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Research on the Design and Application of Financial Accounting Intelligent System Based on Cloud Computing

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SUMMARY: *This paper updates financial accounting information data processing and sharing with the help of cloud computing technology, improves the informatization level of financial accounting management, and establishes a financial accounting intelligent system. Considering the richness and complexity of financial accounting information data, in order to reduce the system energy consumption generated in cloud computing task scheduling, task time adaptation function and equipment energy consumption adaptation function are constructed respectively, and an ant colony algorithm with time constraints is proposed to solve the problem. In order to evaluate the performance of the EACO algorithm in this paper, it is assumed that three different specifications of physical machines are used in each data center to construct the cloud simulation environment, and the execution energy consumption of the algorithm is explored under different numbers of workflow instances, data center resource utilization, and workflow task output data volume. Test the query success rate and average response latency of the financial accounting intelligent system. Under different sizes of workflow task output data volume, the energy consumption of algorithms is ranked as HEFT algorithm > MIHEFT algorithm > NOSF algorithm > EACO algorithm. The maximum energy consumption of EACO algorithm is 2.78E7J, and the EACO algorithm can effectively reduce the energy consumption caused by data transmission. The financial accounting intelligent system built by cloud computing technology has a query success rate of more than 95% and an average query response delay of less than 0.3s, which is able to quickly provide systematic and specialized services for financial accountants.*

KEYWORDS: *EACO algorithm; ant colony algorithm; average response time delay; financial accounting intelligence; computing technology*

1 Introduction

With the rapid development of big data, all industries are facing different degrees of challenges, the traditional financial accounting model faces a bottleneck in data processing capacity, manual entry and reconciliation methods are difficult to cope with tens of thousands of daily transactions accounting needs [1]. The decision support function of management accounting is limited by the depth of data analysis, and the analysis of cost drivers mostly stays at the surface correlation level [2]. Audit efficiency and quality are challenged, and sampling audit methods are difficult to cover all risk points [3]. Compliance requirements continue to escalate, and frequent updates to IFRS require the dynamic adaptability of intelligent systems. The personalized development of customer demand forces financial service innovation, and real-

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time financial consulting and forecasting services become the focus of competition [4, 5]. With the development and application of cloud computing, the design and application of cloud computing-based financial accounting intelligent system is an inevitable choice to enhance the strategic value of the financial sector, and the focus of financial staff will shift from accounting and supervision to value creation [6, 7].

Cloud computing refers to the integration of computer applications in a scalable central server, thus realizing an end-to-end interactive user experience and providing services of software, storage, and computing resources, which has the advantages of lowering the cost of utilization, improving the security of data, and increasing the utilization of resources [8-10]. By designing a cloud-based intelligent system for financial accounting, it helps to provide an ideal solution for big data analysis in financial accounting by leveraging the characteristics of cloud computing such as elastic scaling, resource sharing and on-demand services [11-13]. It can not only help enterprises reduce IT infrastructure investment and maintenance costs, but also centralize the management, real-time update and deep mining of financial accounting data through the big data platform built in the cloud [14, 15].

Since financial accounting involves the sustainable development of enterprises, the design of intelligent system for financial accounting based on cloud computing as well as the application of cloud computing and its related technologies in the field of enterprise financial accounting have become the focus of extensive attention. Literature [16] proposes a new type of intelligent financial management system for cloud computing, CFMSiC, which introduces semantic analysis to strengthen the cognitive parsing of financial data, and puts forward an advanced threshold scheme to guarantee the strategic secure sharing and group management of financial data. Literature [17] studied the system design based on hybrid cloud architecture for the purpose of understanding the integrated financial accounting internal control management system, analyzed the design process of the intelligent cloud platform and carried out experimental validation, and the results showed that the hybrid cloud architecture can significantly shorten the data entry time up to 37.81 seconds, which points out that it has a better operational performance and can better meet the development needs of the financial industry. Literature [18] pointed out that in the context of China's market economy, small and medium-sized enterprises are growing rapidly, accounting informationization is the key to improve their management level, through the application of cloud computing in enterprise accounting management system, the results show that it can effectively improve the economic settlement and enhance the efficiency of management, and at the same time pointed out that it is necessary to establish a secure network protection and rely on strict regulations to cope with the risk of information technology. Literature [19] explores the impact of cloud computing technology on the adoption of cloud accounting and its impact on the company's financial management, analyzes the data of 172 listed companies through structural equation modeling, and points out that system integration and security and privacy are the key factors to promote the adoption of cloud accounting, and cost-benefit analysis, system integration and active use can significantly improve the effectiveness of financial management, but the impact of legal compliance and general cloud platform is limited, and the study emphasizes that the enterprise should The study emphasizes that enterprises should prioritize security and integration and adopt industry-specific solutions, providing an empirical reference for digital transformation in emerging markets.

In addition, literature [20] indicates that cloud computing has the characteristics of low cost, high reliability, etc., which can reduce the threshold of enterprise financial informationization and improve the return on investment, and with the concept of “business-driven value”, it proposes the expense management system based on cloud computing, and the case study shows that after nine years of its implementation, the average financial staff of subsidiaries has been reduced by about 84.7%, and the capital size of enterprises has increased by nearly three times. The case shows that nine years after its implementation, the average financial staff of its subsidiaries has been reduced by about 84.7%, and the capital size of the enterprise has increased nearly three times. Literature [21] emphasizes that the application of big data and cloud accounting technology has changed the mode of enterprise accounting informatization and promoted the change of traditional auditing work. Driven by cloud computing and big data, the scope of auditing, data, risk and technology have changed, giving rise to the innovative mode of "cloud auditing" and analyzing the multidimensional impact of the two on auditing. It also analyzes the multidimensional impact of the two on auditing, constructs an audit implementation framework based on cloud accounting in the big data environment, and describes its business development process. Literature [22] in order to improve the ability of accounting data analysis, put forward a modern accounting data analysis platform construction method based on industrial cloud computing, through the time series model and association rules to extract features, combined with the fuzzy C-mean clustering to improve the parallel computing and statistical analysis ability, simulation shows that the platform can effectively optimize the efficiency of data analysis. Literature [23] aims to explore whether the use of cloud accounting information systems enhances their effectiveness and analyzes the moderating role of firm size, which is found to significantly improve system effectiveness and organizational performance, while AIS effectiveness mediates between the two, emphasizing the importance for SMEs to enhance their profitability through cloud accounting in order to support sustainable development activities. Literature [24] specified that SMEs are an important part of the market economy and their informatization is becoming increasingly critical, and based on sensor monitoring and cloud computing, a new accounting system was designed, proposing a cloud computing SOA architecture and incorporating wireless sensor network technology, and experiments showed that the system's data monitoring accuracy was improved by 13.84%, and the processing efficiency was increased by 14.63%. Literature [25] indicates that the rapid development of cloud computing has profoundly changed the traditional accounting practices, and by comparing and analyzing cloud accounting with traditional systems, it is pointed out that cloud accounting can significantly improve the speed, accessibility and accuracy of financial reports and reduce costs, and at the same time, it analyzes the challenges of data security and network dependence, which provides evidence-based insights and adoption recommendations for academics and practitioners.

