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Data Center Energy Management Based on Cloud Computing and Artificial Intelligence

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Cloud computing (CC hereafter) is a relatively new technology, which has the characteristics of high resource utilization, flexible management and good scalability. However, because a large number of computing and storage resources are concentrated in the cloud, it becomes more difficult to effectively manage energy. Hence, this paper proposes a nonlinear energy consumption model based on artificial intelligence (AI) and CC. The main components of energy consumption, such as central processing unit (CPU), memory and hard disk, were calculated, and statistics and regression analysis were carried out on the utilization rate of each component. Subsequently, the corresponding energy consumption prediction model was obtained. In the energy consumption model, this paper fully considered the influence of CPU on the energy consumption of other components, and designed the influencing factors between components so as to ensure the accuracy of the model. In the energy consumption model, the impact of CPU on the energy consumption of other components was taken into account, and the factors impacting the various components were designed to ensure the accuracy of the model. From the analysis of the nonlinear model, it is evident that the highest and lowest predicted values of the linear segmented model were 147 and 72, respectively. In the linear single-line model, the highest and lowest predicted values were 163 and 80, respectively. The highest and lowest predicted values under the nonlinear single-line model were 153 and 85 respectively. The highest and lowest predicted values under the nonlinear segmented model were 174 and 97, respectively. Therefore, it is very necessary to study the energy management of data center (DC hereafter) by using an AI algorithm.

Keywords: Energy Management, Data Center, Artificial Intelligence, Cloud Computing

1. INTRODUCTION

With the increase of networking and data centralization, the DC is an important part of enterprise information construction and business applications. The business of the DC is also changing in areas such as data processing, data application, data storage and services. Today, with the rapid development of computer and Internet technology, the concept of “green DC” has gradually attracted the attention of the industry due to the close relationship between business enterprises and information technology. With the continuous development of the DC, its role is becoming increasingly prominent and complex, which requires scientific management and effective operation. Facing the increasingly fierce market and policy, all major companies should pay attention to the use and management of IT resources. IT infrastructure is the key to ensuring the normal, orderly, stable and sustainable development of business. The system combines computer technology with advanced networks such as the Internet of Things, digital sensing and distributed computing. It can dynamically monitor, collect data and calculate the consumption of all kinds of energy in real time, and analyze the energy consumption of the DC. This can provide support for the energy-saving transformation and operation of DC.

The research on the energy management of DC is a hot topic at present. Nada has carried out numerical simulation

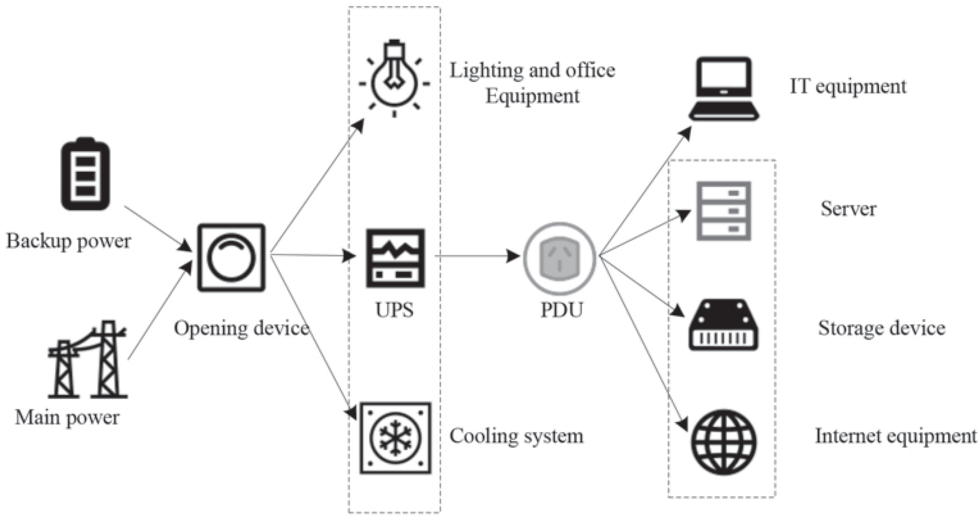


Figure 1 Basic composition of DC.

on the structure of three different cooling units: one with a rack between each two cooling units (configuration A); one with two racks (configuration B) between each two cooling units, and one with three racks (configuration C) between each two cooling units. He established and verified the scaling physical model of the DC rack [1]. In order to analyze the development status of an energy storage system, Li studied several application scenarios involving reducing the output fluctuation, reaching agreement on the output plan of renewable energy generation side, power grid frequency modulation, power flow optimization on the output side [2]. Lu proposed a stable price prediction model based on artificial neural network (ANN) to cope with the uncertainty of future prices [3]. Sudha believes that EcoMultiCloud is an effective way to reduce cloud computing infrastructure costs, as it can improve energy efficiency, sustainability, and power service reliability [4]. However, due to the lack of data sources, these researches are only at the theoretical stage and as yet have no practical significance.

