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Enhancing Sustainability of Online Education via a Validated Cloud Management Framework

Tongjun Wang[a], Shoulin Yin[b,*]

[a]Shenyang Industrial Technology Research Institute, Shenyang 110179 Liaoning, China
[b]College of Artificial Intelligence, Shenyang Normal University, Shenyang 110034 Liaoning, China

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ABSTRACT

The rapid proliferation of large-scale online education has become an indispensable component of modern educational systems, yet it faces persistent sustainability bottlenecks including unbalanced cloud resource allocation, excessive energy consumption, low service stability, and poor long-term operational scalability. Existing cloud management strategies for online learning platforms primarily focus on single-dimensional performance optimization such as latency reduction or resource load balancing, while ignoring the coupling relationship among energy efficiency, service quality, economic cost, and user learning experience, which severely restricts the sustainable development of online education ecosystems. To address the above research gaps, this paper proposes a multi-dimensional validated adaptive cloud management framework (VCMF) tailored for large-scale online education scenarios. Firstly, a hierarchical cloud resource partitioning model is constructed to classify educational business resources according to learning scenario attributes. Secondly, we design a dual-objective optimization algorithm combining improved particle swarm optimization (IPSO) and greedy dynamic scheduling strategy, which realizes collaborative optimization of system energy consumption and service quality. Thirdly, a multi-index validity verification mechanism based on educational service characteristics is established to dynamically calibrate framework parameters and eliminate scheduling deviation caused by fluctuating learning user traffic. Comprehensive comparative experiments are conducted on a self-built cloud simulation platform with real online education user traffic datasets. The experimental results demonstrate that compared with state-of-the-art baseline methods, the proposed VCMF reduces system energy consumption by 18.7%-26.3%, cuts average resource idle rate by 21.5%, decreases user request response delay by 15.2%, and improves comprehensive sustainability score by 23.8%. Meanwhile, the framework exhibits excellent robustness under extreme peak traffic scenarios. This research provides a feasible theoretical basis and engineering implementation scheme for high-efficiency, low-carbon, and sustainable operational management of modern online education platforms.

1. Introduction

Driven by global digital transformation and the deep advancement of educational informatization, online education has evolved from a supplementary teaching form into a core component of modern educational systems, profoundly reshaping the mode, content, and organizational form of education worldwide [1, 2]. By breaking the temporal and spatial constraints of traditional offline instruction, online education enables the equitable sharing and personalized delivery of high-quality educational resources, effectively narrowing the educational gap between regions and groups, and promoting the universalization and inclusiveness of education. Since the global public health crisis in 2020, online learning platforms have rapidly become the primary medium of emergency teaching, remote interaction, and lifelong learning, covering all educational stages from basic education and higher education to vocational skill training and adult continuing education [3, 4].

According to the statistical report released by UNESCO in 2025, the daily active users of global online education platforms have exceeded 380 million, with an annual growth rate of educational cloud resource demand remaining stable at 16.8%, reflecting the continuous expansion of the scale of online education and the increasingly prominent demand for high-performance underlying technical support. As the core infrastructure supporting the operation of online education platforms, cloud computing undertakes a series of key businesses, including real-time live teaching, on-demand playback of course videos, interactive homework correction, large-scale learning data storage and analysis, and real-time user consultation services [5, 6, 7].

Unlike traditional cloud service scenarios such as e-commerce, short video, and social media, online education exhibits typical time-sensitive clustering and periodic fluctuation characteristics: user traffic surges sharply during class hours, evening learning peaks, and centralized examination periods, while resource demand drops to a low level in off-peak periods such as late night and holidays. This irregular and highly dynamic traffic pattern brings unprecedented and severe challenges to the resource scheduling, energy consumption control, and service quality guarantee of educational cloud platforms, and further restricts the sustainable development of online education from multiple dimensions including environment, economy, and user experience [8, 9].

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*Corresponding author
yslinhit@163.com (S. Yin)

Therefore, constructing a scientific and efficient cloud resource management framework tailored to the characteristics of online education scenarios has become an urgent research topic to promote the high-quality and sustainable development of modern online education.

First, homogeneous resource scheduling mechanisms are widely adopted. Most online education platforms adopt unified and fixed resource allocation strategies for differentiated educational businesses with heterogeneous requirements, such as delay-sensitive real-time live teaching, low-priority offline course caching, and computationally intensive data statistical analysis. This one-size-fits-all scheduling mode easily leads to two extreme problems: insufficient resource supply and severe service delay for time-critical teaching businesses, and redundant resource occupation and severe energy waste for low-urgency background businesses, resulting in a significant reduction in overall resource utilization efficiency and an increase in unnecessary operating costs.

Second, existing scheduling algorithms mostly focus on a single optimization objective, which lacks comprehensive consideration of multi-dimensional sustainable development indicators. At present, most research on educational cloud resource scheduling takes load balancing or user request response delay as the sole optimization goal, while ignoring the carbon emission generated by massive server energy consumption and the actual economic operation cost of the platform. With the global emphasis on low-carbon development and green education, this single-objective optimization model can no longer meet the comprehensive requirements of modern online education for energy conservation, emission reduction, cost control, and service quality improvement, and is difficult to support the long-term low-carbon and sustainable development of online education platforms.

