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A Comprehensive Assessment Method Based on the Operation and Resources of a Low-Carbon Cloud Platform

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ABSTRACT

In the context of rapid globalization and informatization, cloud platforms have become a critical tool for enterprises to achieve efficient and precise operations, demonstrating significant practical value. This study proposes a comprehensive evaluation method for cloud resources by establishing a full lifecycle data management mechanism. This approach achieves systematic optimization from the infrastructure layer to the business application layer. Specifically, this paper constructs a comprehensive verification system that covers data collection, processing, analysis, and visualization. Additionally, this paper establishes a cross-layer comprehensive evaluation model spanning the platform and application layers, supporting real-time monitoring of operational differences in heterogeneous systems. Through empirical deployment in 27 regions from January to December 2023, we continuously monitored the operational stability and resource efficiency of cloud systems. Experimental results indicate that this method not only enhances the overall management efficiency and resource utilization of cloud platforms but also provides quantifiable technical support for enterprises to gain strategic advantages in digital competition while ensuring system stability.

1. Introduction

There is a strong relationship between green technology and environmental sustainability, and the more developed the green technology, the better the environmentally friendly industries will be able to drive technological innovation and employment opportunities [1]. Sustainable green technologies not only contribute to environmental protection and economic development but also play an important role in promoting the sustainable development of society [2] .In the field of green cloud computing, researchers work on optimizing the energy consumption of servers in data centers as well as optimizing resource allocation for energy efficiency and environmental friendliness [3].

Green IT frameworks to ensure that they follow the best sustainable IT practices. Salles *et al.* proposed a six-dimensional maturity model framework for organizational sustainability practices [4]. Patón-Romero *et al.*[5] developed the “Governance and Management Framework for Green IT”

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(GMGIT), which establishes the necessary characteristics to implement Green IT in organizations, from the point of view of the governance and management of this area. An example of this is given by Bose & Luo (2011) , who proposed a more comprehensive model that uses virtualization to assess the readiness of an organization to implement a green IT project [6]. The Green IT Readiness Framework proposed by Molla and Cooper (2010) identifies key capability areas for assessing maturity [7] . Patón-Romero (2017) established a maturity model based on SPICE to promote the gradual systematization of green IT governance and management practices within an organization [8]. In the study of Green IT frameworks, it is shown that by providing a rationale for assessing, implementing, and improving sustainable IT practices in organizations, these frameworks help decision-makers to improve operational efficiency and IT energy efficiency more effectively, and also contribute to sustainable development [9].

Green cloud computing is a framework that aims to minimize energy consumption and achieve environmentally friendly cloud architectures through dynamic energy optimization. This optimization framework is based on multi-constraint optimization and aims to improve the energy efficiency of cloud computing. The study also shows that one of the core concepts of green computing is virtualization technology, which revolutionizes cloud computing by optimizing resource utilization. In addition, to achieve high energy efficiency, researchers have proposed energy and performance-efficient task scheduling algorithms to minimize energy consumption in cloud data centers [10]. These techniques and approaches are essential to improve the energy efficiency and environmental sustainability of cloud computing systems, where digital transformation is marked by the adoption of digital technologies such as cloud computing, artificial intelligence, and the Internet of Things (IoT), which have a significant impact on the economic and social sectors [11].

Cloud computing platforms and their applications are one of the primary drivers helping a nation transition to a low-carbon economy while also providing substantial environmental benefits like energy efficiency, carbon emissions reduction, renewable sources integration as well as green design adoption. Bharany *et al.* found that relationship between resource efficiency and energy consumption, by 2025, it is predicted that the overall use of energy could be reduced by as much as 3% due directly to the contributions made possible by large cloud data centers via advanced cooling mechanisms and power management tactics revolutionizing resource usage [12]. These results dovetail with our earlier research in several ways and suggest that large-scale facilities can be operated relatively efficiently when considered holistically, However, the study does not fully account for total network energy consumption to support cloud services. Armbrust *et al.* claim because cloud computing provides elasticity and scalability in resource usage it increases resource efficiency significantly and leads to a related decrease in carbon emission [13]. Nevertheless, insufficient consideration was given in this study for a theoretically possible increase in overall energy consumption when more operations will be migrated into the clouds offering some counter-balance effect. Further, along with increased efficiencies is the continued adoption of renewable energy sources by all major cloud service providers which has cut down on related emissions drastically as well However, much of this research has centered around large companies, leaving us with less insight on the difficulties small-to-medium cloud providers have when transitioning to renewables [14] .

In summary, although cloud computing has contributed a lot to the greening of our economy, future research should take more holistic lifecycle assessment perspectives into account. This also includes energy consumption from infrastructure and client devices as well as exploring how we deal with the ever-growing demand for services migrating towards or between clouds and how can small and medium providers be supported in moving to renewable resources greener design .To sum up, cloud computing platforms have achieved significant results in lowering carbon emissions due to energy efficiency, reliance on renewable energy, and green design. However, there is still room for improvement connected with overcoming existing challenges and unfolding its full potential of carbon emission reduction [15].

2. Literature Review

The cloud computing industry still needs to establish domestic operation and evaluation methods and procedures for cloud resources. Cloud platforms can accurately evaluate the operation status, thereby improving the security, stability and utilization efficiency of cloud resources. Aiming at the above goals, many relevant scholars have conducted a large number of systematic studies and proposed various methods or models.

Efforts to improve the operational efficiency of cloud platforms to reduce costs, improve performance and scalability, and achieve environmental benefits are remarkable. Bauer stresses automation and scalability for decreasing costs; Chiang *et al.* highlight energy-efficient policies that can save idle power consumption and response times[16]. Rista *et al.* make the problem explicit by focusing on network performance improvements to reduce latency and increase throughput [17]. Savchuk and Kozachuk suggest dynamic scaling of peak loads and resource utilization optimization [18]. Another effort by Beloglazov *et al.* and Berl *et al.* points out efficient energy resource allocation and execution to reduce the global carbon footprint or greenhouse gas emission [19]. Awada and Barker introduce intelligent resource scheduling, which can be used to enhance three goals: deployment density — but also related resource efficiency-related quality. these additions help to improve the delivery of cloud services in a more efficient and sustainable manner to accommodate changes across all levels of users and organizations [20].

Operational and energy efficiencies are increasingly interconnected, as operational efficiency gains from improvements in cloud platform operational efficiency improvements are critical to cost and environmental impact improvements [21]. Research reported that the cloud computing can be environmentally friendly by increasing the consumption of data centers due to better system operation and networking; the improvement of operational efficiency also consists of lessening the overall energy consumption, which is very environmentally friendly [22]. Long *et al.* also introduced an effective energy efficiency management system for cloud platforms that consists of real-time monitoring as well as effective energy efficiency management that helps in real-time data analysis by increasing performance optimization of cloud platforms and, in particular, reducing the energy consumption of the cloud platform [23]. Similarly, cloud computing was discussed by Kaur and Chana as a double-edged sword, where on one side it is the major cause of higher energy demand, and on the other side, it facilitates energy wastage by embedding increasing energy-efficient techniques that will increase operational efficiency [24].

3. Methodology

3.1 Problem statement

The association between cloud platforms' operational and energy efficiencies is widely discussed by many researchers as mentioned. Their results together provide a strong indication that making operations energy efficient by techniques like automation, virtualization, and energy-aware resource management not only increases performance and reduces costs, but also better contributes to energy efficiency and a sustainable environment. These performance enhancements address the increased demands of users and businesses, while also reducing the environmental impact of delivering cloud services. This comprehensive way of looking at things highlights the thorough integration of the strategies for operational and energy efficiency in cloud platform design and management.

It is also difficult to systematically assess the operational status of cloud platforms in the context of the digital transformation of enterprises, and the environmental issues arising from the carbon and energy efficiency of cloud platforms have not been taken into account and assessed. This paper attempts to establish a one-of-a-kind comprehensive systematic approach to cloud operations assessment to improve the operational stability of cloud platforms and to enhance resource efficiency to reduce lower energy output and achieve the energy efficiency of cloud platforms. The main issues addressed are as follows:

1.Why do we need to improve operational efficiency and what benefits does it bring?