This paper designs the financial accounting intelligent system architecture, incorporates cloud computing technology, and analyzes the data processing application of cloud computing technology in the financial accounting system. Considering the energy consumption generated under cloud computing task scheduling, design the task completion time adaptation function and equipment energy consumption adaptation function, and propose the ant colony algorithm based on time constraints for the optimization solution of cloud computing task scheduling model. Design the simulation experiment environment to analyze the energy consumption of the EACO algorithm under different numbers of workflow instances, different data center resource utilization rates, and different sizes of workflow task output data volumes. Combine the financial query success rate with the query interface average response delay expression to test the application performance of the financial accounting intelligent system in this paper.

2 Use of cloud computing technology for intelligent systems for financial accounting

2.1 Financial Accounting Intelligent System Architecture and Functions

At present, the intelligent financial accounting system used by enterprises is usually built on the basis of two key technologies, namely cloud computing and artificial intelligence. The combination of the two can not only use the cloud platform intelligent, automated and batch processing of a large amount of work originally done by manual, and the cloud platform itself also has the effect of promoting the collaborative management of various departments, which builds a cloud collaboration, intelligent management system for the enhancement of the operational efficiency of the enterprise is also a great help.

2.1.1 Enterprise Intelligent Financial Accounting System Architecture

At present, enterprises in the application of intelligent financial systems, follow the idea of building a financial management cloud platform, and with the platform's information interaction function, not only can the resources in the business and management departments to share in a timely manner, and many financial reimbursement, accounting, fund management, funding control and other work can also be completed in the cloud platform under the synergy of mutual aid, which will greatly enhance the enterprise's management efficiency and to ensure that the desired management The result will greatly enhance the management efficiency of the enterprise and ensure ideal management results. As for the specific construction of enterprise financial management cloud voucher, its main part can be divided into three layers: business layer, intelligent layer, data layer. The technical architecture of enterprise intelligent financial accounting system is shown in Figure 1.

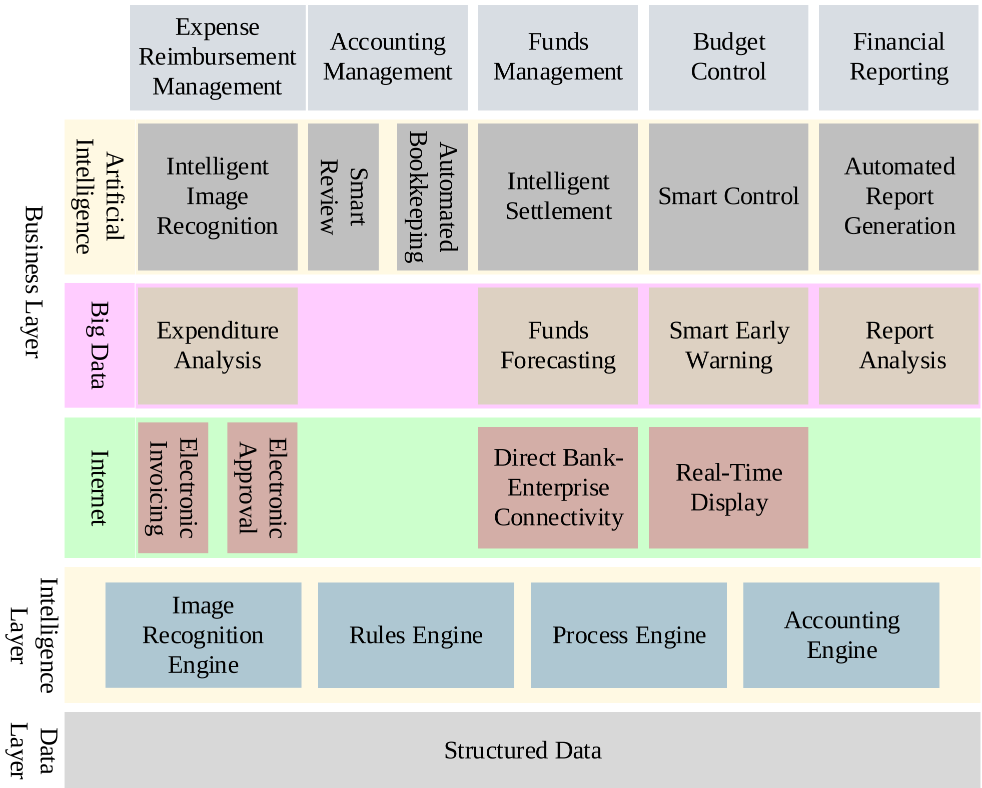

Figure 1: Enterprise intelligent financial accounting system architecture

2.1.2 Functional layers

(1) The business layer is the front-end of the enterprise intelligent financial system, the object is the operator, and the specific functions include all kinds of management related to accounting, such as fund reimbursement, fund accounting, fund control and accounting report. It mainly integrates artificial intelligence, big data, and Internet technologies to realize the pre-processing of financial information and facilitate the information interaction with the intelligent layer.

(2) Intelligent layer is the core part of the enterprise intelligent financial system, and components the key supporting technologies of finance. At the same time, to ensure that the business layer can be applied to more scenarios, the system also adopts the form of engine to provide support. As far as the enterprise intelligent financial system is concerned, the engines it contains are mainly of the following types:

① Image recognition engine. The main role of the engine is to recognize the data in the financial documents, specifically including digital, text and natural semantic understanding technology.