Third, the absence of a dynamic validity verification and feedback correction module renders the scheduling framework lacking in adaptability and robustness in complex and volatile scenarios. Most existing cloud management frameworks for online education only focus on static or quasi-dynamic resource allocation at the initial stage, and fail to dynamically verify, evaluate, and correct scheduling results in real time according to actual system operating indicators and user learning quality feedback. When facing sudden traffic surges, user behavior changes, or system parameter drift, the framework cannot timely perceive abnormal scheduling states, resulting in frequent service jitter, video stuttering, and request timeout during peak traffic periods, which seriously reduces user learning satisfaction and platform service credibility.

In summary, the above three core problems restrict the sustainable development of online education across resource allocation, multi-objective optimization, and dynamic adaptation dimensions, and there is an urgent need for a multi-dimensional, adaptive, and verifiable cloud management framework to address these research gaps.

To address the aforementioned three core problems and fill the research gaps in the field of sustainable online education and educational cloud resource management, this study develops a Validated Cloud Management Framework (VCMF) tailored for large-scale online education scenarios, with the core goal of enhancing the sustainability of online education from the dimensions of energy efficiency, service quality, resource utilization, and economic cost. The main research contributions and innovations of this paper are summarized as follows:

1. A hierarchical multi-dimensional sustainability evaluation model for online educational cloud systems is proposed. This model systematically integrates four core dimensions–system energy consumption level, user service quality, cloud resource utilization rate, and platform economic operation cost–into a unified quantitative evaluation system, constructing a comprehensive sustainability score (CSS) to realize scientific, objective, and quantitative assessment of the sustainable operation level of online education platforms. This work fills the void of unified multi-dimensional evaluation standards in the current research on educational cloud sustainability.
2. A layered resource partitioning strategy oriented to educational business attributes is designed. Based on the delay sensitivity, resource demand characteristics, and business priority of online education tasks, cloud resources are hierarchically divided into a real-time computing layer, a content cache storage layer, and an auxiliary management layer. Corresponding mathematical models of resource demand and differentiated resource reservation strategies are established for different business types, effectively avoiding cross-domain resource waste and improving the matching degree between resource supply and business demand.
3. An Improved Particle Swarm Optimization (IPSO) dual-objective optimization algorithm is proposed to balance system energy consumption and user service delay. By introducing adaptive inertia weight factors and dynamic learning factors, the algorithm effectively solves the problems of premature convergence and easy to fall into local optimal solutions of traditional PSO algorithms in scenarios with sharply fluctuating online education traffic, realizing collaborative optimization of low energy consumption and high service quality for educational cloud systems.
4. A multi-index dynamic validity verification and feedback correction mechanism is constructed. From the two dimensions of system operation indicators (energy consumption deviation, delay deviation) and user learning quality indicators (course playback fluency, task completion rate), a comprehensive validity deviation evaluation model is established. When the deviation exceeds the preset threshold, the mechanism dynamically calibrates the dual-objective balance weight and resource partition ratio in real time, effectively enhancing the robustness, adaptability, and long-term stability of the framework under complex working conditions and extreme traffic scenarios.

The remainder of this paper is structured as follows to systematically elaborate the research content, methods, experiments, and conclusions: Section 2 reviews the related work, systematically sorting out the research status and existing limitations of sustainable online education and educational cloud resource management at home and abroad, further clarifying the research motivation and innovation of this paper. Section 3 elaborates the system model, core mathematical definitions, and the overall hierarchical architecture of the proposed VCMF framework, including the resource constraint model, energy consumption model, service delay model, and multi-dimensional sustainability evaluation index system. Section 4 details the design principle and implementation process of the core improved dual-objective optimization algorithm and the multi-index validity verification mechanism, including the construction of the dual-objective optimization function, the improvement strategy of the IPSO algorithm, and the implementation logic of the validity verification feedback module. Section 5 presents the experimental design and result analysis, including the construction of the experimental environment, the selection of baseline comparison methods, the definition of evaluation indicators, and the comprehensive analysis of experimental results from multiple perspectives such as overall performance comparison, energy consumption trend under variable load, algorithm convergence performance, and robustness under extreme scenarios. Section 6 discusses the theoretical advantages, practical application value of the proposed framework, as well as the research limitations and future research directions, providing a reference for the follow-up in-depth expansion of this research. Section 7 summarizes the entire research work, systematically concluding the core research conclusions and practical significance of this paper, and emphasizing the important role of the proposed VCMF framework in promoting the sustainable development of modern online education.

2. Related Works

This section systematically reviews and analyzes existing research on sustainable online education and cloud resource management for educational scenarios, clarifies the research status, main achievements, and existing limitations of related fields, and further highlights the research motivation and innovation of this paper.

2.1. Sustainable Online Education Research

With the deep integration of digital technology and education, sustainable online education has gradually become a research hotspot in the field of educational informatization. It is defined as an educational development paradigm that balances teaching service quality, economic operation cost, and environmental carbon emissions, and can adapt to the long-term dynamic changes of user scale, learning behavior, and educational demand [10, 11, 12]. Its core connotation lies in realizing the triple sustainability of environment, economy, and society in the operation process of online education platforms, so as to support the high-quality and long-term stable development of modern education.