2.How to effectively assess the relationship between operational efficiency and energy efficiency of cloud platforms?

3. How is data acquired and how is it categorized? How to define the data and what is the scope of the data? What indicators can reflect the operational efficiency of the cloud platform?

4. How to quickly assess the differences between individual applications?

3.2 Proposed framework

To solve the appeal problem, this paper improves the operation efficiency of the operation platform by constructing a cloud operation evaluation model and automating the system to calculate scores and operation evaluation. The main steps are as follows：

3.3 Define the metrics and scope of resource operations for the cloud platform

Basic indicators include underlying physical devices, cloud-based components, and cloud products; physical device indicators include a total of 34 basic indicators for servers, management containers, and network devices; cloud-based components include a total of 198 basic indicators for basic components, core components, and tool components; and cloud products include a total of 298 products for computing, storage, networking, security, databases, middleware, big data, management tools, and monitoring applications. Basic indicators and more than 3,000 monitoring indicators. Cloud operation platform for cloud platform indicator data collection, processing, output, and display functions. It consists of the following sets of independent procedures.

The indicator platform includes data collection, data processing, data interface service, data display, and other functions; data collection includes logs, commands, scripts, procedures, tools, tasks, ASAPI, SDK, HTTP/HTTPS, MiniRDS, and other collection methods to collect and summarise the indicators related to the cloud platform's physical equipment, the cloud platform's base, and the cloud products. data processing carries out data collection, organisation, grouping, cleaning, filtering, calculation, auditing, extraction, sorting, and output of collected or stored indicator data, including retrieving, organising, cleaning, filtering, calculating, reviewing, extracting, and sorting. Data processing of the collected or stored indicator data includes retrieval, organisation, grouping, cleaning, screening, calculation, auditing, extraction, sorting, conversion, the transmission of data, and other steps for subsequent use; Data interface service: adopting RestfulAPI architecture, as shown in figure 1, and rights management of interfaces and data for use by third-party application systems; Data display includes indicator display, indicator data display, interface management, and system configuration. Data display includes indicator display, indicator data display, interface management, system configuration, etc.; The framework of the data collection process is as shown in Figure 2:

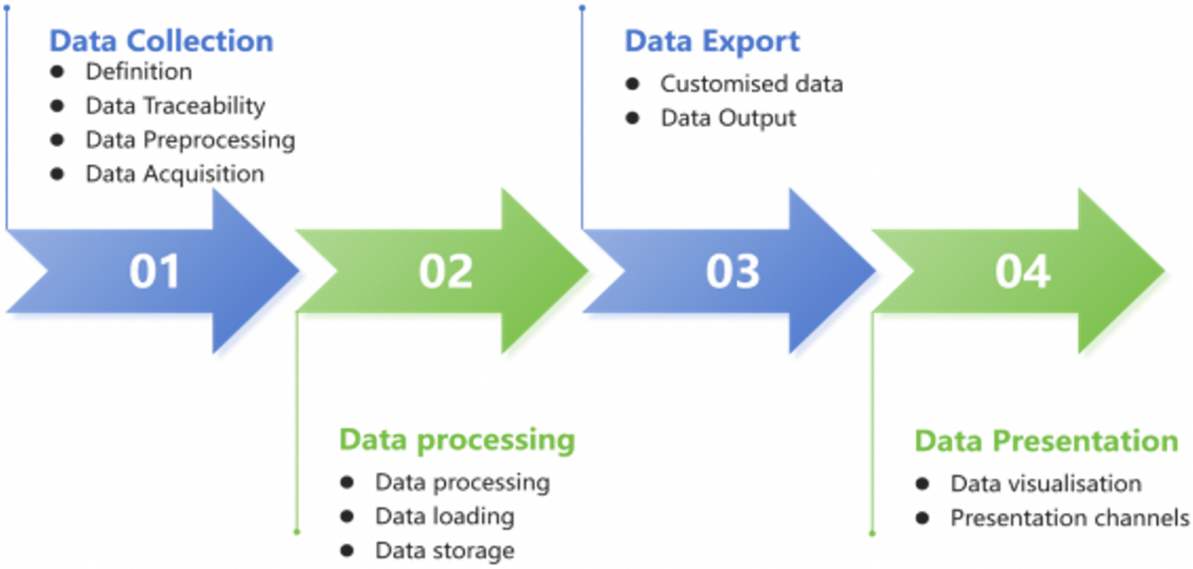

Fig. 1. Data Collection and Acquisition Process

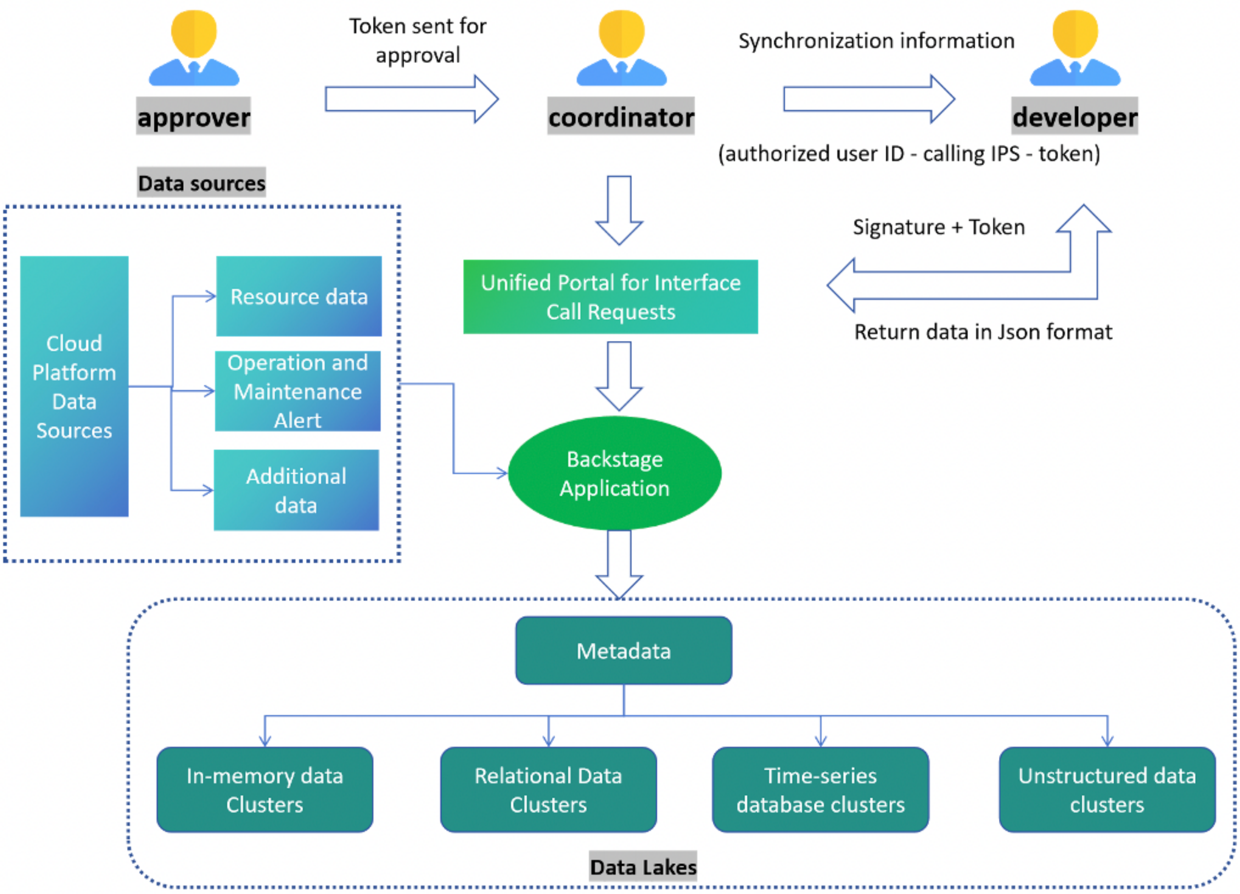

Fig. 2. RestfulAPI Architecture

The indicator collection program collects cloud platform indicator data through logs, commands, scripts, procedures, tools, tasks, ASAPI, SDK, HTTP/HTTPS, MiniRDS, etc; the back-end program enters the processed data into the database through algorithmic analysis, formatting processing and planned task execution; and returns the interface data in the form of json according to the corresponding restful API interface request to provide third-party system platforms with data sharing services. the Framework as shown in Figure 3.

