data, comprehensively demonstrated the measures and effects of algorithm optimization and resource management in the text, and reflected the hierarchical relationship and logical connection between each part.

Aiming at the problem of exponential increase of computational complexity existing in the algorithm prototype, the hierarchical decision mechanism proposed in the literature provides a theoretical basis for solving this problem. In this paper, dynamic pruning strategy is adopted to reduce the dimension of state space. When the task queue length exceeds the threshold value $L_{max} = 2^n$, the system automatically activates the pruning function of branch factor $\beta = 0.6$:

$$\mathcal{P}(s_t) = \bigcup_{k=1}^{\lfloor \beta K r \rfloor} \arg\max_{a \in \mathcal{A}} Q(s_t, a)$$

Table 1 shows the comparison of task scheduling delay before and after optimization, where the response time decreases by 63.2% when $K= $1000.By limiting the size of the candidate action set. The time complexity is reduced from $O(K^2)$ to $\mathcal{O}(K \log K)$, and compared with the linear approximation method in the literature, the execution efficiency is improved while maintaining 97.4% of the optimal solution accuracy.

Table 1 The comparison of task scheduling delay before and after optimization

Task scale	Prototype algorithm (ms)	optimization algorithm (ms)
500	128±5.6	47±2.3
1000	514±18.7	189±9.1
2000	2053±76.5	701±34.2

5. The experiment and the results were analyzed

5.1 Experimental environment and parameter setting

From the hardware and software composition of the experimental environment, to the parameter configuration of the benchmark test scenario, task priority calculation, to the benchmark selection, task set generation and resource allocation strategy, and finally to the network traffic monitoring module, clear hierarchy, logical coherence. The relationship between the parts is clear, which helps

to understand the architecture and design points of the whole experiment. The hardware part explains the configuration of server and network equipment in detail, and the software part explains the implementation mode of container arrangement, network plug-in and task scheduling. The parameter configuration and task priority calculation module of the benchmark scenario provide specific test basis for the experiment; select the benchmark and reproduce the task set mode; the resource allocation strategy and network traffic monitoring module provide solutions to the key problems in the experiment.

The experimental environment was deployed in a heterogeneous cluster consisting of eight physical servers equipped with Intel Xeon E5-2680v4 processors and 128GB DDR4 of memory, with three nodes configured with NVIDIA Tesla V100 GPU acceleration units to support computationally-intensive tasks. The network infrastructure uses Cisco Catalyst 3850 series switches to build a three-layer star topology, the core switching equipment is configured with 10 Gbps full-duplex fiber link, and the edge nodes realize wireless access through IEEE 802.11ax protocol. At the software level, the container choreography system is built based on Kubernetes 1.24, and the micro-service communication is realized with the Calico network plug-in. The task scheduling module is implemented in Golang language and integrated into the Kubernetes scheduler extension framework.

Table 1 lists the key parameter configurations of the benchmark test scenario in detail, where task arrival rate follows the Poisson distribution and time window is set to $\lambda = 15$ times/second, and task computation quantity follows the Weibull distribution $f(x;\beta,\eta) = \frac{\beta}{\eta}\left(\frac{x}{\eta}\right)^{\beta-1} e^{-(x/\eta)^{\beta}}$. The shape parameter $\beta = 1.5$ and the scale parameter $\eta = 2.3$ are set with reference to the typical load characteristics generated by industrial iot devices. The network delay model is described by piecewise function:

$$d_{ij} = \begin{cases} 0.2 + 0.05\delta_{ij} & \text{if RTT} < 5\,\text{ms} \\ 0.8 + 0.15\delta_{ij} & \text{if RTT} \geq 5\,\text{ms} \end{cases}$$

Where δ_{ij} represents the link congestion coefficient of nodes i to j, and this model accurately reflects the time-varying characteristics of wireless links in edge environments. The task priority calculation module implements the improved analytic hierarchy process (AHP). By constructing the judgment matrix $A = (a_{ij})_{n\times n}$, the eigenvector is solved to determine the weight distribution, and the iterative convergence mechanism including dynamic adjustment of the eigenvalue threshold $\epsilon = 1e^{-5}$ is realized in detail.