② rules engine. The rule engine is to judge, audit, and classify the relevant structured data by setting the enterprise financial rules.

③ Process engine. The process engine is the approval process for major economic operations and special matters developed by the enterprise according to its own situation.

Accounting engine. Accounting engine corresponding to the content of the original documents and project information, the specific role is to manually define the way to generate accounting entries and reports, in order to complete the classification of the original documents, project information and other information and records.

(3) Compared with the traditional financial system, the data layer of the enterprise intelligent financial system has expanded the dimension of the original data. Traditional financial system data information is usually entered into the financial system in a manual way. The intelligent financial system can automatically fill in the information, and can be structured to transform the financial information data with the support of image recognition technology, which can facilitate the subsequent analysis of financial data.

2.2 Application of cloud computing technology in financial accounting systems

2.2.1 Financial data processing steps

The financial data processing method based on cloud computing includes the following steps:

(1) The data receiving module in the center of the financial data processing system receives various financial data and stores them in the cloud database, which is encrypted through the encryption module. The cloud database stores accounting information, payroll information, business transaction information, report information and cashier information.

(2) The fund checking system in the financial data processing system checks the collected financial data and sends them to the financial classification system for data classification after checking correctly.

(3) The statement analysis system generates financial statements for the classified financial data. The data in the financial statement include single cost data, single profit data, total cost data and total profit data.

(4) The wage settlement system retrieves the data in the financial statement and calculates them according to the pre-entered wage calculation formula, obtains the wage settlement table of each employee and saves it to the local memory.

(5) The warehouse management system accesses the data in the financial statement and

calculates according to the pre-entered calculation formula for incoming and outgoing warehouses to get the cost settlement table for incoming and outgoing warehouses.

(6) Finally, the audit system checks each statement and saves it after checking it correctly.

2.2.2 Financial data processing and queries

The cloud-based financial data processing method includes running multiple application server instances based on the same application code on a cloud cluster server. The server running instances of the tenants are dynamically allocated through load balancing, and the customization requirements of the tenants are supported in a configurable manner. Unified authentication and privilege management for tenants based on their security control mechanisms and privilege management requirements for different platform services. This cloud computing system and method improves the database storage and unified security authentication and permission management method, which is applicable to cloud platforms under various business domains.

The cloud computing-based financial data query method includes: a user node receives a query request submitted by a user, parses the query request and checks the query request. decomposing the query request into a plurality of subqueries, based on a plurality of data sources to be accessed by said plurality of subqueries, converting the plurality of subqueries into a plurality of query languages targeting said plurality of data sources, executing said plurality of query languages and obtaining a plurality of intermediate results respectively; and composing the plurality of intermediate results into a query result. This method can obtain more comprehensive query results in a cloud computing network and avoid unnecessary query operations in order to more rationally utilize computing resources and reduce data transmission costs.

2.3 Cloud Computing Task Scheduling Algorithm for Energy Optimization

In order to optimize the cloud computing task scheduling of the whole financial accounting intelligent system, this section sets out the cloud computing task scheduling function to reduce the overall execution time and device energy consumption of the financial accounting intelligent system.

2.3.1 Cloud Computing Task Scheduling

The goal of task allocation in the mobile cloud computing environment is to reasonably allocate N parallelizable sub-tasks to M mobile devices for execution, minimize the task execution time and system power consumption, improve the task execution efficiency, and reduce the total system energy consumption. In this paper, based on the task time and device energy consumption calculation method, we constructed the task time adaptation function and device energy consumption adaptation function respectively, and divided the task submitted by the user into N sub-tasks that can be processed in parallel, and set $T = \{T_1, T_2, \cdots, T_N\}$ to denote the set of tasks.

(1) Task completion time adaptation function

The mobile resources for executing tasks in the mobile cloud computing environment are dynamic and heterogeneous, and the completion time of the same task on different mobile devices may be different, because it is related to the computational capability of the devices themselves. In general, the cloud server assigns a task T_i to a certain device D_j, and its execution time te_{ij} depends on the length L_i of the task T_i itself and the processing power of the CPU of that device $C_j\left(MIPS\right)$, so the execution time expression is:

$$te_{ij}=\frac{L_i}{C_j\times\left(1-u_{cpu}\right)} \tag{1}$$

where: u_{cpu} denotes the CPU utilization rate of the mobile device, it should be noted that the consideration of u_{cpu} is mainly based on the fact that the time consumed by the CPU in the mobile device, whether it is in the idle state or the busy state, will surely affect the overall execution time of the task.

The completion time of each mobile cloud task is not only related to the computing power of the device, but also usually related to the transmission capacity of the network in which the device is located. It is set that for a task T_i assigned to a mobile device D_j, the task mapping time and return time are ts_{ij} and tr_{ij}, respectively, which are mainly determined by the size of the input data, d_i^{in} and d_i^{out}, as well as the network bandwidth of the device, B_j, respectively:

$$ts_{ij}=d_i^{in}\big/B_j \tag{2}$$

$$tr_{ij}=d_i^{out}\big/B_j \tag{3}$$

Thus the time t_{ij} for some mobile device D_j to complete the task T_i is:

$$t_{ij}=te_{ij}+ts_{ij}+tr_{ij} \tag{4}$$

The final completion time of task T_i is the time taken by the subtask that takes the longest time, i.e., the expression for t_T is:

$$t_T=\max_{ij}t_{ij} \tag{5}$$

Therefore the time fitness function fit_t for the completion of this task is:

$$fit_t=\min_{ij}t_T \tag{6}$$

(2) Device energy consumption adaptation function

According to the energy consumption of the hardware modules such as CPU, memory, Wi-Fi, etc. of the mobile device, the energy consumption model of the mobile device is:

$$p_{ij}=\beta_{ij}\times c_j \tag{7}$$

where: p_{ij} denotes the power consumption generated by the j th hardware device of the i th sample in the test sample. β_{ij} denotes the utilization of the j th hardware device involved in the i th sample. c_j denotes the power consumption coefficient associated with the utilization rate of the j th hardware device. The power consumption of the computer is linearly related to the CPU utilization rate, which is expressed as:

$$E_{cpu} = \alpha_{cpu} \times \mu_{cpu} + \gamma_{cpu} \tag{8}$$

where: E_{cpu} denotes CPU energy consumption. μ_{cpu} denotes the utilization rate. α_{cpu} and γ_{cpu} denote the fixed coefficients respectively. With the help of the above model and the characteristics of terminals in mobile cloud computing, the power consumption mainly comes from CPU and memory modules, so the energy consumption generated by the mobile device D_j to perform the task T_i is as follows:

$$er_{ij} = \mu_{cpu} \times c_{cpu} \times te_{ij} + u_{mem} \times c_{mem} \times te_{ij} \tag{9}$$

where: μ_{cpu}, u_{mem} denote CPU utilization and memory utilization respectively. c_{cpu}, c_{mem} denote the power consumption coefficients of CPU and memory modules, respectively. te_{ij} is the execution time of task T_i on device D_j.

According to the proportional relationship between the energy consumption of data transmission of mobile devices and the size of transmitted data, the energy consumption ed_{ij} caused by data transmission of mobile devices in this paper is set to be expressed as follows:

$$ed_{ij} = d_i^{in} \times ts_{ij} \times c_n + d_i^{out} \times tr_{ij} \times c_n \tag{10}$$

where: d_i^{in}, d_i^{out} denote the input data size and output data size of task T_i, respectively. c_n is the power consumption factor of the network transmission module. ts_{ij} is the task mapping time. tr_{ij} is the result return time.

The energy consumption e_{ij} of the mobile resource device D_j to complete the task T_i is denoted as:

$$e_{ij} = er_{ij} + ed_{ij} \tag{11}$$

The finalized energy consumption of task T_i is the sum of energy consumption of all tasks, i.e., e_T is denoted as:

$$e_T = \sum_{ij} e_{ij} \tag{12}$$

Therefore, the adaptation function for the energy consumption of the equipment is as follows:

$$fit_e = \min_{ij} e_T \tag{13}$$

2.3.2 Design of Ant Colony Algorithm Based on Time Constraints

In this paper, the ant colony algorithm is used to solve the multi-objective optimal scheduling problem of cloud tasks with deadline constraints. Based on the characteristics of the ant colony algorithm in the iterative optimization process according to the pheromone and heuristic information seeking, the deadline time of the task is introduced into the pheromone updating rules of the ant colony algorithm and the heuristic information is redefined, and the algorithm finally carries out the multi-objective constraint function of the completion time and the energy consumption under the The final algorithm performs iterative optimization under the multi-objective constraint function of completion time and energy consumption to achieve the multi-objective optimization balance of task completion rate, completion time and energy consumption.

In the cloud task multi-objective optimal scheduling of this paper, the pheromone is represented by the combination of task and VM, $\tau_{i,j}$ denotes the pheromone value that assigns the task i to the VM j, and the initial value of the pheromone is very important, which has a great influence on the optimization seeking efficiency of the ant colony algorithm, and the initial value of pheromone, τ_0 is set to:

$$\tau_0 = \frac{1}{N} \tag{14}$$

Besides pheromone, heuristic information is another important factor in ACO algorithm. In this paper, the heuristic information $\eta_{i,j}$ is represented by the combination of execution time and energy consumption required for task i to be executed on VM j, and the larger $\eta_{i,j}$ indicates that shorter execution time and energy consumption can be obtained by assigning task i to VM j. The mathematical expression for $\eta_{i,j}$ is as follows:

$$\eta_{i,j} = \begin{cases} \dfrac{1}{ect_i^j \times E_i^j}, & ft_i^j \le d_i \\ 10^{-3}, & otherwise \end{cases} \tag{15}$$

where E_i^j denotes the energy consumption of task i after execution on VM j.

During each iteration of the ACO algorithm's optimization search, the ants select the next target based on the value of the product of the pheromone and the heuristic information and decide which VM will be selected next according to a probabilistic behavioral selection rule called pseudo-random proportionality, which has the following expression:

$$j = \begin{cases} \arg\max\left\{\left[\tau_{i,j}\right]^{\alpha} \cdot \left[\eta_{i,j}\right]^{\beta}\right\}, & q \le q_0 \\ J, & otherwise \end{cases} \tag{16}$$

where q_0 is a value located at $[0,1]$, q is a parameter uniformly distributed between $[0,1]$, and α and β are weighting factors, which determines the degree of importance between the two factors. J is a random variable. $\tau_{i,j}$ and $\eta_{i,j}$ denote the pheromone value and the heuristic information for task i to select VM j, respectively, and the value of $\left[\tau_{i,j}\right]^{\alpha} \cdot \left[\eta_{i,j}\right]^{\beta}$

denotes the value of pheromone and heuristic information by the element and heuristic information jointly determines the expected value of task i to select VM j. Eq. (16) indicates that the probability that the ant chooses the optimal task and VM mapping scheme is q_0.

At this point the ant continues to develop the existing knowledge while exploring other possible scheduling schemes with probability $(1-q_0)$ to avoid falling into local optima. In this paper, the random variable J is used to select the target VM in the form of roulette.The probability of roulette is formulated as:

$$p_{i,j} = \frac{\left[\tau_{i,j}\right]^{\alpha} \cdot \left[\eta_{i,j}\right]^{\beta}}{\sum_{v_j \in V} \left[\tau_{i,j}\right]^{\alpha} \cdot \left[\eta_{i,j}\right]^{\beta}} \tag{17}$$

$p_{i,j}$ denotes the probability that task t_i selects VM v_j, and α and β are the weighting coefficients, which determine the relative influence of the pheromone and heuristic information, respectively.

A pseudo-random proportionality rule is used to select the target VM for each task, and when $q \le q_0$, the task will select the VM with the maximum value of the product of pheromone and heuristic information.After each task selects the target VM, it needs to perform a local pheromone updating, and the process increases the probability of other ants selecting the same VM by evaporating some of the pheromone, which makes the probability of other ants selecting the same VM relatively less, and increases the chance of the other un chances of selected VMs, the expression is as follows:

$$\tau_{i,j} = (1-\xi) \times \tau_{i,j} + \xi \times \tau_0 \tag{18}$$

where ξ is the pheromone evaporation coefficient, which satisfies $0 < \xi < 1$, indicating the degree of pheromone evaporation, and τ_0 is the value of the initial pheromone. The smaller ξ is, the more pheromone is evaporated, otherwise, the more pheromone is left behind.