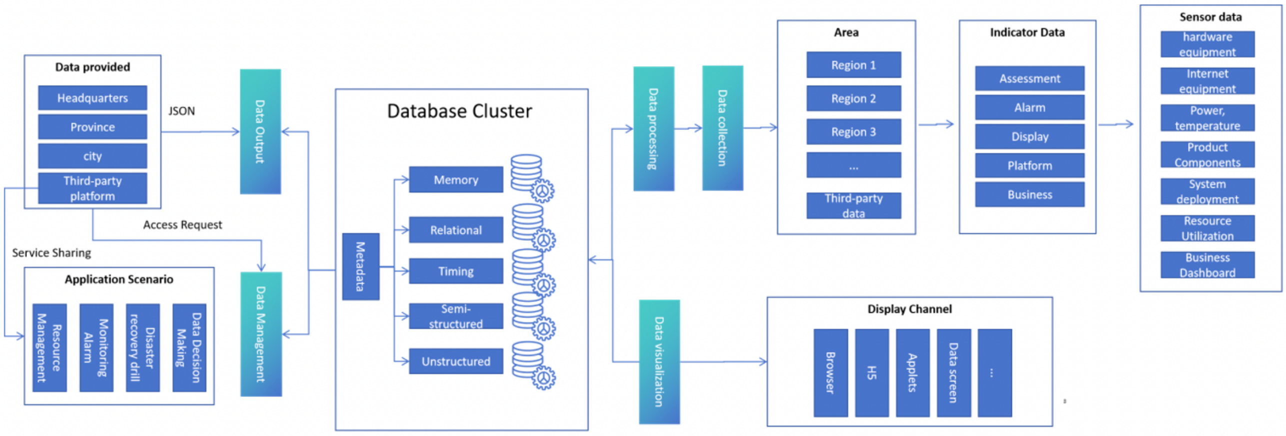

Fig. 2. Operational Metrics Data Operational Framewor

3.4 Data collection methodology for establishing operational metrics for cloud platforms

The indicator sharing platform serves as the basis for the collection means, while the data storage layer comprises three different types of databases: Redis cache database, ES log storage and analysis database, and RDS relational database. The data processing layer also includes interfaces, SQL statements, and monitoring data of the operation and maintenance services. Resource and service monitoring are part of the application service layer. The data is intended for use by various staff members, including those involved in business analysis, system operation and maintenance, management decision-making, and external evaluation. Figure 4 depicts the architecture. From data collection, processing, and storage to service application, the diagram as a whole depicts a comprehensive closed-loop system that covers a wide range of resource, business, microservice, and interface monitoring, as well as data support and services for higher-level roles.

1. **Monitoring objects** : The system's monitoring objects show that the architecture is made to keep an eye on different kinds of applications.
2. **Collection** : This layer collects data from the monitoring objects using the System Collection Tool API, which acts as a link between the upper-level data storage and the underlying application.
3. **Data Storage** : Project IDs, exception data, performance alerts, and other data are stored in Redis. TraceId, Span, CPU architecture, CPU usage, JVM GC information, service response time, and other details are stored in the ES log and analysis database. Business lists, application lists, interface lists, and other structured data are stored in RDS relational databases.
4. **Data Processing** : This involves keeping an eye on system resources (CPU, memory) and platform resources (servers, storage) to make sure the infrastructure is operating normally. Business system monitoring is the process of keeping track of the number of service invocations, failure rate, request elapsed time, and error logs in order to assess the system's performance. Microservice monitoring: Use inter-service call relationship analysis (call chaining), full-link tracing (e.g., TraceId correlation), SQL performance analysis (slow query, execution plan), etc., to make sure the microservice architecture is stable. In order to guarantee the quality of interface services, service interface status monitoring keeps an eye on the volume of interface requests (QPS), response time, number of instance requests, network resource usage (bandwidth, latency), etc. External evaluation:

provide evaluation data, including the system's overall state and component status statistics, and set monitoring threshold alarms (e.g., triggering alarms for resource usage exceeding the threshold).

5. **Application & Service** : It offers resource monitoring, business analysis, system operation, and maintenance services to support decision-making and operation for various roles, such as management, system operation, business analytics, etc.

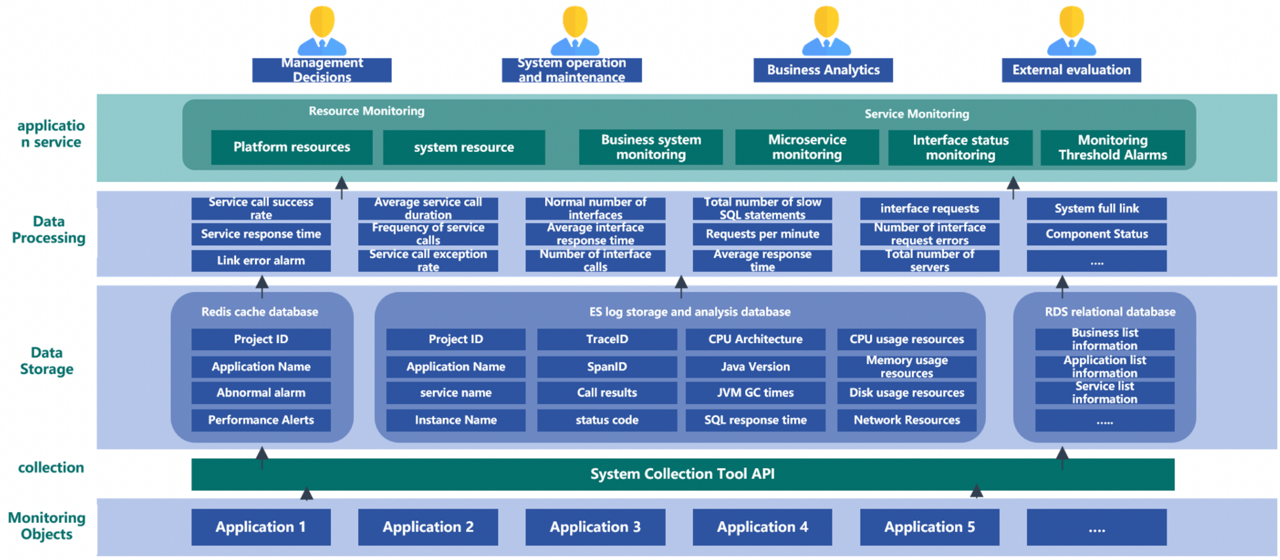

Fig. 3. Cloud Platform Operational Data Evaluationlogical Architecture

3.4.1 Data collection strategy

3.4.1.1 Multi-source heterogeneous data collection

Log Collection: Capture the running logs (such as CPU/memory usage peak, I/O throughput) of servers, containers, and databases in real time through Flume, with a collection frequency of 1 time/second, and support log level filtering (ERROR/WARNING/INFO).

API Interface Collection: Obtain data from infrastructure layer (physical machine/virtual machine status), platform layer (middleware/database performance), application layer (user access logs, service response time) via Restful API (OpenStack API, SDK), and adopt interface rights management to ensure data security.

Scripts and Probes: Deploy custom Python scripts (based on Prometheus probes) to regularly scan the bandwidth utilisation rate and packet loss rate of network devices (switches/routers), with scanning intervals of 5 minutes, and support the automatic recollection of abnormal data (manual verification is triggered if 3 consecutive abnormalities occur).