An innovative approach is to study the energy management of DC using AI algorithms. Qi proposed an energy-efficient virtual machine allocation strategy with an asynchronous multi-sleep mode and an adaptive task migration scheme [5]. To reduce energy consumption, Madhumala combined the improved first-fit decline (FFD) algorithm with the particle swarm optimization algorithm to obtain optimal virtual machine packaging in an active physical machine [6]. Patel proposed a hot and cold spot mitigation method based on multivariate resource use prediction. This method considered the current and future use of resources with time complexity [7]. Mahapatra improved home design architecture by adopting the concept of green buildings to reduce residents' energy consumption [8]. However, due to the traditional thinking and definition, the two cannot be highly integrated, preventing them from giving full play to their advantages.

The main innovations of this paper are as follows: (1) a self-power supply scheme is proposed for a green power system that can reduce energy consumption; (2) an energy management system based on AI is proposed for DCs. With this method, corresponding response strategies can be formulated based on different electricity price mechanisms, while ensuring the quality of service provided to users, reducing energy consumption, and conserving energy.

2. DATA CENTER ENERGY MANAGEMENT BASED ON CC

2.1 Energy Management of a Data Center

A DC comprises a refrigeration system, uninterruptible power supply (UPS), information technology (IT) equipment, lighting and office equipment, power distribution system and backup power supply, as shown in Figure 1.

With the development and improvement of cloud technology, the traditional DC has gradually changed to CC. The CC has three layers: service layer, platform layer and software layer. The bottom layer includes environmental protection infrastructure such as refrigeration and UPS as well as IT equipment. At all levels of the cloud DC, resources, configurations and activities are closely related to the energy utilization of the entire DC.

The management and optimization of energy consumption is closely related to the business supported by cloud DC [9-10]. The early management and optimization of energy consumption are usually carried out at various levels, with the focus on the energy-saving optimization of computer room cooling, servers, network equipment, etc., while the impact factors on each level are relatively small. With the deepening of research, more and more scholars are beginning to pay attention to the management and optimization of energy consumption oriented by service quality. In order to improve overall efficiency, energy monitoring and collection are usually required for DC at all levels. This allows the optimal utilization and continuous improvement of resources while ensuring the energy consumption at all levels, joint perception of services, collaborative scheduling of resources, and quality of service.

In this paper, a cross-level CC data center system is proposed based on energy perception, energy control, and optimal resource scheduling. The operation of the energy

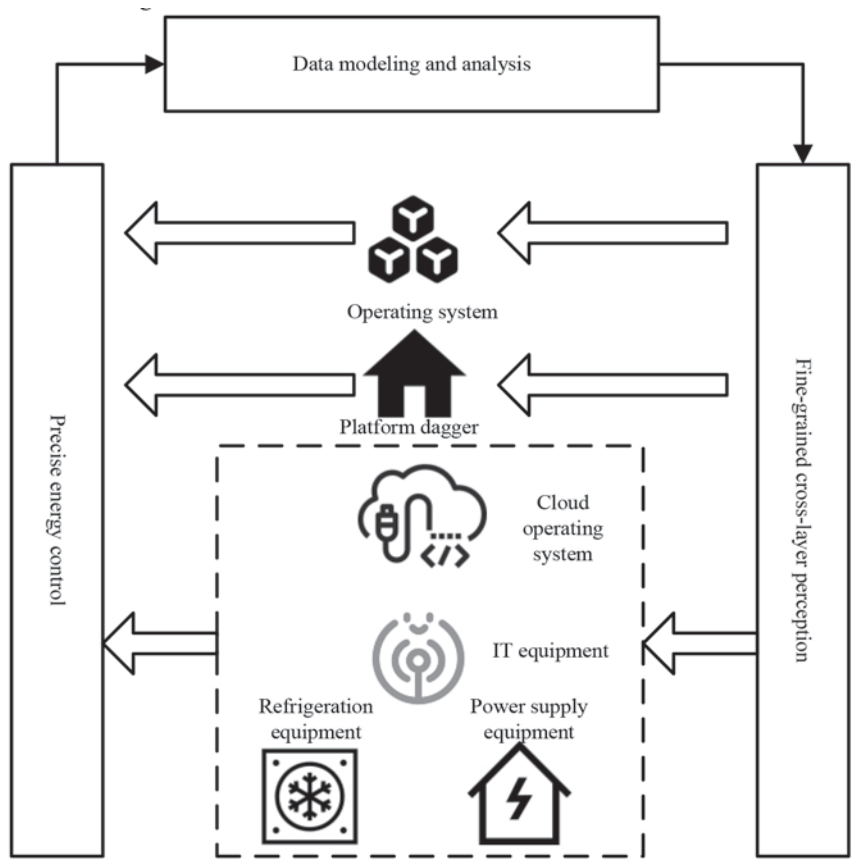


Figure 2 Energy consumption perception and precise energy management framework of CC data center.

management system involves energy consumption and business data collection, energy data modeling and analysis, resource optimization and scheduling, and accurate energy control, as shown in Figure 2.