In this paper, the scheduling goal is to minimize the completion time, energy consumption and improve the task completion rate, according to the objective function using the standard ant colony algorithm for optimization, the obtained scheduling scheme can only obtain the minimum completion time and energy consumption, so the task deadline time is introduced into the pheromone updating rule, so as to achieve the goal of maximizing the task completion rate. The improved pheromone local update rule is as follows:

$$\tau_{i,j} = \begin{cases} (1-\xi) \times \tau_{i,j} + \xi \times \tau_0, & ft_i^j \le d_i \\ \tau_{i,j} \times \varphi, & otherwise \end{cases} \tag{19}$$

where φ is the penalty coefficient and $0 < \varphi < 1$, it means that the pheromone combination (t_i, v_j) that fails to satisfy the deadline is penalized to minimize the pheromone, so that the other ants will have the smallest chance to choose this VM.

The scheduling scheme S^* generated by the optimal ants is used as the optimal scheduling scheme for this iteration, and the global pheromone is updated according to this scheme as follows:

$$\tau_{i,j} = (1-\xi) \times \tau_{i,j} + \xi \times F\left(S^*\right) \tag{20}$$

Global pheromone updating increases the pheromone concentration of each combination in the optimal scheduling scheme S^* by increasing the chances of the ants selecting these combinations in subsequent iterations, allowing the ants to aggregate in the optimal direction. In the local pheromone update rule, the task deadline condition is introduced into the pheromone update rule. Similarly, in the global pheromone update rule, the task deadline condition is introduced to modify the global pheromone update rule, and the modified global pheromone update rule is as follows:

$$\tau_{i,j} = \begin{cases} (1-\xi) \times \tau_{i,j} + \xi \times F\left(S^*\right) & ft_i^j \le d_i \\ (1-\xi) \times \tau_{i,j} & otherwise \end{cases} \tag{21}$$

The new update rule (21) indicates that in the current optimal scheduling method S^*, only combinations that satisfy the task deadline are allowed to release the pheromone, otherwise, these combinations only evaporate the pheromone without releasing it, thus increasing the chances that other VMs that can satisfy the task deadline will be selected.

3 Simulation experiment and result analysis

In this paper, analog simulation is used for testing and validation of algorithms. Simulation is widely used in many fields to experiment and validate algorithms, etc. In this paper, we use Java language to simulate the software environment. In this paper, we use Java language to simulate the software environment, which is widely used in various large-scale projects and has abundant tool libraries and frameworks. At the same time, Java has a multi-threaded concurrency mechanism that can well support multi-task parallelism, which is a common technology for high-performance background services and big data processing services. Therefore, this experiment also uses JAVA language for simulation. The specific parameters of the experimental environment are shown in Table 1.

Table 1: Specific parameters of the experimental environment

Environment	Configuring	Parameter
Hardware environment	Processor model	12thGen Intel(R)Core(TM)i5-12500H
	Memory size	32.00GB
	Graphics model	Intel(R)Iris(R)Xe Graphics
Software environment	Operating system	Windows 11
	JDK version	OpenJDK 1.8.0_312

3.1 Simulation experiment of energy consumption optimization algorithm

3.1.1 Parameter setting

To analyze and evaluate the performance of the EACO algorithm proposed in this paper. It is assumed that each data center uses three different specifications of physical machines to build the cloud simulation environment, and three cloud service providers with a total of 15 different types of virtual machine instances are set up to conduct the simulation experiments, and the parameter settings of the virtual machine instances of the three cloud service providers are shown in Table 2.

Table 2: 3 cloud service provider virtual machine instance parameter Settings

<table>
<tr><th></th><th>Numbering</th><th>Virtual machine type</th><th>The owner of the cloud service provider</th><th>Computing core</th></tr>
<tr><td rowspan="5">Cloud service provider 1</td><td>1</td><td>m4.large</td><td rowspan="5">Amazon EC2</td><td>3</td></tr>
<tr><td>2</td><td>m4.xlarge</td><td>6</td></tr>
<tr><td>3</td><td>m4.2xlarge</td><td>12</td></tr>
<tr><td>4</td><td>m4.4xlarge</td><td>24</td></tr>
<tr><td>5</td><td>m4.10xlarge</td><td>48</td></tr>
<tr><td rowspan="5">Cloud service provider 2</td><td>6</td><td>DS1v2</td><td rowspan="5">Microsoft Azure</td><td>1</td></tr>
<tr><td>7</td><td>DS2v2</td><td>3</td></tr>
<tr><td>8</td><td>DS3v2</td><td>6</td></tr>
<tr><td>9</td><td>DS4v2</td><td>12</td></tr>
<tr><td>10</td><td>DS5v2</td><td>24</td></tr>
<tr><td rowspan="5">Cloud service provider 3</td><td>11</td><td>n1-standard-1</td><td rowspan="5">Google Compute Engine</td><td>1</td></tr>
<tr><td>12</td><td>n1-standard-3</td><td>3</td></tr>
<tr><td>13</td><td>n1-standard-6</td><td>6</td></tr>
<tr><td>14</td><td>n1-standard-12</td><td>12</td></tr>
<tr><td>15</td><td>n1-standard-24</td><td>24</td></tr>
</table>

In the experiment, each data center is set up to use three physical machines with different specifications, and the specific structure of the physical machines and the related energy consumption settings are shown in Table 3.

Each cloud service provider has three data centers, with an internal bandwidth of 300MB/s, a data transfer bandwidth of 200MB/s between different data centers belonging to the same cloud service provider, and a data transfer bandwidth of 100MB/s between data centers belonging to different cloud service providers.