3.4.1.2 Data verification mechanism

Adopting the 3σ method to detect numerical data anomalies (e.g. CPU utilisation >100% or <0% is considered invalid), combined with business logic verification (e.g. storage capacity must not be negative), the anomalous data is marked as "to be confirmed" and triggers manual verification. The collected data is presented in the Table 1:

Table 1
Data collection strategy

Data Type	Collection Object	Technical Tool	Protocol	Frequency	Storage Format
Hardware Metrics	CPU/Memory/Disk	Prometheus Probe	HTTP/ HTTPS	1 time/300 sec	JSON+Protobuf
Network Metrics	Bandwidth/Latency/ Packet Loss Rate	sFlow/ NetFlow	UDP	1 time/300 sec	CSV+Parquet
Platform Metrics	Virtual Machine/Database Status	OpenStack API	RESTful	1 time/300 sec	XML+JSON
Application Metrics	User Requests/Response Time	Microservice Tracing (SkyWalking)	gRPC	Real-time	Binary Logs

3.4.2 Data processing techniques
3.4.2.1 Cleaning and standardising data

Missing value processing: discrete data (like equipment status) are marked as "unknown" and kept in the original record, while continuous data (like memory usage) are filled in by linear interpolation. To remove naming ambiguity, resource names are given a common naming convention (such as "ECS-Region-01") and timestamps from various sources are converted to the ISO 8601 standard (YYYY-MM-DDTHH:MM:SS).

3.4.2.2 Algorithm for calculating indicators

Method for calculating the 95th percentile value: Fit the curve, remove the top 5% of the data, and use the highest value of the remaining data as the 95th percentile peak CPU and memory resource utilisation. This is done by taking the peak CPU and memory utilisation at 5-minute intervals. For instance, the following formula is used to determine the monthly (30-day) cloud host resource utilisation:

(I) Determine the 95th percentile of a single cloud host's peak performance data at the 5-minute level every hour. Then, use the highest value of the 95th percentile of a single cloud host's 24-hour level every day as the resource utilisation rate of cloud host resources at the day level.

[25] Determine the monthly level resource utilisation using the 95th percentile calculation method by computing the 30 95th percentile peaks of a single ECS over 30 days.

(III) To determine resource utilisation at the Region level, all cloud host resources are weighted based on the number of CPU cores and memory resources.

(IV) The following is the calculation formula:

CPU utilisation is calculated as (number of cloud host CPU cores x 95th percentile peak of cloud host CPU utilisation) / (number of cloud host CPU cores) x 100%.

Cloud host MEM utilisation = (cloud host MEM capacity x cloud host MEM utilisation 95th percentile peak) / (cloud host MEM capacity) x 100%

3.4.3 Data visualisation design

Infrastructure Layer: The geographic distribution and load status of physical and virtual machines are displayed using a heat map, where blue indicates low load (less than 20% utilisation) and red indicates high load (more than 80% utilisation).

Platform Layer: A line graph showing the permitted range of fluctuation (10%) between the actual and expected values of CPU/memory allocation ratios (measured against industry standards and data from past best practices).

Layer of application: Utilise a histogram to display user activity, service response time, and other business indicators; a flow diagram can be used to illustrate how business traffic is distributed among various microservice nodes and pinpoint traffic bottleneck nodes.

Interactive features: Data export (Excel/PDF format), exception alarm (email/text message notification, threshold can be customised), and drill-down analysis (click a region to view all servers in that region, for example) are supported.

3.5 Building a Cloud Resource Lifecycle Management Model

To solve the bottleneck of resource efficiency improvement, further optimize the resource allocation of the cloud platform, and achieve efficient management of cloud resources, a closed-loop management model throughout the whole life cycle of cloud resources is formed concerning PDCA management methodology by combining the planning, application, allocation, adjustment, and recovery of cloud resources, and finally, the resource efficiency improvement is examined through the resource evaluation model,as shown in Figure 5.

Fig. 5. Cloud Resource Lifecycle Management Model

Efficient resource management is a series of processes that are interconnected, and these can be increased by a cloud resource lifecycle management strategy. The resource planning commences with the analysis of the resource allocation capability available for the current year, the rate of growth of the resource and the user volumes, and the estimated reserve demand for the coming digital projects, which results in the determination of the annual needs of the software and hardware resources. That is how the future demands being taken care of without over-provisioning. The resource application considers the system concurrency and provides the business parameters related to the system concurrency analysis, to calculate the resource consumption of the cloud system. This process that translates business wants into specific resource needs facilitates the accurate identification of resource declarations. From this position of superiority, businesses will not waste but wisely use more resources where and when they are needed. The resource allocation also follows the minimum allocation principle, making that business a system of higher plant efficiency to be deployed. Following this principle can save resources as it provides only the amount necessary for standard operation of the service - resource-saving costs and maximum utilization of the existing infrastructure. Cloud resource life cycle management and regular resource adjustment are very important partitioning. It includes anticipative assessments, as well as scenario-driven analysis to deal with resource amplification and sizing down efficiently This means that by "airing" resources more often, organizations detect underutilized resources to automatically readjust allocations on the fly in response to fluctuating demand. The result is greater efficiency in resource utilization and consistent peak performance across a wide spectrum of different loads. Recovering resources is where you either reclaim resources that are no longer actively used, or when a part of a business system goes offline, and the resources can be destroyed safely. This is key to keeping your resource environment effective, as it releases unused memory over time and avoids the costs of idle resources. Furthermore, the introduction of governance policies and compliance checks across the resource lifecycle permits resource allocation and usage to meet organizational standards and regulatory requirements. With this approach, Resource utilization can be optimized better and Cloud Environment efficiency and reliability can be increased.

These steps work together to deliver a complete strategy for managing the cloud resource lifecycle which takes a cloud resource from its inception through the initial planning and allocation, then continues to manage it as it runs and provides value, and finally recovers the resource after its useful life. This approach helps optimize your resources, keeps costs low, and provides a view to ensuring that you can satisfy the demands of the business and pace with alacrity.

Cloud resource evaluation is an important means to improve cloud service providers and users understand the utilization of resources and take corresponding measures to optimize and adjust, to improve the performance and efficiency of the cloud computing platform. The evaluation model is divided into three aspects: IAAS, PAAS, and SAAS.

3.5.1 IAAS

The objects of the management layer are mainly the underlying hardware and physical resources of the cloud platform, and their index definitions, calculation methods, and evaluation criteria are shown below.To achieve better resource efficiency in the cloud environment, it will be necessary to keep the resource redundancy in a range of 20 to 60%, so that the physical resources will not be over-allocated. When the utilization ratio of the resource is lower than 20%, the actual physical resource is already at a tight supply level, it is recommended to purchase more physical machines before the service bottleneck. Further advanced resource recovery processes can also result in higher resource efficiency by reverting underutilized resources to the market. If resource redundancy is greater than 60%, it means top-layer physical spare resources are in surplus. In these cases, it is recommended to decrease the acquisition of extra physical machines so as not to unnecessarily overspend while keeping the cost-effectiveness. This middle-of-the-road tack to halting resource overlies allows the cloud infrastructure to continue to be strong, elastic, and economical in meeting demand.The calculation method is as follows:

$$\mathrm{R}_r = \frac{\sum (1 - R_{\mathrm{c}}) * \mathrm{N}_{\mathrm{i}}}{\mathrm{N}} \times 100\% \tag{1}$$

R_r : Resource redundancy

R_{c} : Component Resources

N : Total number of physical machines

N_{i} : Number of physical machines for the component

3.5.2 PAAS

Platform layer objects are mainly cloud platform core component resources, such as: virtual machines, relational databases, big data components, The calculation method is as follows:

$$\mathrm{R}\ (\mathrm{allocated})_{cpu} = \frac{\sum \mathrm{N}_{\mathrm{i}}}{\mathrm{N}} \times 100 \tag{2}$$

$\mathrm{R}\ (\mathrm{allocated})_{cpu}$: CPU Resource allocation ratio

N : Total CPU capacity

N_i : CPU capacity already allocated

$$R\ (\text{allocated})_{MEM} = \frac{\sum N_i}{N} \times 100 \tag{3}$$

$R\ (\text{allocated})_{MEM}$: MEM resource allocation ratio

N : Total MEM capacity

N_i : MEM capacity already allocated

$$R_{balance} = \frac{R\ (\text{allocated})_{CPU}}{R\ (\text{allocated})_{MEM}} \tag{4}$$

$R_{balance}$: Balanced rate of distribution of resources

3.5.3 SAAS

The SaaS layer primarily encompasses cloud-based applications and monitors their operational status on the cloud.The calculation method is as follows:

1）Resource utilization： Peak CPU and memory utilization are taken at certain time intervals, the highest 5% of the data points are excluded, and the maximum value of the remaining data is taken as the resource utilization indicator.