The collection of data on energy consumption and business is the basis of energy management. It uses indicators such as L1 layer (cooling, power supply), L2 layer (IT equipment) energy consumption data, and power use efficiency (PUE). This can be used to understand the energy consumption and changes of the CC data center, and subsequently find the equipment and systems with large energy consumption so as to establish corresponding countermeasures. The energy consumption of a cloud operating system, platform software and application software can be calculated based on the characteristics and business model of the system by collecting the working status and service quality of IT equipment. This can lay the foundation for resource optimization and scheduling [11]. The perceived accuracy of energy consumption is directly related to the precision and frequency of energy consumption data, while the precise monitoring and collection of energy requires many IT resources. This is the case for a typical big data business, so it needs an efficient and high-speed big data processing system to support data storage and processing.

For AI and data mining, some data for energy management purposes must be processed rapidly and in real time. For example, if the power consumption of the server exceeds the specified range, the power control must be completed within tens of milliseconds. This requires real-time monitoring and processing of all servers in the DC. The energy consumption model and analysis of CC data center cover the energy consumption model including air conditioning and refrigeration equipment, IT equipment, and virtual machine and application processes. The energy consumption of a power system was simulated based on the factors such as equipment composition, resource utilization rate and events. The AI technologies involved include regression analysis, neural network, decision tree.

2.2 Balance Between Energy Consumption, Efficiency Loss and Communication Cost of Data Center

This paper contains a discussion of the method used to optimize the DC with CC technology, and reports the in-depth research conducted on its energy consumption, efficiency loss and network overhead. As shown in Figure 3, the DC scheme in different locations was studied.:

As shown in Figure 3, the system first sends the user's load to the local domain name system (DNS). Next, the DNS server determines how these loads are distributed (which loads are sent to which DC). Here, only the regional load balancing of DNS servers was considered. That is, when the user's load is transferred to a specific DC, it is not transferred to other DC for processing. The DC studied here depends on the power grid on the one hand, and utilizes locally generated renewable energy on the other hand. However, only some DCs

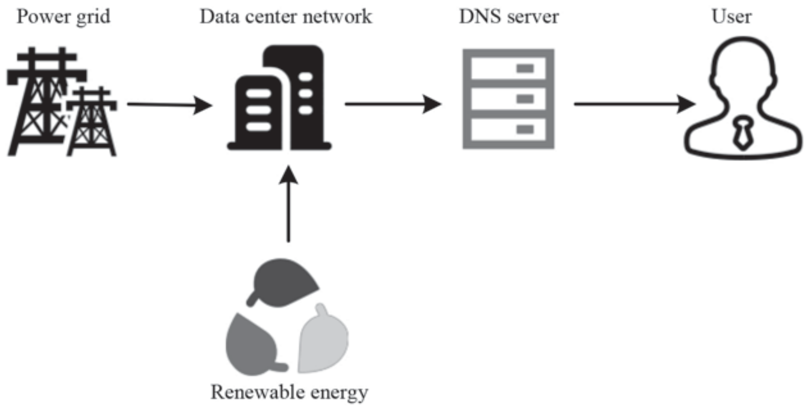


Figure 3 Regional load balancing example.

have installed renewable energy power generation equipment locally [12–13]. Therefore, a management method based on demand response and energy supply is proposed in this paper. It should be noted that users do not know which DC is responsible for the load. That is, without user authorization, the geographic load balancing of the DC wouldn't be disclosed to users.

2.3 Data Center Energy Management Methods Based on Cloud Computing

In this study, the following were taken into account: the energy consumption of IT equipment, the energy consumption of non-IT equipment, and the additional energy consumption of IT equipment caused by switching the DC server. Here, PUE is used to estimate the energy consumption of non-IT equipment in the DC, and E_{pue} represents PUE in the DC. In addition, $P_m[t]$ (kW) and $P_o[t]$ (kW) represent the power consumption of the IT devices in the DC within the time slot of t and the increased energy consumption due to the shutdown of the server. Therefore, the average power consumption of the DC in time slot t, expressed as $p[t]$, is modeled as follows:

$$P[t] = E_{pue}\left(P_m[t]+\tfrac{P_o[t]}{T}\right), \quad \forall t. \tag{1}$$