Table 3: Physical machine structure and related energy consumption Settings

Physical hardware configuration	Base energy ratio/W
HP ProLiant ML110 G4 (Intel Xeon 3040, dual-Processor clocked at 1860 MHz,4GB of RAM)	89
HP ProLiant ML110 G5 (Intel Xeon 3075, dual-Processor clocked at 2660 MHz,4GB of RAM)	94.1
HP ProLiant SL390s G7 (Intel Xeon 5649, dual-Processor clocked at 3060 MHz,16GB of RAM)	196

To evaluate the performance of EACO algorithms, the following five algorithms are selected as comparison algorithms:

(1) Online Multiple Workflow Scheduling Framework (NOSF), which is a representative meta-heuristic. By using the energy consumption calculation model in this paper, the EACO algorithm compares the cost and energy consumption required to execute workflows with this algorithm.

(2) Energy-aware virtual machine scheduling method (EVMS). the EACO algorithm compares the required energy consumption with this algorithm.

(3) Improved Particle Swarm Optimization Algorithm (Improved PSO). the EACO

algorithm is compared with this algorithm in terms of energy consumption.

(4) Highest Earliest Fulfillment Time (HEFT) and Multi-Objective Earliest Fulfillment Time (MOHEFT) algorithms for heterogeneous computing environments.HEFT is the classical list scheduling algorithm and EACO algorithm is compared with it in terms of cost.

3.1.2 Energy consumption optimization algorithm experiment and analysis

The experimental results comparing the performance of each algorithm under the condition of varying the number of workflow instances are shown in Fig. 2. The performance comparison of the EACO algorithm is shown in Fig. 2. The execution energy consumption of the EACO algorithm is 2041 $\times 10^4$, 1.5 $\times 10^4$, 2×10^4 , 2.5 $\times 10^4$ and 3×10^4 for the number of workflow instances respectively, the execution energy consumption is 2041J, 2607J, 3546J, 4384J, and 5213J.

The EACO algorithm outperforms the other algorithms in terms of energy saving because the Improved PSO algorithm and EVMS algorithm find the right type of VM for the task, but they do not consider the VM reuse, and the computational resources of the VMs are idle leading to wastage of resources.The NOSF algorithm takes into account the VM reuse, but ignores the effect of the output dataset on the algorithm's performance The NOSF algorithm, although considering VM reuse, ignores the impact of the output dataset on the algorithm performance.

The experimental results in Fig. It can be seen that as the number of scheduled workflow instances grows, the more effective the EACO algorithm is in reducing energy consumption compared to other algorithms.

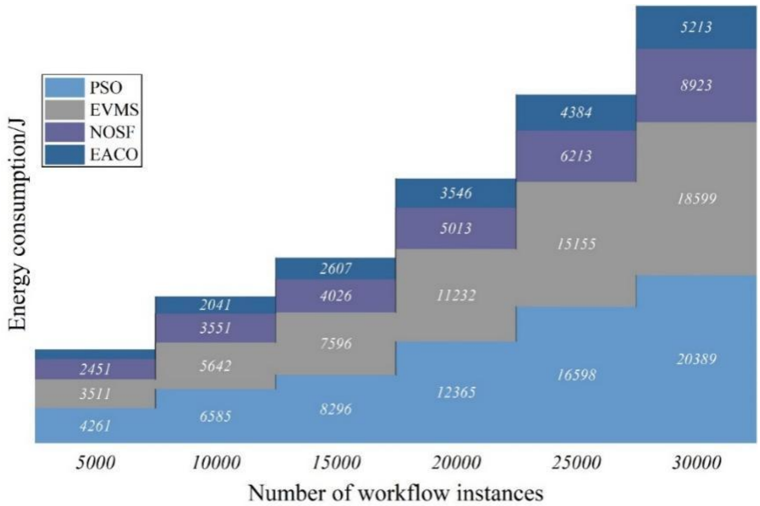

Figure 2: The algorithm performance of workflow instance quantity changes

The experimental results comparing the performance of each algorithm under different data center resource utilization are shown in Fig. 3. Among them, the initial resource utilization of 60% means that 60% of the physical machine resources have been occupied before the workflow tasks to be scheduled arrive at the data center.

From the result comparison, it can be seen that as the initial resource utilization of the data center becomes higher, the higher the probability that the tasks cannot be processed in the same data center. Therefore the growth rate of all the algorithms' result trend curves has been increasing, but it can be seen that the EACO algorithm is the slowest growing. When the initial resource utilization of the data center reaches 90%, the execution energy consumption of the EACO algorithm is 4.05E7J. This is due to the fact that the task group selection policy in EACO assigns multiple consecutive tasks to the same virtual machine for execution, which greatly reduces the data transmission loss.

It is worth mentioning that the execution expense of the HEFT algorithm does not change with the initial resource utilization of the data center, this is because the HEFT algorithm allocates the highest level VM for each task, so there exists a large amount of idle time of the VM that can be used for cross-data-center data transfers, then the execution expense remains unchanged.

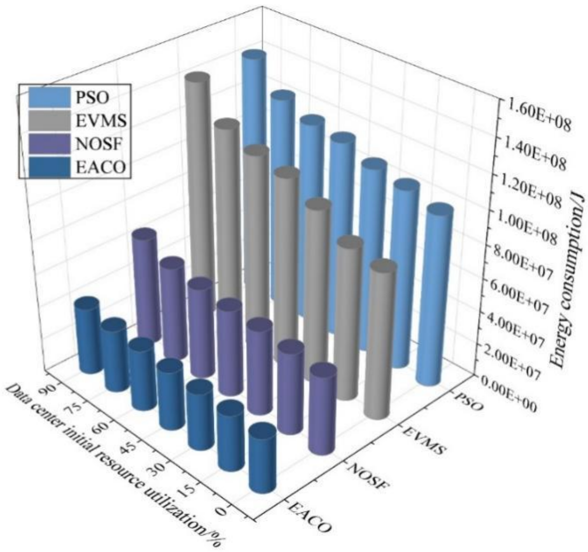

Figure 3: The performance of different data center resource utilization

The experimental results of comparing the performance of each algorithm under different sizes of workflow task output data volume are shown in Fig. 4. The maximum energy consumption of the EACO algorithm is 2.78E7J, which is significantly lower than that of the NOSF algorithm, MIHEFT algorithm, and HEFT algorithm. The energy consumption is sorted as HEFT algorithm > MIHEFT algorithm > NOSF algorithm > EACO algorithm.The change trend of the results of EACO algorithm is more gentle than that of NOSF algorithm. This indicates that the task group selection strategy in the EACO algorithm can effectively reduce the energy and cost caused by data transmission.