2）Resource inactivity rate：

$$R_{idle}(\text{CPU}) = \frac{\sum N_i}{N_{allocated}} \times 100 \tag{5}$$

N_i : Number of CPU cores with idle resources

$N_{allocated}$: Total CPU cores allocated

$$R_{idle}(\text{MEM}) = \frac{\sum N_i}{N_{allocated}} \times 100 \tag{6}$$

N_i : Number of CPU cores with idle resources

$N_{allocated}$: Total Memory capacity allocated

3.6 Establishment of an operational evaluation methodology for business system applications

The business operation evaluation method focuses more on the status of the application system on the cloud and consists of three parts: evaluation of system development quality, evaluation of operation status, and evaluation of application effectiveness. Among them, the R&D quality evaluation mainly reflects the system code quality and technical support, the operation status evaluation reflects the system resource usage and operation and maintenance support, and the application effect evaluation reflects the system usage and promotion. The scoring framework of the business system application is shown in Figure 6:

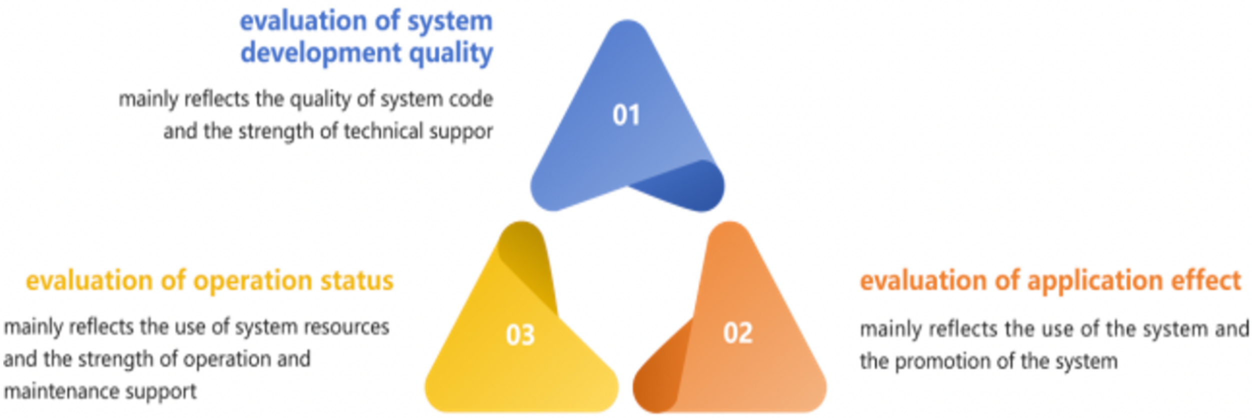

Fig. 6. Application scoring framework for business systems

3.7 Constructing a visualisation of the evaluation of operational resources

According to the scoring model achieve the system operation state assessment, a total of 2 kinds of indicators, one is to assess the current system state value, and one is the expected standard value of the business recommendation, by comparing the current value and the expected value can be quickly assessed for each different business operation state, which the resource assessment feature value can quickly get the current system ID within the resource allocation and the use of the efficiency of the situation. After evaluating the system as a whole, the overall diagram of the system operation is obtained, as shown in Figure 7. After the system gets a comprehensive score, the system operation scoring model is weighted and calculated, and a system ranking list can be obtained for management decision-makers.

In summary, The cloud service operation evaluation model we have designed is able to rapidly analyze the status of cloud service operation and individual system operational differences through automatic evaluation system and score ranking, and can therefore more accurately improve the overall operation efficiency and resource efficiency of cloud services. By establishing a cloud-wide resource evaluation model and calculation method, this model covers all stages of data from data definition to data classification, from data collection to data governance, and realizes the automatic system portrait and automatic scoring and evaluation of the system, greatly improving operational efficiency, referring to the idea of cloud platform operation and enterprise data-based transformation.

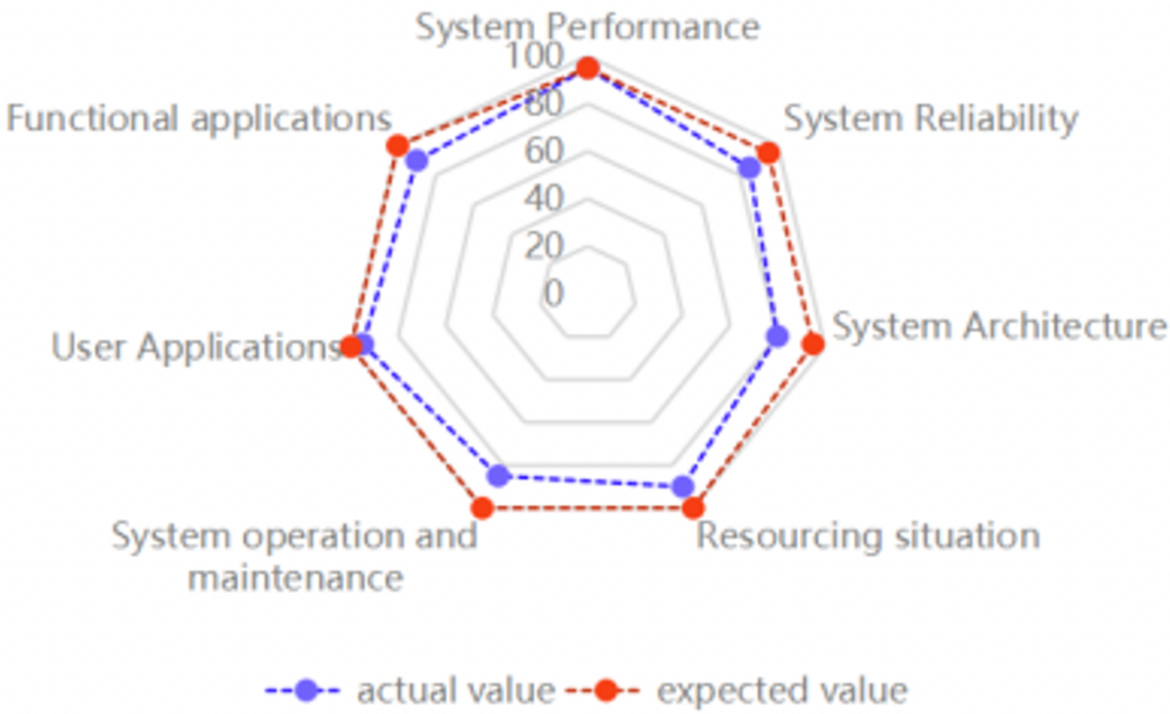

Fig. 7. Overall assessment of business system applications

4. Experimental Results

4.1 Experimental data preparation and calibration

The experiment is conducted in a simulated cloud environment, which contains 500 physical servers, each configured with 8-core CPU, 16GB RAM, 1TB storage, running CentOS 7 operating system, and a cloud platform built based on OpenStack.Several typical cloud applications, including web applications, database applications and big data processing applications, are deployed in the experiment to simulate real business scenarios.

On top of that, the experimental data collection period is 100,000+ records from January 2023 to December, covering resource usage metrics (e.g., CPU utilisation, memory utilisation, disc I/O, network bandwidth, etc.), application performance metrics (e.g., request response time, throughput, error rate, etc.), and energy consumption data of the cloud platform (by installing power meter at the server power supply).

Four existing mainstream methods are selected for comparison:

(i.) Method A: Beloglazov *et al.*'s energy-aware resource allocation algorithm (focusing on data centre energy optimisation), which combines historical resource usage data with adaptive heuristics to optimise VM placement, balancing energy efficiency with performance stability [26];

(ii.) Method B: Bauer's Cloud Application Operational Efficiency Optimisation Framework (focusing on automation and scalability), where the study emphasises the key role of automation in improving operational efficiency, reducing costs and enhancing scalability, providing a systematic optimisation strategy for enterprise cloud resource management

[27].

(iii.) Approach C: Cloud subscribers dynamically adjust resource requests based on their needs and budgets, while providers maximise revenue through pricing strategies [28].