The average power consumption of IT equipment in the DC at t time slot is modeled as follows:

$$P_m[t] = m[t]\left(P_{idle} + \left(P_{peak} - P_{idle}\right)u[t]\right), \quad \forall t. \tag{2}$$

Here, $m[t]$ represents the number of servers in the slot when t is turned on. P_{idle} (kW) and P_{peak} (kW) represent the power consumption of individual servers at idle and full speed, and $\forall t$ is the average utilization rate of server servers in t slot, so that:

$$m[t] = \sum_{t'=1}^{t}\left(m_{on}[t'] - m_{off}[t']\right) + m[0], \quad \forall t. \tag{3}$$

Here, $m_{on}[t']$ and $m_{off}[t']$ represent the number of servers that are open and closed in the time slot, and $m[0]$ represents the number of servers that are open in the DC in the initial condition. Here, the $m[t]$ is the number of servers that are turned on at time slot t and can load immediately. Because the newly-enabled server needs a long time to prepare for processing the load, the DC must start the server in advance. For example, if there is a server $m_{on}[t']$ in the time slot t to be started, the DC must be started before the time slot, so that when the time slot t is started, the service can be used immediately for load calculation, so that:

$$u[t] = \frac{\lambda[t]}{N * m[t]}, \quad \forall t. \tag{4}$$

In the formula, $\lambda[t]$ represents the number of loads processed in time slot t, and N represents the maximum number of loads that the server can handle at full speed. It is assumed that all loads in the DC are the same; that is, all loads require the same resources and processing time [14]. This assumption does not conform to the actual situation, but all loads in the DC can bedivided into different units, and each unit requires the same DC resources and processing time.

$$P_o[t] = o_{on}m_{on}[t] + o_{off}\, m_{off}[t], \quad \forall t \tag{5}$$

Here, o_{on} (kWh) and o_{off} (kWh) represent the additional energy consumption caused by switching on a server. In fact, switching the server on and off would cause additional energy consumption, because the server is not able to handle the load; also, the process of turning it on or off consumes energy. According to the above formula, the single-line linear energy consumption model $\bmod\ le_{liner\_\sin gle}$ is obtained:

$$P_{total} = \gamma_c U_c + \gamma_m U_m + \gamma_d U_d + \gamma \tag{6}$$

where, P_{total} represents the overall energy consumption of the system, and U_c is the processor utilization. U_m is the memory utilization and U_d is the hard disk utilization. γ_c, γ_d, γ_m are the coefficient of the corresponding variables, so the energy consumption models are as follows:

$\bmod\ le_{liner\_\sin gle}$ formula:

$$P_{total} = \gamma_c U_c + \gamma_m U_m + \gamma_d U_d + \gamma_0 \tag{7}$$

γ_0 is the coefficient of the corresponding variable. $\text{modl}_{\text{liner\_segment}}$ formula:

$$\begin{cases} P_{total} = \gamma_c^1 U_c + \gamma_m^1 U_m + \gamma_d U_d + \gamma_0^1 \\ P_{total} = \gamma_c^2 U_c + \gamma_m^2 U_m + \gamma_d U_d + \gamma_0^2 \end{cases} \tag{8}$$

Table 1 Description of experimental environment.

Serial number	Item	Describe
1	Node	One Management Node, Four Computing Nodes
2	Operating System	Cent0S release 6.3 (Final)
3	Programming Environment	Java 1.7 & gcc
4	Cloud Computing Environment	Hadoop 0.20.2
5	Acquisition Frequency	2 times/second
6	CPU	Intel (R) Xeon(R) CPU E5-2650 0@2.00GHz,8GB memory, 1TB hard drive

modl$_{\mathrm{nonliner_segment}}$ formula:

$$P_{total} = \gamma_c U_c + f(U_c)U_m + \gamma_d U_c U_d + \gamma_0 \tag{9}$$

modl$_{nonliner_segment}$ formula:

$$\begin{cases} P_{total} = \gamma_c^1 U_c + f(U_c)U_m + \gamma_d^1 U_c U_d + \gamma_0^1 \\ P_{total} = \gamma_c^2 U_c + f(U_c)U_m + \gamma_d^2 U_c U_d + \gamma_0^2 \end{cases} \tag{10}$$

3. EXPERIMENT ON DATA CENTER ENERGY MANAGEMENT BASED ON ARTIFICIAL INTELLIGENCE

3.1 Introduction to Experimental Environment and Real Scenario Simulation Tools

According to the content, this paper simulated the relationship between $\{U_c,\ U_m,\ U_d|P\}$, so people need to collect processor utilization, memory utilization, hard disk utilization and energy consumption. In addition, in order to prove the portability of the model, this paper would run three different types of parallel algorithms [15]. Therefore, the experimental environment of this group of experiments is shown in Table 1:

In addition, in different environments, a benchmark was used to test processor utilization, memory utilization and disk utilization. A benchmark can also be used for real-world simulation tests. Benchmark is divided into three categories according to its working mode: computer, hard disk and network. This paper selected the computer energy model based on SPEC2006. These courses include linear programming, editor, robot weiqi, weather prediction, image coding, genetic sequence search, quantum computation, molecular dynamics, hydraulics, discrete event simulation, etc. [16].