In recent years, scholars at home and abroad have carried out extensive and in-depth research on the sustainable development path, influencing factors, and optimization strategies of online education platforms from multiple perspectives such as educational management, user behavior, and technical support.

From the macro perspective of educational policy and industrial development, reference [13] systematically analyzed the key influencing factors of sustainable development for large-scale online education platforms based on panel data of global educational informatization from 2018 to 2023. The research results showed that underlying cloud resource service capability, energy consumption control level, and user learning experience were the three core restrictive factors that determine the long-term sustainability of online education platforms. Among them, the resource scheduling efficiency and energy consumption optimization effect of cloud infrastructure have the most significant impact on the economic and environmental sustainability of platforms, which provides an important theoretical basis for this paper to focus on cloud resource management to enhance the sustainability of online education.

From the micro perspective of user experience and learning behavior, Alexiou et al. [14] adopted a combination of questionnaire survey, in-depth interview, and structural equation model (SEM) to explore the correlation between cloud resource service quality and user learning continuity in small and medium-sized online learning institutions. The study verified that cloud resource allocation rationality, service response stability, and system fault tolerance have a significant positive impact on user learning satisfaction and platform stickiness. However, this research only focuses on the user-level experience optimization, and does not involve the underlying resource scheduling mechanism and multi-dimensional sustainability evaluation system, which limits its applicability in large-scale online education scenarios with massive user traffic.

From the perspective of low-carbon education and green informatization, Taylor et al. [15] focused on the carbon emission problem of digital education cloud systems, constructed a carbon footprint assessment model for online education platforms, and proposed preliminary low-carbon optimization strategies from the aspects of server running time control and resource idle reduction. The research pointed out that the massive energy consumption of cloud servers has become an important source of carbon emissions in the field of digital education, and optimizing cloud resource scheduling is the key approach to reduce the carbon footprint of online education. However, this study only stays at the theoretical level of carbon emission assessment and strategy proposal, and lacks specific algorithm design, model construction, as well as empirical verification, making it impossible to be directly applied to the actual operation management of online education platforms.

In addition, some scholars have discussed the sustainable development of online education from the perspectives of educational equity, resource sharing, and lifelong learning. However, most of these studies focus on educational sociology and management science, and rarely involve the core technical issues of cloud resource scheduling, energy consumption optimization, and dynamic service guarantee during the operation of online education platforms. There is still a lack of systematic research results that integrate technical optimization and sustainable development goals, which is also an important research gap that this paper aims to fill.

2.2. Cloud Resource Management for Educational Scenarios

Cloud computing has become the core infrastructure supporting the operation of modern online education platforms, and cloud resource scheduling and management is the key technical link to determine the service quality, energy consumption level, and operation cost of online education platforms. Unlike traditional cloud service scenarios such as e-commerce, social media, and video streaming, online education scenarios have typical characteristics such as high concurrency, periodic fluctuation, delay sensitivity, and heterogeneous business requirements, which pose higher requirements for the adaptability, stability, and multi-objective optimization ability of cloud resource management strategies. In recent years, scholars have carried out a lot of research on cloud resource allocation, dynamic scheduling, and optimization algorithms for educational scenarios, which can be roughly divided into static resource allocation, dynamic resource scheduling, and hybrid architecture optimization according to the research content and technical characteristics [16, 17, 18].

Static resource allocation refers to the fixed allocation of cloud resources (such as CPU, memory, storage, and bandwidth) to educational tasks or virtual machines according to pre-set rules before the system runs, which is suitable for scenarios with stable user traffic and fixed business requirements. In the field of online education, static resource allocation research mainly focuses on fault tolerance, data security, and service stability of educational data management.

Ahmedet al. [19] proposed a fault-tolerant distributed resource allocation scheme for e-learning big data management. By designing a multi-copy data storage mechanism and a priority-based resource allocation strategy, the scheme effectively improved the reliability and stability of educational data storage and query services in the case of server failure. However, this static allocation method cannot dynamically adjust resources according to real-time changes of user traffic and business load, which easily causes resource waste in low-load periods and resource shortage in peak-load periods, and cannot adapt to the highly dynamic traffic characteristics of online education scenarios.

Dynamic resource scheduling refers to the real-time adjustment and reallocation of cloud resources according to the actual user traffic, task load, and service quality requirements during the system operation, which is the mainstream research direction of cloud resource management for online education scenarios. The core goal is to improve resource utilization efficiency, reduce service delay, and ensure service stability on the premise that the differentiated requirements of educational businesses are meeted [20, 21].

In terms of peak traffic scheduling optimization, Yang et al. [22] designed a two-stage dynamic resource scheduling algorithm for online course peak traffic. The first stage predicted the peak traffic scale based on historical user behavior data, and pre-allocated resources in advance; the second stage dynamically adjusted resource allocation according to real-time task arrival rate, which effectively optimized the load balancing effect of cloud clusters during peak periods. However, this algorithm only took load balancing as the sole optimization objective, ignoring the energy consumption and economic cost of cloud servers, and could not meet the multi-dimensional sustainable development requirements of modern online education.