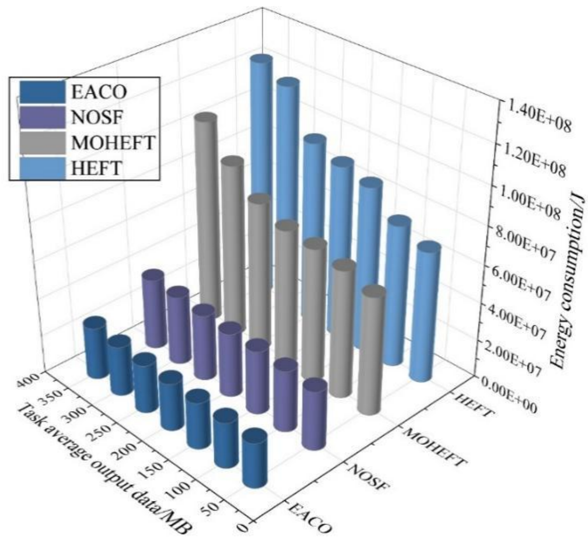

Figure 4: The results of the experimental results of the workflow task output data

3.2 Financial Accounting Intelligent System Simulation Experiments

3.2.1 Experimental subjects and related settings

Based on the design system test requirements, a modern financial accounting intelligent database is selected as the experimental object, 11000 financial data are randomly selected from the database, which is randomly divided into 10 experimental groups, and the specific experimental conditions are set up as shown in Table 4.

Table 4: Experimental condition setting

The experimental group	Financial data	Class quantity
1	1050	15
2	1200	10
3	950	9
4	1100	17
5	1000	12
6	850	6
7	1100	14
8	1250	16
9	1150	13
10	1350	18

Based on the above extracted experimental samples, the relationship between the experimental parameter γ and the number of financial categories is tested, and the schematic diagram of the relationship between the parameter γ and the number of financial categories is shown in Figure 5. As can be seen from the figure, when the experimental parameter γ takes the value of 6, the number of financial categories to reach the minimum value of 6, more conducive to the design of the system application performance verification experiments. Therefore, the optimal value of the experimental parameter γ is determined to be 6.

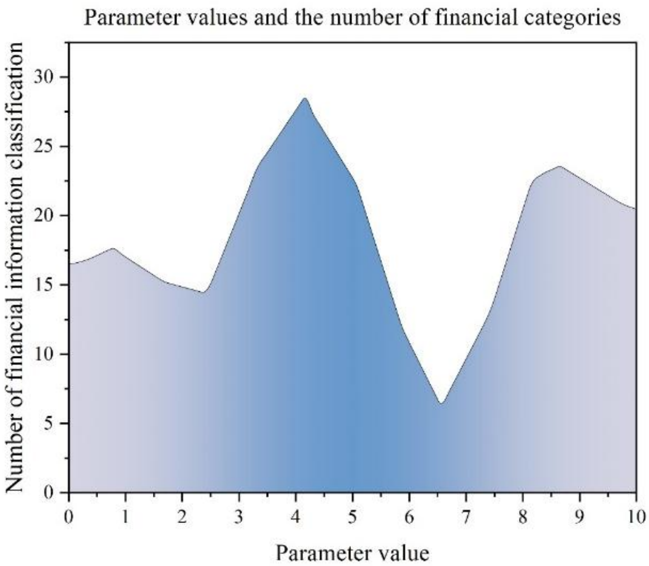

Figure 5: The parameter and the number of financial categories

3.2.2 Experimental indicators

The financial query results and their query interface response latency are recorded, and the financial query success rate and query interface average response latency are calculated with the expression:

$$K = \frac{q}{q_{all}} \times 100\% \tag{22}$$

$$T = \frac{T_z}{q_{all}} \tag{23}$$

where K and T denote the financial query success rate and the average response delay of the query interface, respectively. q represents the number of successful financial queries. q_{all} denotes the total number of financial inquiries, and T_z denotes the total response delay of the query interface.

3.2.3 System query success rate

In order to verify the effectiveness of the financial accounting intelligent system constructed based on cloud computing technology in this paper, the system of this paper, system A and system B are used to conduct experimental tests to verify the effect of the query success rate of each system, and the comparison of the query success rate of the three systems is shown in Fig. 6.

The information query correct rate of this paper's system is stable between 95% and 100%, the highest correct rate of information query of this paper's system is 99.52%, the highest correct rate of information query of System A and System B is 79.25% and 85.65%. It can be seen that the correct rate of information query of this paper's system is significantly higher than that of the comparison method, which indicates that this paper's method is more accurate and practical.

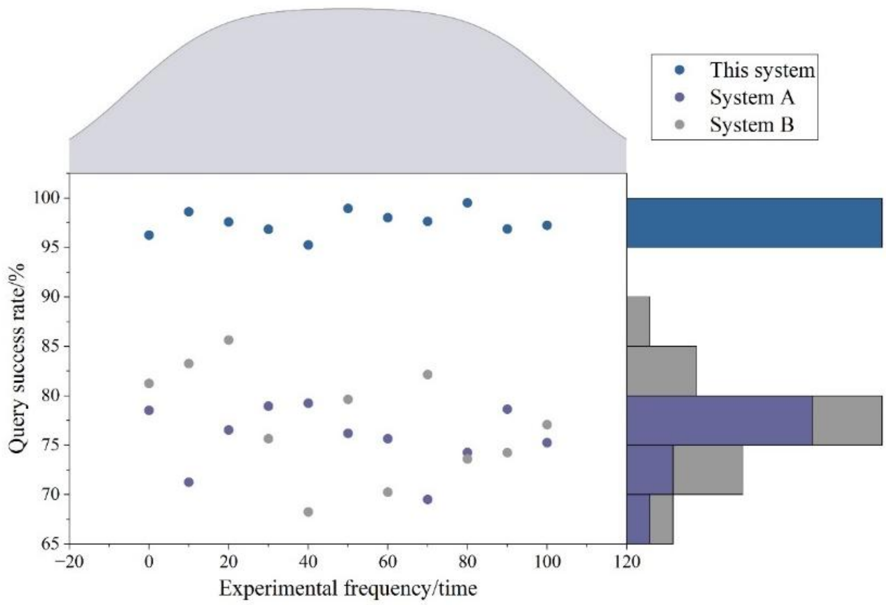

Figure 6: Comparison of query success rate of 3 systems

3.2.4 Average system query response latency

In order to further verify the practicality of this paper's method, the average response latency of the system query is used as the experimental index for experimental testing.The comparison results of the average response latency of the three systems are shown in Fig. 7.