3.2 Experimental Results

In this paper, the program (Benchmark and SPEC2006) was used to simulate the change of the utilization rate of each component in a stand-alone environment, and the corresponding energy consumption was collected simultaneously. The accuracy of the processor before and after segmentation can be tested first in a stand-alone environment, and then the accuracy of the four models can be compared. Finally, this paper compared the performance of each model in an actual scenario, and finally validated each model in a CC environment.

(1) Comparison of accuracy of single-line type and segmented type models

Formula (7) is a typical single-line processor utilization model, while Formula (8) is the segmented processor utilization model proposed in this paper [17]. The segmented energy consumption model is better than the single linear model. The conclusions are verified by experiment 1. The actual energy consumption value is the average value of energy consumption near the processor utilization range, as shown in Figure 4.

In Figure 4 (a), the peak value of single-line energy consumption is 157, while the minimum value is 82. In Figure 4 (b), the peak value of segmented energy consumption is 166, and the minimum value is 103. In Figure 4 (c), the actual energy consumption value is 157 at the highest and 91 at the lowest. Therefore, it can be seen from Figure 4 that the segmented energy consumption model is superior to the single-line model in most cases. The former shows good accuracy at each stage of processor utilization, but the accuracy of the single-line energy consumption model fluctuates. Experiment 1 confirms the superior performance of the method proposed in this paper, since the segmented model greatly improves the accuracy.

(2) Comparison of accuracy of each final energy consumption model

This experiment was conducted to compare the accuracy of the models represented by the four formulas. According to the main changes of the initial model, this paper makes two assumptions: the piecewise linear energy consumption model and the single-line nonlinear energy consumption model are better than the single-linear model. In addition, the piecewise nonlinear energy consumption model is better than both the piecewise linear model and the single-line model. Experiment 2 compares the predicted value of each data point model with the actual value, as shown in Figure 5.

In Figure 5 (a), the maximum predicted value of the linear segmented model was 147 and the minimum was 72. In Figure 5 (b), in the linear single-line model, the highest predicted value was 163 and the lowest was 80. In Figure 5 (c), the maximum predicted value under the nonlinear single-line model was 153 and the minimum was 85. In Figure 5 (d), the maximum predicted value under the nonlinear segmented model was 174 and the minimum was 97. From Figure 5, this paper can draw three conclusions:

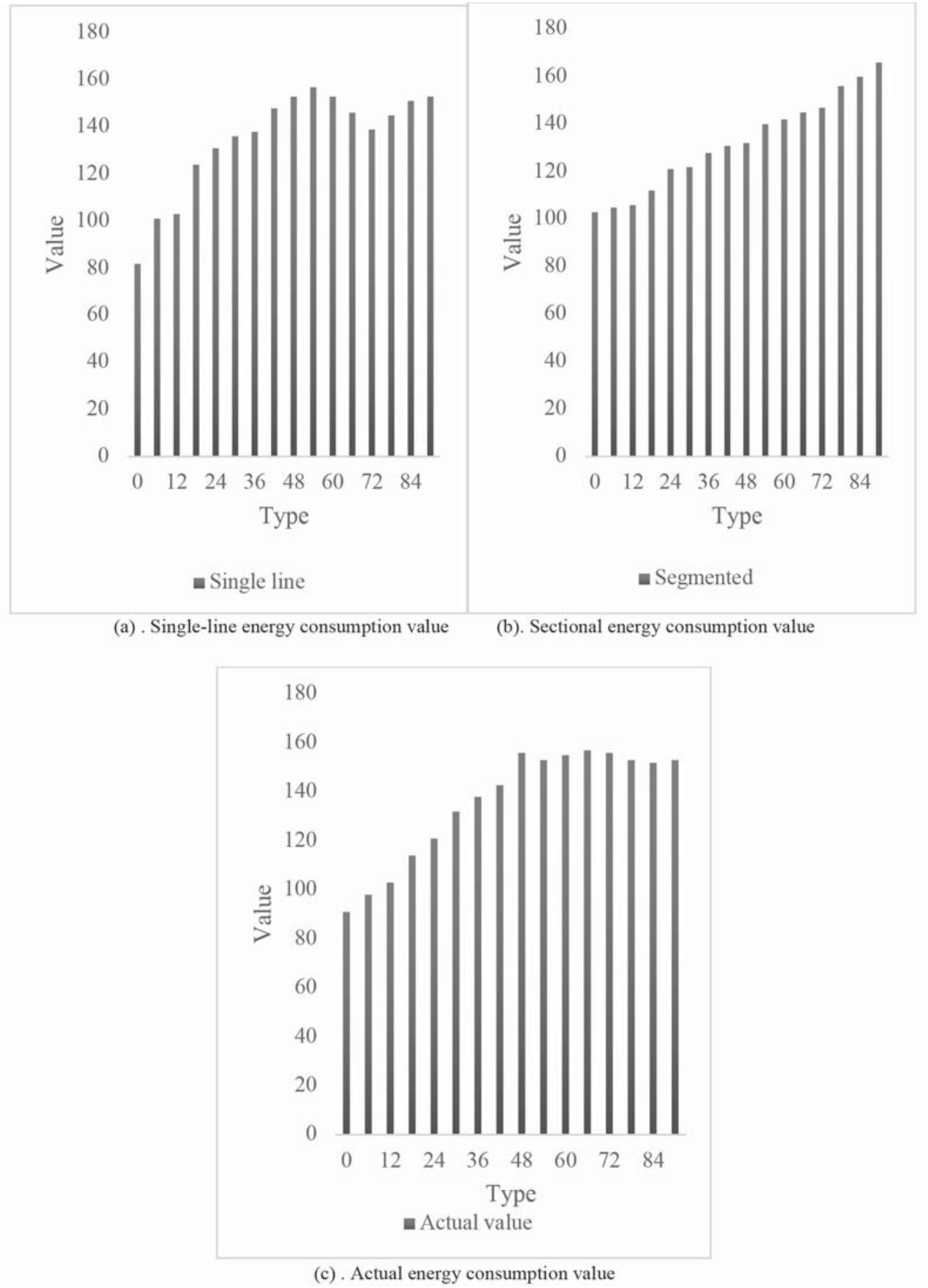


Figure 4 Accuracy comparison of single-line type and segmented type models.

First, the predicted value of the linear model fluctuates greatly, while the nonlinear model shows a relatively smooth feature.

Secondly, the piecewise linear energy consumption model is more accurate than the linear linear model. Compared with the linear model, the single-line nonlinear energy consumption model has higher accuracy.

Thirdly, the segmented nonlinear energy consumption model has better prediction accuracy than the segmented linear model and the single-line nonlinear energy consumption model.

In addition, the experiment determined the accuracy of each model, as shown in Table 2.

The accuracy data in Table 2 further validates the assumption made in this paper. Segmental design and nonlinear calculation can improve the accuracy of the model to a certain extent, and their integrated segmented nonlinear energy consumption model reaches the peak of accuracy.

(3) The performance of each model in the real scene

Both Experiment 1 and Experiment 2 use data from a virtual scenario, which does not represent the performance of the model in a real-world scenario. The comparison between the real value and predicted value of each energy consumption model in the real-world scenario under different algorithms is shown in Figure 6.

(a)model linear_ Comparison between segment and real value
(b)model linear_ Compare single with true value

(c) model nolinear_ Single and real value comparison
(d) model nolinear_ Comparison between segment and real value

Figure 5 Statistical chart of comparison between four models and real values.

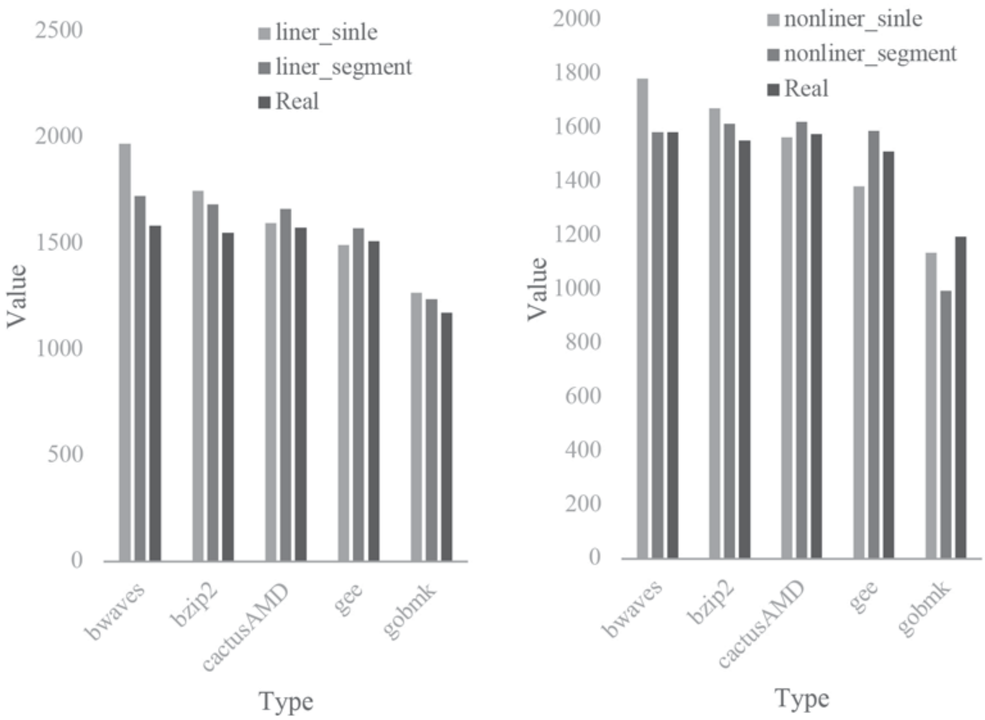
Table 2 Accuracy of each model.