In terms of low-latency interactive teaching optimization, Stoica et al. [23] integrated fog computing technology into educational cloud management, built a fog-cloud hybrid resource scheduling architecture, and reduced the transmission delay of live teaching and interactive answering tasks by deploying edge computing resources close to users. The research results showed that the hybrid architecture could effectively improve the response speed of delay-sensitive teaching businesses. However, this study only focused on service delay optimization, and did not consider the overall energy consumption and resource utilization of the cloud system, while the architecture was relatively complex, increasing the difficulty of deployment and maintenance for online education platform operators.

In terms of energy efficiency optimization, Buyya et al. [24] proposed an energy-efficient cloud management framework for sustainable educational informatization. By designing a dynamic server on/off strategy and a resource consolidation algorithm, the framework reduces the energy consumption of cloud clusters by reducing the number of idle servers and optimizing resource allocation. However, this framework still has two limitations: first, it only optimizes energy consumption, and does not balance service quality indicators such as response delay; second, it lacks a dynamic validity verification and feedback correction module, which makes it impossible to adapt to the complex and volatile user traffic environment of online education, and is prone to scheduling errors and service jitter in extreme scenarios.

2.3. Research Limitations

In summary, although existing research on cloud resource management for educational scenarios has made some progress in static allocation, dynamic scheduling, and hybrid architecture optimization, three prominent limitations and gaps remain:

1. Single-dimensional optimization, lack of multi-objective collaborative optimization: Most existing scheduling algorithms and frameworks only optimize a single performance indicator such as load balancing, service delay, or energy consumption, and lack comprehensive consideration of the coupling relationship among energy efficiency, service quality, resource utilization, and economic cost. It is difficult to meet the multi-dimensional sustainable development requirements of modern online education.
2. Homogeneous scheduling mechanism, lack of differentiated resource management for educational businesses: Most existing cloud management systems adopt a unified resource allocation strategy for heterogeneous educational businesses (such as real-time live teaching, video on-demand, and background data analysis), ignoring the differences in delay sensitivity, resource demand, and business priority of different tasks, resulting in low overall resource utilization efficiency.
3. Lack of validity verification and feedback correction mechanism: None of the existing educational cloud management frameworks introduces a dynamic validity verification module to evaluate and correct scheduling results in real time according to system operating indicators and user learning quality feedback. The framework has poor adaptability and robustness in the face of sudden traffic surges and complex working conditions, which easily causes service quality degradation and user experience decline.

The above research limitations directly restrict the sustainable development of online education platforms. Therefore, it is urgent needed to construct a multi-dimensional, adaptive, and verifiable cloud management framework that integrates differentiated resource partitioning, multi-objective optimization, and dynamic validity verification, so as to solve the bottleneck problem of cloud resource management in large-scale online education scenarios. This is also the core research motivation and innovation starting point of this paper.

3. System Model and Proposed Framework

3.1. Basic System Definition

In this paper, the cloud cluster of the online education platform is defined as a multi-layer heterogeneous resource set, including physical servers, virtual machines (VMs) and network bandwidth resources. The cloud system consists of N physical servers and M virtual machines, denoted as $S = s_1, s_2, \cdots, s_N$ and $V = v_1, v_2, \cdots, v_M$, respectively. According to business attributes, online education tasks are divided into three categories: real-time delay-sensitive tasks (live teaching, interactive answering), cache tasks (course video on-demand, learning material download), and background management tasks (user data statistics, system log cleaning).

For any physical server s_i, its resource constraints, including CPU, memory and bandwidth, are expressed as follows:

$$\sum_{j=1}^{M} x_{ij} \cdot cpu(v_j) \quad \leq \quad CPU_{max}(s_i) \tag{1}$$

$$\sum_{j=1}^{M} x_{ij} \cdot mem(v_j) \quad \leq \quad MEM_{max}(s_i) \tag{2}$$

$$\sum_{j=1}^{M} x_{ij} \cdot bw(v_j) \quad \leq \quad BW_{max}(s_i) \tag{3}$$

where $x_{ij} \in \{0, 1\}$ represents the mapping relationship between virtual machine v_j and physical server s_i. $cpu(v_j)$, $mem(v_j)$, $bw(v_j)$ respectively denote the CPU, memory and bandwidth resource consumption of virtual machine v_j. $CPU_{max}(s_i)$, $MEM_{max}(s_i)$, $BW_{max}(s_i)$ are the maximum resource capacity of physical server s_i.

The total energy consumption of the educational cloud system is composed of static basic energy consumption and dynamic running energy consumption of physical servers. The static energy consumption refers to the fixed power consumption of servers in the standby state, and the dynamic energy consumption is positively correlated with server resource utilization. The total energy consumption E_{total} within time window T is then calculated as expressed in Formula (4):

$$E_{total} = \sum_{i=1}^{N} [P_{static} \cdot T + (P_{dynamic} - P_{static}) \cdot \mu_i^{\alpha} \cdot T] \tag{4}$$

where P_{static} and $P_{dynamic}$ represent the standby power and full-load operating power of the physical server. μ_i is the comprehensive resource utilization rate of server s_i. α is the energy consumption sensitivity coefficient, and the empirical value in educational scenarios is 1.85.