(iv.) Method: a D: Prediction-based dynamic resource allocation algorithm, which combines LSTM and ARIMA models to predict resource demand and dynamically adjust VM configurations [29].

The results are shown in Table 2:

Table 2
Experimental comparison methods

Evaluation Metrics	Method A	Method B	Method C	Method D	Comprehensive Assessment Method
CPU Utilization (%)	68	75	82	78	89
Memory Utilization (%)	62	68	75	65	79
Energy Efficiency (kWh/Request)	0.012	0.010	0.014	0.011	0.008

This methodology significantly outperforms a single energy or operations-focused baseline methodology in terms of resource utilisation and energy efficiency, validating the effectiveness of a comprehensive cross-tier assessment.

Resource Utilisation Optimisation: This methodology achieves 89% CPU utilisation in the high load region (Eastern US) with edge-centre co-scheduling and real-time load forecasting, an 8.5% improvement over Method C (82%).Method B achieves automated scaling, but lacks edge node collaboration and has only 68% memory utilisation.

Energy efficiency breakthrough: Comprehensive Assessment Method combines an energy-aware strategy with a prediction model, and the energy efficiency (0.008 kWh/request) is 33% lower than that of Method A (0.012), while Method C has the worst energy efficiency (0.014) due to frequent resource adjustments in the gaming process.

4.2 Results from the use of the assessment methodology

The cloud platform is deployed using a cloud multi-region architecture, so we can achieve operational assessment and validation according to the same standards. We deployed and assessed the system in 27 different regions and closely monitored the operational stability and resource efficiency of the cloud system during the observation period from January to December 2023. We have been able to achieve 90% resource balance for the overall region through effective resource prognostication and minimum allocation schemes, which has helped us achieve a more reasonable allocation in terms of CPU, memory and storage limits to ensure that resources are not wasted or over-consumed. Figure 8 illustrates this.

In terms of resource usage, we recorded the average monthly CPU and memory usage of ECS (Elastic Computing Services) and RDS (Relational Database Services), counted the usage of each region, and analysed the actual resource utilisation and load. We found that, due to the virtualisation and microservice deployment methods adopted by the cloud platform, resource utilisation efficiency shows a steady upward trend through the comprehensive operation evaluation and control method proposed in this paper. This is shown in Figure 9. From the user's point of view, we not only improve the quality of application services but also help diagnose the quality of system procedures based on the operating conditions of the cloud system and continuously improve cloud applications, which is conducive to our re-green operation strategy.