Sequence	Type	Accuracy
1	Model liner_single	0.87696
2	Model liner_segment	0.9488
3	Model noliner_single	0.92386
4	Model noliner_segment	0.95675

In Figure 6 (a), the peak value of the linear energy consumption model in the real scenario is 1972, and the minimum value is 1174. In Figure 6 (b), the peak value of the nonlinear energy consumption model in the real scenario is 1782, and the minimum value is 994. Figure 6 indicates that all energy consumption models perform well in real scenarios as a whole, although the segmented nonlinear energy consumption model is still the most accurate.

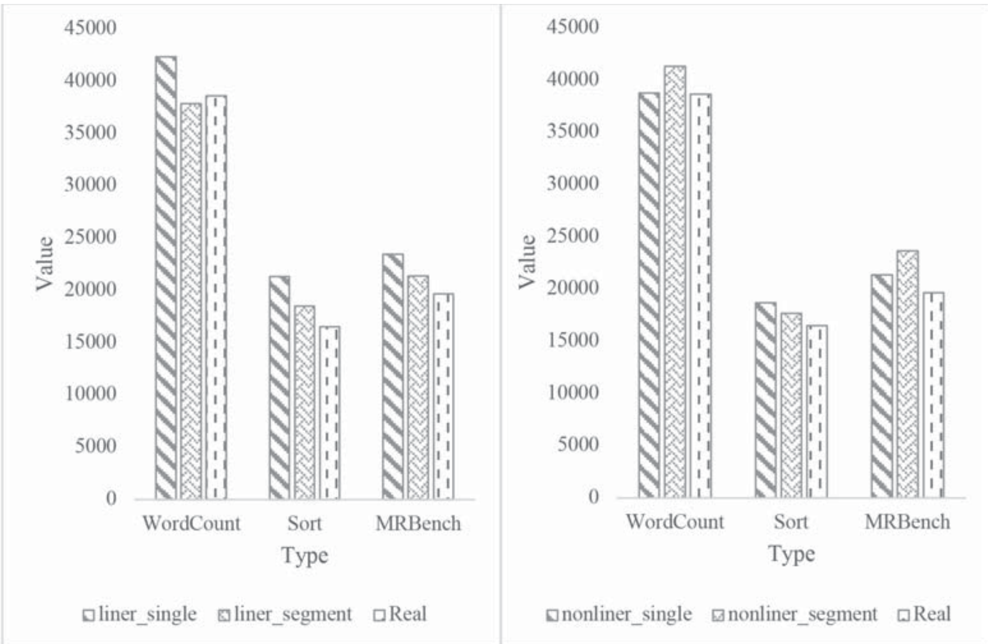
(4) Performance of various models in a CC environment

In order to verify the transferability of the energy consumption model, this paper selected three different types of parallel algorithms as examples of CC in this paper. In the context of CC, three algorithms with 1G capacity were used to collect data and compare them with traditional computing methods, as shown in Figure 7.



(a) Performance of linear energy consumption model in real scenarios
(b) Performance of nonlinear energy consumption model in real scenarios

Figure 6 Performance of various energy consumption models in real scenarios.



(a) Performance of linear energy consumption model using three CC algorithms
(b) Performance of nonlinear energy consumption model using three CC algorithms

Figure 7 Performance of each model using three CC algorithms.

It can be seen from Figure 7 (a) that the linear energy consumption model reached its peak with the WordCount CC algorithm, with a peak of 42385. It reached the lowest level in the Sort CC algorithm, 18496. In Figure (7) b, the nonlinear energy consumption model reached the highest value (41326) with the WordCount CC algorithm, the lowest value (17658) with the Sort algorithm, as shown in Figure 7. All models can adapt well to the CC environment, and the conclusions obtained in the CC environment have also been verified. The segmented nonlinear energy consumption model still performs best.

First of all, this paper found that CPU utilization was distributed in a piecewise linear manner, and on this basis found the internal relationship between memory energy consumption and CPU. The formula of CPU that influences memory was obtained, and the hard disk was added as the final energy consumption model. The experimental results show that these two methods can improve the accuracy of the segmented nonlinear energy consumption model.