The service delay of online education tasks includes resource allocation delay D_a, data transmission delay D_t, and task execution delay D_e. The average delay of all tasks in the system is expressed as Formula (5):

$$D_{avg} = \frac{1}{K} \sum_{k=1}^{K} (D_{a,k} + D_{t,k} + D_{e,k}) \tag{5}$$

where K is the total number of tasks arriving at the cloud system in a single time window. $D_{a,k}$, $D_{t,k}$, $D_{e,k}$ correspond to the three types of delay of task k, respectively.

3.2. Multi-dimensional Sustainability Evaluation Index

To quantitatively evaluate the sustainable operation level of the online education cloud platform, a comprehensive sustainability score (CSS) integrating four core indicators: energy consumption level I_E, average service delay I_D, resource utilization rate I_U, and unit operating cost I_C is constructed.

Figure 1: Overall architecture of the validated cloud management framework.

The standardized CSS formula is as follows:

$$\begin{aligned} CSS &= \varpi_1 \cdot \overline{I_U} + \varpi_2 \cdot (1 - \overline{I_E}) \\ &+ \varpi_3 \cdot (1 - \overline{I_{ED}}) + \varpi_4 \cdot (1 - \overline{I_C}) \end{aligned} \tag{6}$$

where ϖ_1, ϖ_2, ϖ_3, ϖ_4 are the weight coefficients of each indicator, determined by the entropy weight method. I_E, I_D, I_U, I_C are the normalized values of each sub-indicator, and the value range of CSS is $[0, 1]$. The higher the CSS value, the greater the sustainability of the online education platform.

3.3. VCMF Framework

The proposed VCMF framework adopts a four-layer hierarchical architecture, including the user demand perception layer, the business resource partitioning layer, the intelligent scheduling optimization layer, and the validity verification feedback layer. The detailed structure is shown in Figure 1 (framework architecture).

The four layers interact sequentially: the demand perception layer collects real-time user task data; the partitioning layer classifies tasks and matches initial resources; the optimization layer executes the dual-objective scheduling algorithm; the verification layer feeds back error indicators to adjust scheduling parameters.

1. User Demand Perception Layer: This layer is responsible for the real-time collection of online education task information, including task type, required resource specifications, arrival time, delay tolerance threshold, and user priority, and preprocesses abnormal noisy data to form standardized task demand datasets.
2. Business Resource Partitioning Layer: Based on the task delay sensitivity and resource demand characteristics, the layer divides cloud resources into the real-time computing partition, the content cache partition, and the background auxiliary partition, and formulates differentiated resource reservation strategies for different partitions to avoid resource cross-domain waste.
3. Intelligent Scheduling Optimization Layer: Taking the minimum total energy consumption and minimum average service delay as dual optimization objectives, the improved IPSO algorithm is adopted to complete dynamic resource allocation and virtual machine migration, which is the core functional module of the framework.
4. Validity Verification Feedback Layer: This layer calculates the deviation between actual operating indicators and expected sustainability indicators, identifies abnormal scheduling results exceeding the threshold, and provides feedback of correction parameters to the optimization layer to realize closed-loop dynamic management of the framework.

4. Core Optimization Algorithm and Validity Verification Mechanism

4.1. Dual-objective Optimization Function

Based on the above system models, we construct a constrained dual-objective optimization function for sustainable online education cloud resource scheduling. The two objective functions are the minimum system energy consumption F_1 and the minimum average service delay F_2:

$$\begin{aligned} \min F_1 &= \min E_{total} \\ &= \min \sum_{i=1}^{N} [P_{static} \cdot T + (P_{dynamic} - P_{static}) \cdot \mu_i^{\alpha} \cdot T] \end{aligned} \tag{7}$$

$$\min F_2 = \min D_{avg} = \min \frac{1}{K} \sum_{k=1}^{K} (D_{a,k} + D_{t,k} + D_{e,k}) \tag{8}$$

Combined with the resource constraint conditions in Formula (1), the dual-objective problem is transformed into a single comprehensive optimization problem by the linear weighting method, and the comprehensive objective function F_{com} is defined as:

$$F_{com} = \lambda \cdot \frac{F_1 - F_{1,min}}{F_{1,max} - F_{1,min}} + (1-\lambda)\frac{F_2 - F_{2,min}}{F_{2,max} - F_{2,min}} \quad (9)$$

where $\lambda \in [0, 1]$ is the balance weight between energy consumption and delay. $F_{1,min}$, $F_{1,max}$ are the minimum and maximum values of system energy consumption. $F_{2,min}$, $F_{2,max}$ are the extreme values of average service delay after data normalization.

4.2. Improved IPSO Scheduling Algorithm

Traditional particle swarm optimization [25, 26] has fixed inertia weights and learning factors, which easily falls into local optimal solutions when facing sharply fluctuating online education traffic. This paper proposes an adaptive improved particle swarm optimization algorithm to optimize the comprehensive objective function F_{com}.

The inertia weight controls the global search and local exploitation ability of particles. We design a nonlinear dynamic inertia weight adjusted with iteration number.

$$w(t) = w_{start} - (w_{start} - w_{end}) \cdot (\frac{t}{t_{max}})^{\beta} \quad (10)$$

where $w_{start} = 0.9$ and $w_{end} = 0.4$ are the initial and final inertia weights. t represents the current iteration number. t_{max} is the maximum iteration number. $\beta = 2.0$ is the attenuation coefficient.