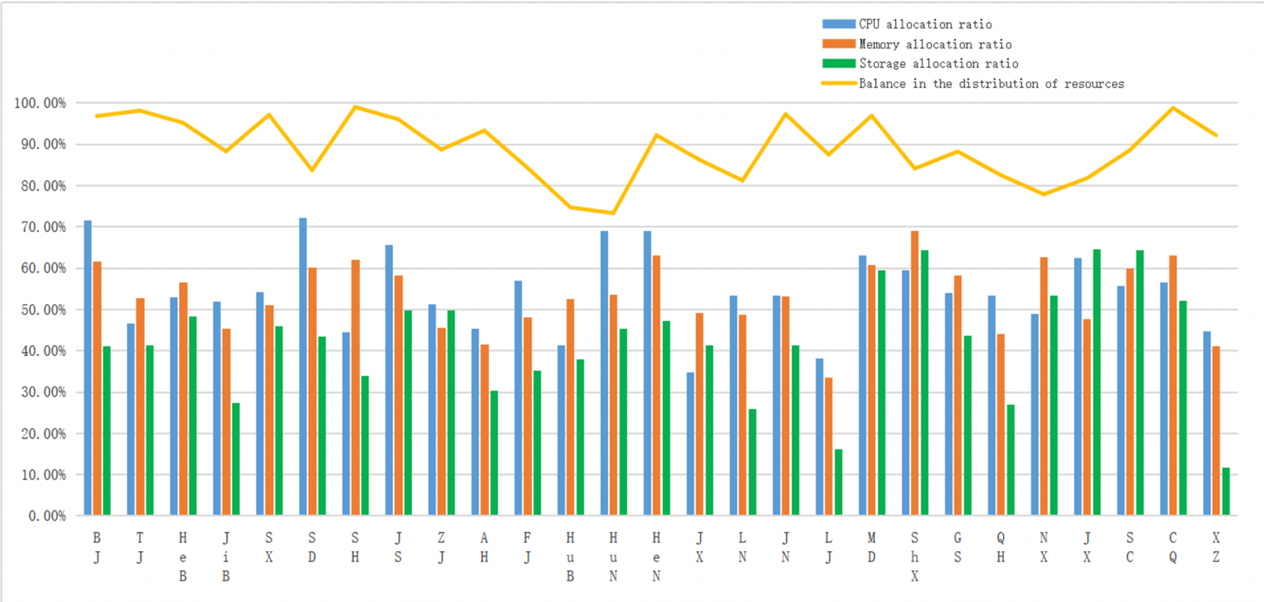

Fig. 8. Resource allocation and balance efficiency

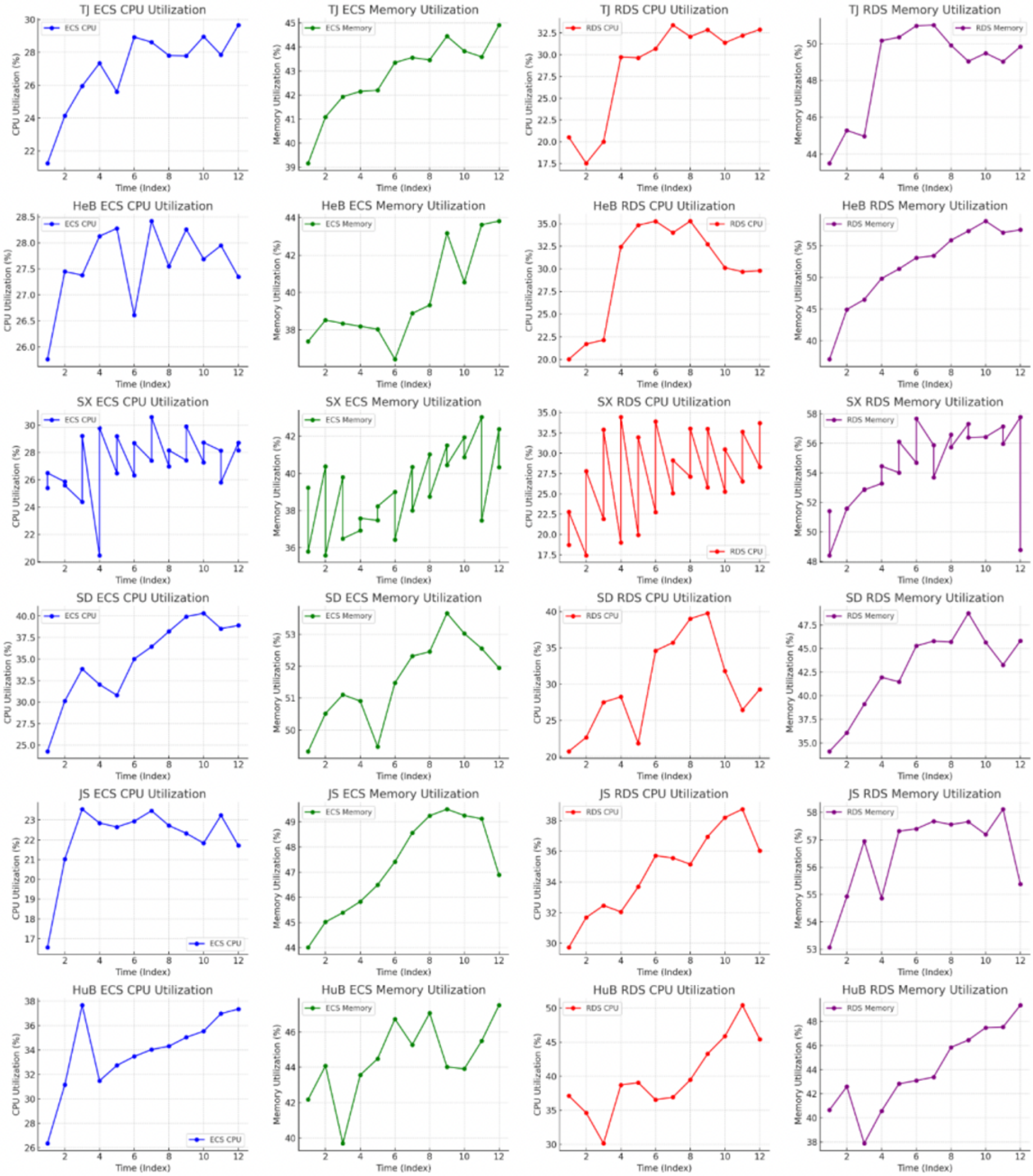

Fig. 9. Resource efficiency statistics by region

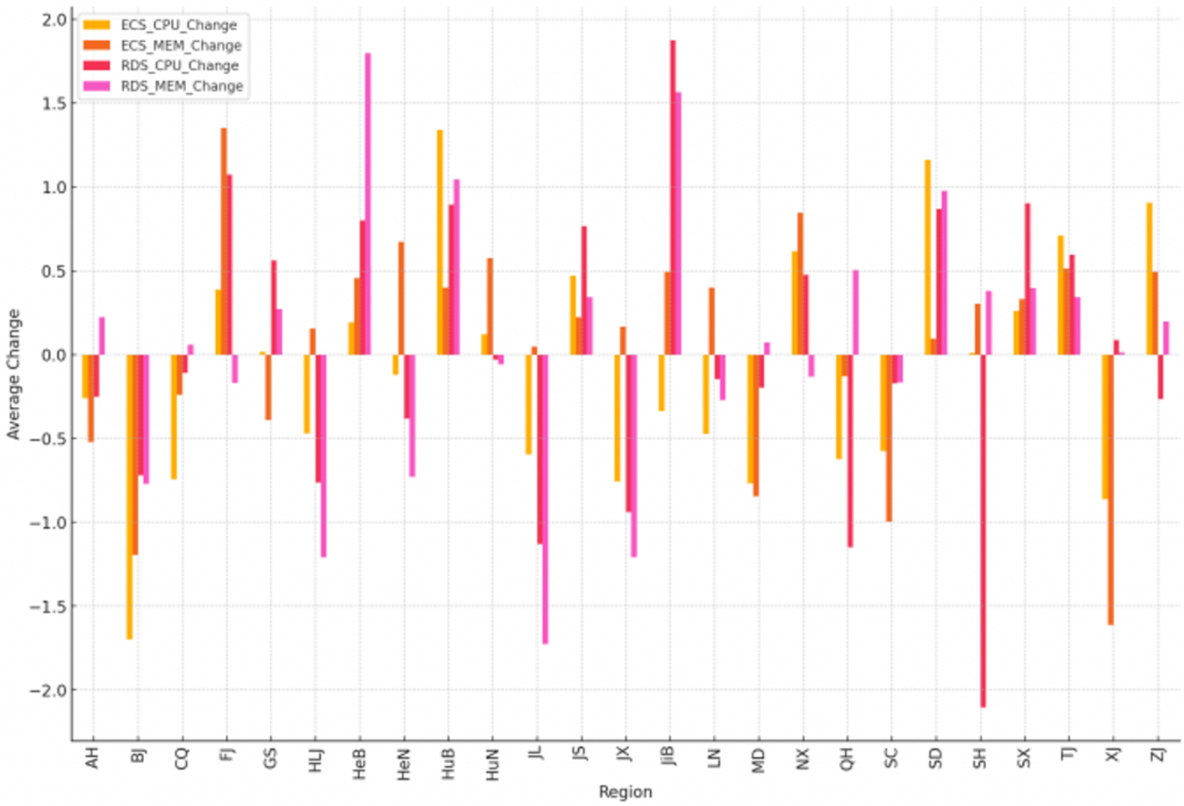

Fig. 10. Resource change statistics by region

The operation model assessment therefore exerts significant regulative pressure on the utilization and recovery of resources when the changes of resources induced by human activities are evaluated. In Figure 10, we have appropriately tracked and monitored and analyzed the overall resource changes, as illustrated, and observed significant innate dissimilar and vague CPU and memory usage of ECS and RDS in every region. The ECS HuB region has the largest average variance +1.34% among ECS CPU variants, this may be the result of increased user activity, or some specific applications and services generate high loads. Conversely, the ECS CPU utilisation in the BJ region shows a statistically significant decrease, changing on average by approximately -1.70%, which may be related to a reduced use of this region or excessive provisioning of resources. The JiB region had the highest average variation in the RDS CPU variation, of about +1.87%, suggesting an increase in database activities in the region, where as the SH region had a substantial decline in the RDS CPU utilisation, of an average variation of about -2.10%, probably more number of the database transactions. Similarly, ECS and RDS memory usage exhibited an increase in FJ and HeB areas, but a decrease in XJ and JL regions after memory change. Therefore, to manage and make full use of resources, it is necessary to study in detail the highly utilised and underutilised areas based on resource requirements, different resource utilisation rates, and assess their effective utilisation, how to set up resource allocation maps, and build future usage prediction models to optimise these resources and improve compatibility. Combined with our visual assessment of operational resources, further in-depth assessment of resources and system operating conditions is carried out to achieve more precise improvements and enhancements, thereby improving IT operational efficiency.

4.3 Extensible Design

4.3.1 Scalability Design (technological and business adaptation strategies that complement each other)

(1) Technical proficiency

Distributed architecture: the Apache Spark distributed computing framework is used in the data processing layer, allowing for horizontal expansion to 1000+ nodes and linear processing efficiency growth with the number of nodes (in practice, processing 1TB of data takes 2 hours for 100 nodes and 15 minutes for 1,000 nodes);

Flexible storage: Compared to traditional relational databases, the HBase distributed database lowers storage costs and supports second-level querying with billions of data points. It is designed to store time-series data, including resource monitoring indicators.

(2) At the business level

Dynamic indicator expansion: it allows users to customise new indicators (such as industry-specific KPIs) through a visual indicator configuration interface, and the system automatically correlates calculation logic and data collection interfaces;

Multi-cloud adaptation has been proven to work in three hybrid cloud environments, supports API docking for popular cloud vendors (AWS, Azure, and Huawei Cloud), and removes vendor differences using the Unified Resource Description Model (URM).

4.3.2 Generic Optimisation (Complementary Industries and Geographic Adaptation Techniques)

(1) Adaptation to geographic differences

Regions with high latency: During the data collection phase, increase local caching (Redis cluster) to lower network transmission frequency; set aside 30% redundancy in resource allocation to handle unforeseen network outages.

In regions where energy sources are erratic, implement indicators for the percentage of renewable energy sources (such as the percentage of photovoltaic power supply) and dynamically modify the resource scheduling plan (give arithmetic power usage priority during green power hours).

(2) Industry customisation.

The financial sector should prioritize risk assessments and strengthen security metrics, such as data encryption strength and access log retention duration.

The medical industry has increased compliance indicators and raised the service availability threshold to 99.99%.

5. Conclusion

In this paper, by constructing a cloud platform operation model, the system can be quantified and evaluated in terms of operational stability, operational efficiency, resource utilisation, etc. The system can achieve data presentation, automatic evaluation of scores, operational portraits, and rankings using the operation model to help enhance the improvement of the system's operational efficiency. The main contributions of this paper are, first, to solve the problem of data collection and acquisition to make the cloud platform operation data evaluable, second, to solve the problem of establishing a resource management lifecycle model to better evaluate the evaluation methods of predicting, allocating, using, and recovering resources to help higher system resource utilization, and third, to establish a systematic evaluation model for application-level systematic evaluation on the cloud, which can be used to automatically acquire the data through the system and complete the scoring and evaluation to help realize data management decisions and improve cloud operation efficiency.