The query average response delay of the system in this paper is up to 0.24 s, and the query average response delay of system A and system B is up to 0.37 s and 0.41 s. The query response delay of the system in this paper is significantly lower than that of system A and system B, and it achieves the expected effect of the system development without any obvious defects and problems, which fully confirms that the system has a better application performance.

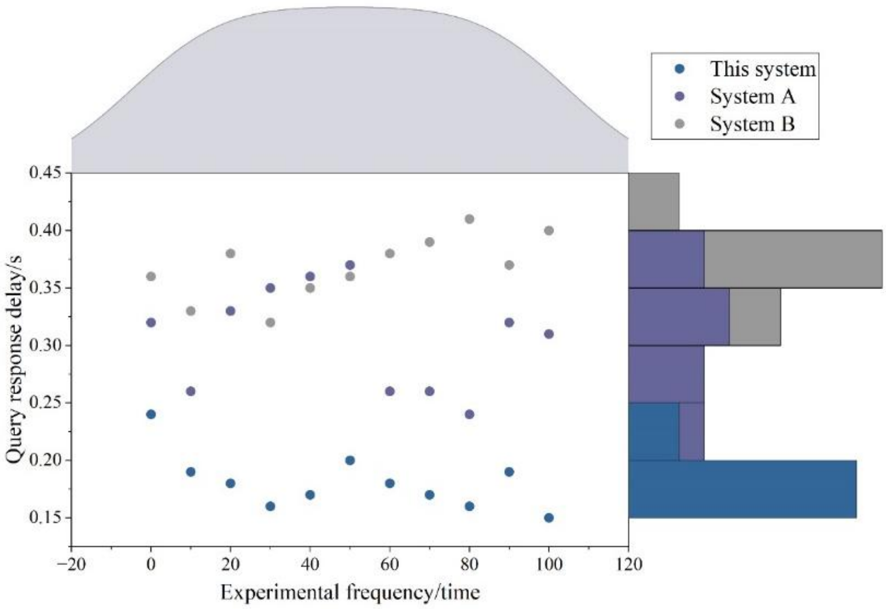

Figure 7: The average response of the three systems is the delay

In order to further validate the application performance of the modern financial information management system based on cloud computing technology, the system throughput index is introduced, which reflects the pressure that the system server can withstand, and there is a link between the throughput and the number of virtual users when no performance bottleneck is encountered, which is calculated by the formula:

$$F = \frac{VUB}{T} \tag{24}$$

where F denotes the system throughput. VU denotes the number of virtual users. B denotes the number of requests issued by each virtual user, and T denotes the time used to test the system performance. Based on equation (24) the throughput of the system is obtained as shown in Fig. 8.

From the results of the figure, it can be seen that with the increase in the number of virtual users, the throughput of the system also shows a rapid growth trend. When the number of virtual users reaches 300, the corresponding rising trend of system throughput slows down, and when the number of virtual users is 600, the basic throughput of the system is about 1000bps, which is a better performance to ensure the operation and processing speed of the system, and verifies that the system has a better application performance.

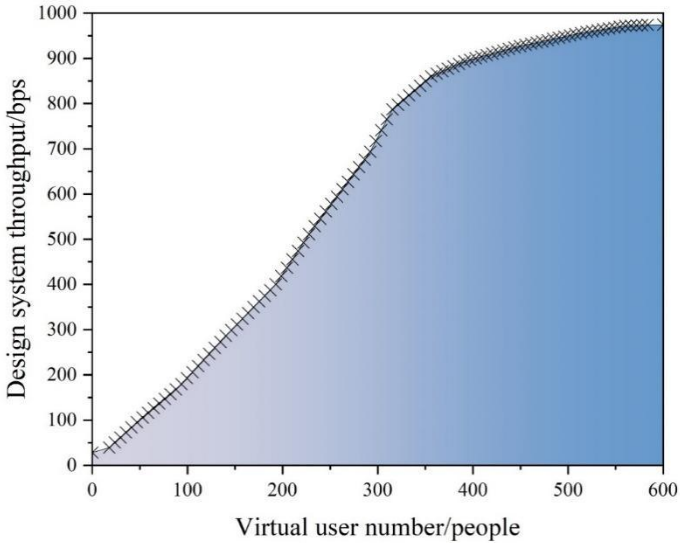

Figure 8: System throughput

4 Conclusion

This paper designs the architecture and main functions of financial accounting intelligent system, and proposes the time constraint-based ant colony algorithm for optimizing the scheduling of financial accounting data and information, taking into account the optimization of energy consumption. We analyze the performance of the time-constrained ACO algorithm in energy consumption optimization and conduct simulation tests on the financial accounting intelligent system constructed based on cloud computing technology in this paper.

(1) When the number of workflow instances is 3×10^4 , the execution energy consumption of the EACO algorithm is 5213J, and the execution energy consumption of the EACO algorithm of this paper is the least under the conditions of different numbers of workflow instances. When the initial resource utilization rate of the data center reaches 90%, the execution energy consumption of the EACO algorithm is 4.05E7J, which is significantly lower than other algorithms. When the workflow task outputs the largest amount of data, the execution energy consumption of the EACO algorithm is 2.78E7J, and the EACO algorithm can effectively reduce the energy consumption caused by data transmission.

(2) The experimental parameter γ takes the value of 6, and the number of financial categories is more suitable for financial accounting intelligent system to carry out verification experiments. In this paper, the information query success rate of the financial accounting intelligent system constructed based on the EACO algorithm of cloud computing technology is stable at more than 95%, and the average response delay of the query does not exceed 0.3s.

The financial accounting intelligent system based on cloud computing technology has a high financial query success rate in simulation experiments, shorter query interface average response time delay, providing more powerful support for financial management, and helping to improve the modern financial information management level.

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