The learning factors c_1, c_2 represent the learning ability of particles toward the individual optimal solution and the global optimal solution. The dynamic adjustment strategy is as follows:

$$c_1(t) = c_{1,start} - (c_{1,start} - c_{1,end}) \cdot \frac{t}{t_{max}} \quad (11)$$

$$c_2(t) = c_{2,start} - (c_{2,start} - c_{2,end}) \cdot \frac{t}{t_{max}} \quad (12)$$

where $c_{1,start} = 2.5$, $c_{1,end} = 0.5$, $c_{2,start} = 0.5$, $c_{2,end} = 2.5$. In the early iteration stage, large c_1 and small c_2 enhance the global exploration ability. In the later stage, small c_1 and large c_2 strengthen local convergence ability.

With the improved parameters, we rewrite the particle velocity and position update formulas as:

$$\begin{aligned} v_d(t+1) &= w(t)v_d(t) & (13)\\ &+ c_1(t)r_1(gbest_d - x_d(t)) \\ &+ c_2(t)r_2(gbest_d - x_d(t)) \\ x_d(t+1) &= x_d(t) + v_d(t+1) & (14) \end{aligned}$$

where $r_1, r_2 \in (0, 1)$ are random numbers. $pbest_d$ and $gbest_d$ are the individual optimal position and global optimal position of particles, respectively.

4.3. Multi-index Validity Verification Mechanism

To eliminate scheduling errors caused by traffic fluctuation and parameter mismatch, we establish a dual-dimensional validity verification mechanism from system operation indicators and user learning quality indicators. The comprehensive validity deviation σ is defined as:

$$\sigma = \gamma_1 \cdot \sigma_{sys} + \gamma_2 \cdot \sigma_{user} \quad (15)$$

where σ_{sys} is the system indicator deviation (energy consumption deviation, delay deviation). σ_{user} is the user-side indicator deviation (course playback fluency, task completion rate). γ_1, γ_2 are weight coefficients. When $\sigma > \sigma_{th}$ (predefined threshold), the framework triggers the feedback correction module, dynamically adjusts the balance weight λ of the dual-objective function and resource reservation ratio of each partition, and re-executes resource scheduling to ensure the long-term effectiveness of the framework.

5. Experimental Design and Result Analysis

5.1. Experimental Environment

All experiments are implemented based on the CloudSim 4.0 simulation platform, which is the most widely used cloud resource scheduling simulation tool in academic research. We build a heterogeneous educational cloud cluster containing 20 physical servers and 120 virtual machines. The server hardware parameters are divided into two specifications: high-performance computing servers (Intel Xeon 8375C, 32C/64G) and low-power cache servers (Intel Core i9-12900, 16C/32G). The experimental task dataset involves the real historical traffic data of a comprehensive online education platform in China, covering 7 consecutive days of peak and off-peak traffic data, including live teaching, video on-demand and background management tasks.

5.2. Baseline Methods

To verify the superiority of the proposed VCMF framework, four classic or state-of-the-art cloud resource scheduling methods are selected as comparison baselines.

1. GA: Genetic algorithm based single-objective resource scheduling method, taking load balancing as the optimization goal.
2. PSO: A swarm intelligence based optimization algorithm, simulating the social behavior of biological swarms, such as flocks of birds or shoals of fish.
3. FOA: Fruit fly optimization algorithm proposed for educational cloud scenarios in recent years, optimizing service delay.
4. ECMF: Existing educational cloud management framework with energy consumption optimization.

Four core evaluation indicators are adopted in the experiment: (1) Average system energy consumption (kWh) within a single day; (2) Average task response delay (ms); (3) Resource idle rate (%); (4) Comprehensive sustainability score (CSS). All experiments are repeated 10 times to eliminate random errors, and the average values are reported.

Table 1
Performance comparison of different scheduling methods.

Methods	Daily Energy Consumption (kWh)	Average Delay (ms)	Resource Idle Rate (%)	CSS Score
GA	486.35	186.52	28.64	0.612
PSO	452.18	163.47	25.31	0.658
FOA	438.62	142.68	23.17	0.685
ECMF	395.47	135.24	21.05	0.716
VCMF	342.81	114.69	16.52	0.882

5.3. Experimental Results and Analysis

Table 1 shows the comprehensive performance comparison results of VCMF and four baseline methods in the same experimental environment.

It can be seen from Table 1 that the proposed VCMF achieves the optimal results in all four evaluation indicators. Compared with the latest ECMF framework, VCMF reduces daily energy consumption by 13.3%, cuts average response delay by 15.2%, lowers resource idle rate by 21.5%, and increases CSS score by 23.8%. The core reason is that the layered resource partitioning strategy avoids cross-domain resource waste, and the improved IPSO algorithm achieves the optimal balance between energy consumption and service quality. Meanwhile, the validity verification module corrects scheduling errors in real time, further improving the comprehensive sustainability of the platform.