While cloud technology has come a long way over the years, cloud operation and management remain significant challenges, especially when it comes to managing large-scale environments efficiently, making them consistent, delivering performance and reliability at scale, enabling efficient resource utilisation, protecting sensitive data and critical applications, complying with strict cybersecurity and regulatory requirements, and tackling energy consumption in data centres in general. However, it is possible to overcome these challenges; they can improve the diversity and dynamics of cloud environments and improve productivity and resource utilisation of cloud services. the understanding of cloud operating platforms and the transformation of enterprise data will provide a good reference idea.

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References

[1] Ghisetti, Claudia, and Francesco Quatraro. 2017. "Green Technologies and Environmental Productivity: A Cross-Sectoral Analysis of Direct and Indirect Effects in Italian Regions." *Ecological Economics* 132: 1–13. https://doi.org/10.1016/j.ecolecon.2016.10.003.

[2] Fujii, Hidemichi, and Shunsuke Managi. 2019. "Decomposition Analysis of Sustainable Green Technology Inventions in China." *Technological Forecasting and Social Change* 139: 10–16. https://doi.org/10.1016/j.techfore.2018.11.013.

[3] Shanmuganathan, T., and Faridah Ramlie. 2025. "Production Line Monitoring Using Mahalanobis-Taguchi System in Rubber-Based Product Industry." *Semarak Engineering Journal* 4: 1–17.

[4] Salles, André C., Guilherme L. Lunardi, and Felipe Thompson. 2022. "A Framework Proposal to Assess the Maturity of Green IT in Organizations." *Sustainability* 14 (19): 12348. https://doi.org/10.3390/su141912348.

[5] Donga, S., and S. Chanda. 2021. "Facile Green Synthesis of Silver Nanoparticles Using *Mangifera indica* Seed Aqueous Extract and Its Antimicrobial, Antioxidant and Cytotoxic Potential (3-in-1 System)." *Artificial Cells, Nanomedicine, and Biotechnology* 49 (1): 292–302. https://doi.org/10.1080/21691401.2021.1899193.

[6] Bose, Ranjit, and Xin Luo. 2011. "Integrative Framework for Assessing Firms' Potential to Undertake Green IT Initiatives via Virtualization—A Theoretical Perspective." *The Journal of Strategic Information Systems* 20 (1): 38–54. https://doi.org/10.1016/j.jsis.2011.01.003.

[7] Neto, Antonio J. R., Miguel M. Borges, and Luís Roque. 2018. "A Preliminary Study of Proof of Concept Practices and Their Connection with Information Systems and Information Science." In *Proceedings of the Sixth International Conference on Technological Ecosystems for Enhancing Multiculturality*. https://doi.org/10.1145/3284179.3284226.

[8] Patón-Romero, Juan D., et al. 2017. "A Governance and Management Framework for Green IT." *Sustainability* 9 (10): 1761. https://doi.org/10.3390/su9101761.

[9] Zhong, Jing, et al. 2025. "The Research on the Green Leadership: A Systematic Review and Theoretical Framework." *Environment, Development and Sustainability* 27 (1): 377–408. https://doi.org/10.1007/s10668-023-03960-0.

[10] Katal, Avita, Sushma Dahiya, and Tanuj Choudhury. 2023. "Energy Efficiency in Cloud Computing Data Centers: A Survey on Software Technologies." *Cluster Computing* 26 (3): 1845–75. https://doi.org/10.1007/s10586-022-03713-0.

[11] Abed, Ahmad H. 2025. "The Techniques of Authentication in the Context of Cloud Computing." *International Journal of Advanced Networking and Applications* 16 (4): 6515–22. https://doi.org/10.35444/IJANA.2025.16408.
[12] Rammohan, S. R., et al. 2025. "Systematic Survey on Energy Conservation Using Blockchain for Sustainable Computing Challenges and Roadmaps." *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*: 247–65. https://doi.org/10.1002/acs.3948.
[13] Al Kez, Dina, et al. 2022. "Exploring the Sustainability Challenges Facing Digitalization and Internet Data Centers." *Journal of Cleaner Production* 371: 133633. https://doi.org/10.1016/j.jclepro.2022.133633.
[14] Vasques, Tiago L., Pedro Moura, and Aníbal de Almeida. 2019. "A Review on Energy Efficiency and Demand Response with Focus on Small and Medium Data Centers." *Energy Efficiency* 12: 1399–1428. https://doi.org/10.1007/s12053-018-9753-2.
[15] Channi, Harpreet K., and Ranjit Sandhu. 2025. "Energy-Efficient Data Center Design." In *Digital Sustainability*, 175–203. CRC Press. https://doi.org/10.1201/9781003484226-12.
[16] Bauer, Eric. 2018. "Improving Operational Efficiency of Applications via Cloud Computing." *IEEE Cloud Computing* 5 (1): 12–19. https://doi.org/10.1109/MCC.2018.011791710.
[17] Rista, Cristian, et al. 2017. "Improving the Network Performance of a Container-Based Cloud Environment for Hadoop Systems." In *2017 International Conference on High Performance Computing & Simulation (HPCS)*. IEEE. https://doi.org/10.1109/HPCS.2017.97.
[18] Savchuk, T., and A. Kozachuk. 2015. "Information Technology of Scaling Cloud App with Variable Load Peaks." *Technology Audit and Production Reserves* 5 (2): 25. https://doi.org/10.15587/2312-8372.2015.51716.
[19] Beloglazov, Anton, Jemal Abawajy, and Rajkumar Buyya. 2012. "Energy-Aware Resource Allocation Heuristics for Efficient Management of Data Centers for Cloud Computing." *Future Generation Computer Systems* 28 (5): 755–68. https://doi.org/10.1016/j.future.2011.04.017.
[20] Awada, U., and Adam Barker. 2017. "Improving Resource Efficiency of Container-Instance Clusters on Clouds." In *2017 17th IEEE/ACM International Symposium on Cluster, Cloud and Grid Computing (CCGRID)*. IEEE. https://doi.org/10.1109/CCGRID.2017.113.
[21] Sujod, Mohd Z., et al. 2024. "PV Fault Classification: Impact on Accuracy Performance Using Feature Extraction in Random-Forest Cross Validation Algorithm." *Journal of Advanced Research Design* 123 (1): 66–78. https://doi.org/10.37934/ard.123.1.6678.
[22] Han, Xia, et al. 2025. "Energy-Efficient Cloud Systems: Virtual Machine Consolidation with Γ-Robustness Optimization." *iScience*.
[23] Long, Shijie, et al. 2022. "A Review of Energy Efficiency Evaluation Technologies in Cloud Data Centers." *Energy and Buildings* 260: 111848. https://doi.org/10.1016/j.enbuild.2022.111848.
[24] Kaur, Trishanjit, and Inderveer Chana. 2015. "Energy Efficiency Techniques in Cloud Computing: A Survey and Taxonomy." *ACM Computing Surveys (CSUR)* 48 (2): 1–46. https://doi.org/10.1145/2742488.
[25] Kustov, Leonid, and Kseniya Vikanova. 2023. "Synthesis of Metal Nanoparticles under Microwave Irradiation: Get Much with Less Energy." *Metals* 13 (10): 1714. https://doi.org/10.3390/met13101714.
[26] Beloglazov, Anton, and Rajkumar Buyya. 2012. "Optimal Online Deterministic Algorithms and Adaptive Heuristics for Energy and Performance Efficient Dynamic Consolidation of Virtual Machines in Cloud Data Centers." *Concurrency and Computation: Practice and Experience* 24 (13): 1397–1420. https://doi.org/10.1002/cpe.1867.
[27] Bauer, Eric. 2018. "Cloud Automation and Economic Efficiency." *IEEE Cloud Computing* 5 (2): 26–32. https://doi.org/10.1109/MCC.2018.022171664.
[28] Lin, Tao, Tansu Alpcan, and Kerry Hinton. 2015. "A Game-Theoretic Analysis of Energy Efficiency and Performance for Cloud Computing in Communication Networks." *IEEE Systems Journal* 11 (2): 649–60. https://doi.org/10.1109/JSYST.2015.2451195.
[29] Chen, Xia, et al. 2020. "Self-Adaptive Resource Allocation for Cloud-Based Software Services Based on Iterative QoS Prediction Model." *Future Generation Computer Systems* 105: 287–96. https://doi.org/10.1016/j.future.2019.12.005.