In the comparative experimental design, this paper selects the deterministic scheduling method of literature and the partitioned scheduling framework of literature as the benchmark, and the task set generator strictly reproduces the medical iot data flow mode defined by the literature. The resource allocation strategy implements the dynamic allocation algorithm based on Buddy system. The key code segment adopts the memory pool pre-allocation technology:

--------Go Code code----------

type GPUPool struct {

blocks map[int]*Block

mutex sync.RWMutex

```
}
func (p *GPUPool) Alloc(size int) *Block {
p.mutex.Lock()
defer p.mutex.Unlock()
order := int(math.Ceil(math.Log2(float64(size))))
if blk, exists := p.blocks[order]; exists {
delete(p.blocks, order)
return blk
```

5.2 Experimental results and analysis

With the performance verification of the experimental platform algorithm as the core, all aspects of the experiment are fully displayed. Starting from the construction of the experimental platform and the verification conditions, the experimental basis and environment are defined. The benchmark algorithms used for the comparison are listed for the comparison algorithm section. The performance indicators presents key indicators such as task processing delay, time, throughput and resource utilization in detail, reflecting the advantages of the proposed algorithm. The burst flow test and task assignment section further shows the performance of the algorithm in special scenarios. Finally, the advantages and disadvantages of the algorithm are summarized, which provide the direction for the subsequent research. The overall structure is clear and distinct, and can summarize the text content well.

The experimental platform is based on the Kubernetes edge computing framework, deploying a test cluster containing 12 heterogeneous nodes and constructing a mixed task set containing two typical scenarios of vehicle trajectory tracking and industrial sensor data analysis. To verify the robustness of the proposed algorithm in a dynamic environment, the task arrival rate is generated and simulated with the network bandwidth fluctuation range of ±30%. Three benchmark algorithms are traditional polling scheduling (RR), Q-learning based reinforcement learning scheduling (QLS) and scheduling method (CMS) based on comprehensive matching degree. Table 1 shows the average performance index over 2000 task processing cycles, where the task processing delay of the proposed algorithm is (23.6 ±4.8) ms, which is 38.2%, 21.7% and 15.4% lower than RR, QLS and CMS, respectively. Its task processing time T_{proc} can be expressed as:

$$T_{\text{proc}} = \frac{\sum_{i=1}^{n} (t_{\text{complete}}^{i} - t_{\text{arrival}}^{i})}{n}$$

Where n is the number of completed tasks, t_{arrival}^{i} and t_{complete}^{i} are the arrival and completion time stamps of tasks respectively [6]. When the task load density increases to 150 requests / s, the throughput of the proposed algorithm reaches 128.3 tasks / s, which is 17.2% higher compared with the CMS method. This performance advantage stems from the effective control of the calculated resource fragmentation rate by the multidimensional resource matching mechanism, and the standard deviation of node resource utilization drops from 0.38 in CMS to 0.21, which verifies the applicability of the resource equilibrium theory proposed in the literature in dynamic scenarios.

In the burst flow test, when the task arrival rate jumps from 80 requests / s to 240 requests / s in 30s, the delay fluctuation range of this algorithm is controlled within ±8ms, while the QLS method appears with delayed spikes of more than 45ms. This stability benefits from the advance identification of resource bottlenecks by the edge node state prediction module, and its prediction accuracy reaches 87.6%. The task allocation heat map shown in Figure 3 shows that this algorithm

preferentially schedules 52.3% of the image processing tasks to the edge nodes equipped with GPU accelerator in the bandwidth-limited period, which is consistent with the heterogeneous resource scheduling principle proposed in literature [9].

The experimental data show that the proposed algorithm systematically improves the resource utilization efficiency dimension compared with the existing methods. Especially in the scenario of network condition degradation, its elastic allocation strategy based on historical state data shows strong adaptability, but the node failover mechanism has a delay increment of about 6.9% for computationally intensive tasks. This phenomenon is consistent with the fault-tolerant cost problem pointed out in literature [12], which provides the improvement direction for subsequent research.

6. Conclusion and outlook

This study proposes a low-latency scheduling algorithm, based on dynamic priority queue and resource-aware feedback mechanism, reducing the average end-to-end latency to 8.3ms and improves by 32.7% in simulated industrial IoT scenarios. The real-time evaluation model of transmission link quality is introduced. In the mobile vehicle communication scenario, the task interruption rate is less than 0.4%, and the stability is improved by 2.8 times. The algorithm builds a three-dimensional weight evaluation system to solve the problem of heterogeneous resource mismatch of edge nodes. The algorithm adopts the sliding window mechanism to handle the burst flow, keeping the scheduling success rate above 94% and reducing the response time fluctuation by 27%. However, in the scenario of super-scale node cluster, the scheduling decision delay is nonlinear, which has a performance gap with the elastic expansion ability of server-less architecture. The uniform distributed task model used in the experimental environment is different from the actual industrial scenario and needs to be improved.

Future studies will address the multi-objective optimization problem, especially the energy consumption and delayed Pareto frontier determination. It is planned to introduce TSN technology to build a double safeguard mechanism and establish an end-to-end delay upper bound model. Use the medical Internet of Things system architecture to deal with the frequent offline situation of edge nodes. A more stringent evaluation system needs to be established to cover the microsecond level requirements of 5G URLLC scenarios.

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