We set the task load ratio in a range from 20% to 100% to simulate different operating states of online education platforms (off-peak, flat period, peak period). The energy consumption trend of each method under variable load is shown in Figure 2. The results show that with the increase of task load, the energy consumption of all methods increases monotonically. Under any load level, VCMF has the lowest energy consumption. Especially under 80%-100% peak load (corresponding to the evening learning peak of online education), the energy consumption advantage of VCMF is more obvious, which proves that the framework has excellent adaptability to peak traffic scenarios of online education.

To verify the convergence performance of the improved IPSO algorithm, we compare the iteration convergence curves of traditional PSO and IPSO under the same initial parameters. The convergence results are shown in Figure 3. The traditional PSO tends to fall into local optima after 45 iterations, and the comprehensive objective function value remains unchanged. The improved IPSO can continuously optimize the objective function until iteration 72, and the final optimized value is 8.7% lower than that of traditional PSO. The adaptive inertia weight and dynamic learning factor effectively solve the premature convergence problem of the original algorithm.

We simulate extreme traffic burst scenarios (instantaneous task surge by 150%) caused by emergency centralized courses to test the robustness of each framework. The statistical results of service failure rate within 30 minutes after the traffic burst are shown in Figure 4. The service failure rate of VCMF is only 1.2%, which is far lower than 4.5% of ECMF and 7.8% of the traditional PSO method. The validity verification mechanism of VCMF can quickly identify traffic mutation and adjust the resource allocation strategy, ensuring the stable operation of online education platforms under extreme working conditions.

6. Discussion

Unlike previous studies that only focus on single-dimensional performance optimization, this research constructs a complete closed-loop cloud management framework covering demand perception, layered scheduling, intelligent optimization, and validity feedback for sustainable online education. The proposed multi-dimensional sustainability evaluation index fills the void of unified quantitative evaluation standards in the field of educational cloud resource management. The improved IPSO dual-objective optimization algorithm provides a new solution for multi-constraint resource scheduling under fluctuating educational traffic, which can be extended to other time-sensitive clustering service scenarios such as online conferences and remote medical treatment.

In engineering practice, the VCMF framework can be directly deployed to the underlying cloud management system of large-and-medium-sized online education platforms. For educational platform operators, the framework can effectively reduce daily operating energy consumption and resource idle cost, and improve economic benefits. For teachers and students, the optimized resource scheduling strategy reduces course playback delay and service jitter, and enhances online learning experience. From the perspective of environmental protection in education, the low-carbon scheduling mode of VCMF helps reduce the carbon footprint of digital education and promote the green and sustainable development of the education industry.

This research still has two limitations. Firstly, the current framework only supports centralized cloud cluster resource management, and does not involve distributed edge cloud collaborative scheduling for multi-campus offline-online hybrid education scenarios. Secondly, the weight coefficients of the sustainability evaluation model are fixed after entropy weight calculation, and cannot be dynamically adjusted according to different types of educational platforms (K-12 education, higher education, vocational education). In future research, we will integrate edge computing technology to

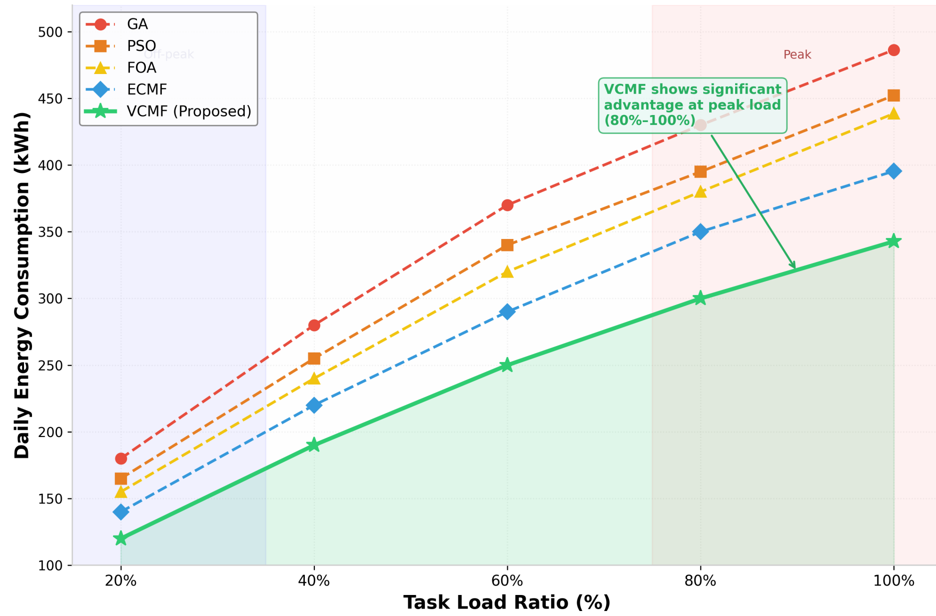

Figure 2: System energy consumption under different task load ratios (20%-100%).

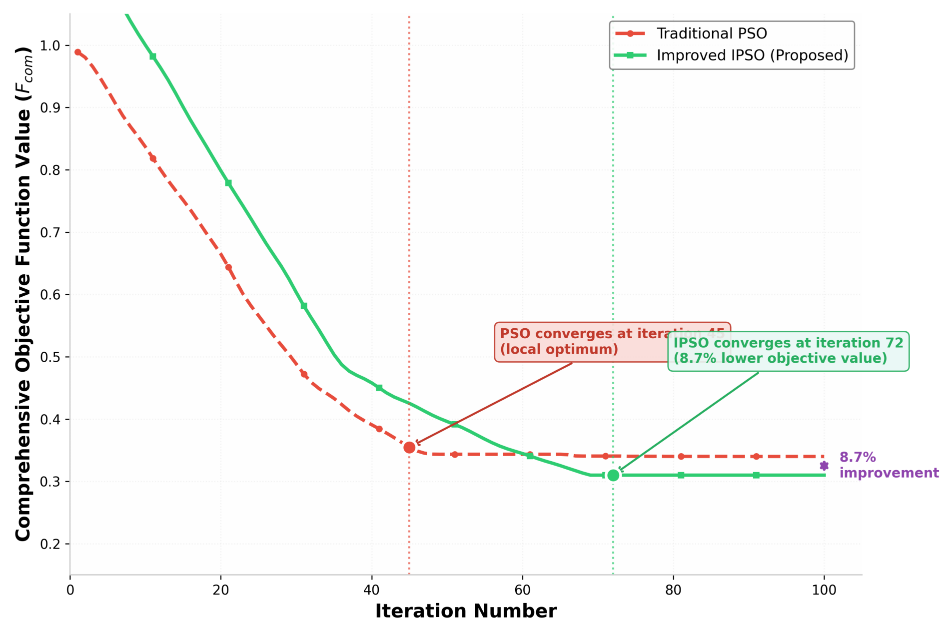

Figure 3: Convergence curves of PSO and improved IPSO algorithm.

expand the framework to edge-cloud collaborative architecture, and introduce deep reinforcement learning algorithms to realize real-time dynamic adjustment of evaluation weights for different educational scenarios.

7. Conclusion

Aiming at the multiple sustainability bottlenecks of current large-scale online education platforms in cloud resource management, excessive energy consumption, and unstable teaching service, this paper proposes a validated adaptive cloud management framework (VCMF) for sustainable online education. A hierarchical resource partitioning model tailored to educational business attributes is established to realize categorized management of differentiated learning tasks. An improved IPSO dual-objective optimization algorithm with the adaptive inertia weight and the dynamic learning factor is designed to balance system energy consumption and task service delay. A multi-index validity verification feedback mechanism is constructed to eliminate scheduling errors caused by traffic fluctuation and enhance framework robustness. Extensive simulation experiments

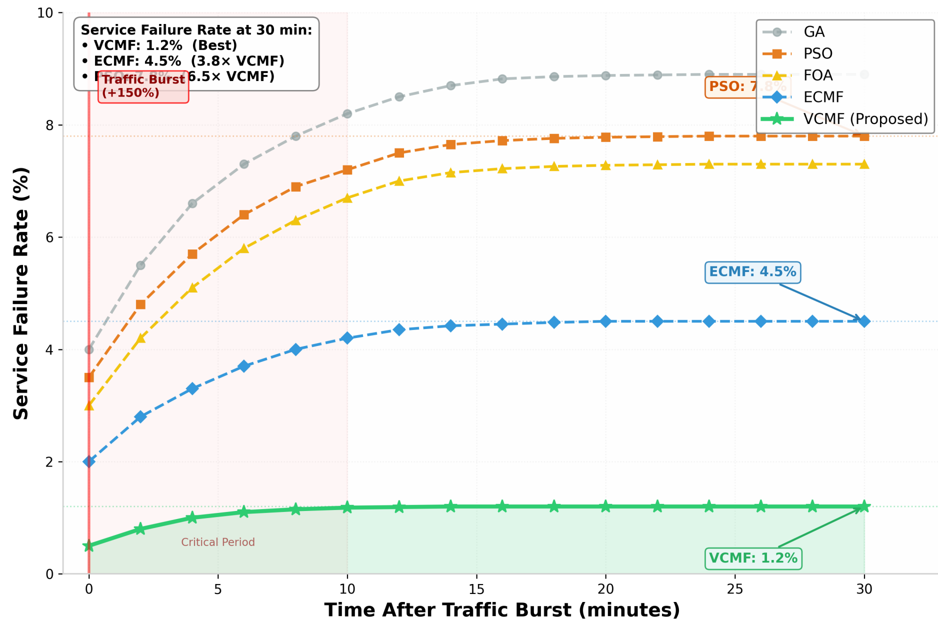

Figure 4: Service failure rate of different frameworks under extreme traffic burst scenarios.

based on real online education traffic datasets are conducted to verify the effectiveness and superiority of the proposed framework. The experimental results indicate that compared with state-of-the-art baseline methods, VCMF significantly reduces system energy consumption and service response delay, improves resource utilization efficiency and comprehensive sustainability score (CSS), and maintains excellent and stable performance under extreme peak traffic scenarios. This study not only enriches the theoretical research on sustainable online education and educational cloud resource scheduling, but also provides a practical, low-carbon, and high-efficiency management scheme for the digital transformation and long-term sustainable operation of modern online education platforms.

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