4. ENERGY MANAGEMENT COUNTERMEASURES AND OPTIMIZATION OF DATA CENTER AND COMPUTER ROOM

4.1 Energy Management and Optimization of Computer Room

The energy management of the computer room of a CC data center mainly involves the setting of operational parameters and management of the status of refrigeration and IT equipment. At the same time, it also requires a reasonable layout to ensure the normal operation of the DC. The cooling mode and temperature characteristics of the computer room would inevitably seriously affect its energy consumption, and this impact is continuous, and therefore necessitates the optimization of the computer room. The core function of the computer room cooling system is to maintain all IT equipment at a suitable working temperature. The computer room's overall consumption of cooling power is affected by many factors including not only the cooling mode, but also the layout of the machine room and the direction of heat flow. When cooling such areas, it is necessary to consider not only the cooling demand, but also the overall energy consumption of various types of auxiliary equipment. At present, the use of linear programming, neural network design and other related technologies can effectively reduce the overall power consumption of the computer room, while ensuring that the equipment operates at the appropriate temperature.

In a DC, power supply and physical space are both scarce resources, so it is necessary to set up IT equipment in the computer room as efficiently as possible to ensure an adequate supply of power resources. At present, for the purpose of energy management and optimization of the computer room, AI technology is being applied to establish the power monitoring system of the DC. The system can effectively collect information about the power consumption of the equipment during operations, and accurately judge the power limit of each piece of equipment so that the machine room can accommodate more equipment, thus ensuring the quality of service provided by the system. In addition, in order to optimize the cooling of the computer room at this stage, the traditional refrigeration strategy can be effectively optimized by using a large number of monitoring data. This can transform the strategy design problem into an energy minimization problem under temperature constraints. By transforming the problem, the problem solution is less complex, thus simplifying the energy management and control of the computer room. It is optimized through in-depth reinforcement learning method, thus effectively preventing the occurrence of high temperatures in the system. In this paper, the energy saving of air conditioning in a cloud computer room was studied. It was found that such energy saving was related to the layout of the computer room, heat circulation, and power consumption of IT equipment, among other factors. The key to energy-saving control was to ensure that the working environment of the computer room facilitated the reduction of the energy consumption of various auxiliary types of equipment, enabling the ongoing operations of an energy-saving computer room.

4.2 Energy Management and Optimization of IT Equipment

Area DC has many types of IT equipment, including servers, security equipment, network equipment, etc. The servers account for the largest amount of equipment, and the energy consumption at runtime is also the largest. With the rapid development of China's information technology and CC technology, the software-defined network technology has gradually matured and is beginning to replace the traditional dedicated equipment. There is little doubt that, in China, the server will become one of the main pieces of DC equipment that will be undergo further development. At present, the technology for reducing the energy consumption of servers includes dynamic voltage and frequency regulation technology and dynamic power switching technology. The basic aim is to optimize the efficiency of DCs by considering network traffic requirements combined with the saving of energy consumed by network equipment. This approach not only ensures that vital equipment has an adequate supply of energy, but also reduces the additional energy consumption of idle equipment. For active devices, dedicated traffic channels can be established, while inactive ports are set to sleep mode.

A data processing system (DPS) and other technologies can improve the sleep quality of the device, which is a classic means of energy saving and consumption reduction for IT devices at present. Along with China's technological progress, energy management and intelligent optimization technology can also be widely used in future development. At the same time, more new fields would be developed, making the joint optimization effect of CPU and new hardware more ideal. Virtual technology is a basic technical feature. It can divide a single server into multiple levels and use it in the core energy system of an enterprise to provide automatic online detection, real-time data sharing, and other functions.

4.3 Data Center Energy Management and Optimization

Local management of the energy consumption of a DC is one of the important aspects of DC construction. At present, DC energy management can be applied to a single DC or to multiple DCs according to the specific processing content. When managing the energy consumption of multiple data stations, more attention should be paid to each one's individual energy load and energy consumption. From the perspective of overall cost, it is necessary to regulate the energy of each major system. The energy management requirement of the DC is to build the current energy consumption model of the DC, obtain the PUE value, and evaluate the current energy consumption according to the model. The DC performance model can be established to analyze the problems in energy management and improve the efficiency of energy utilization. Through the analysis of sensor data, the load of each main equipment is determined, and corresponding temperature control is carried out according to different operating temperatures.

The operating power of the equipment is affected by many factors, including indoor and outdoor temperature, current equipment load, and the number of overall adjustable cooling equipment. It therefore requires a more comprehensive sensor coverage. By determining the relevant data through the data acquisition and data processing system, the cooling equipment parameters can be established scientifically to achieve the best energy utilization efficiency. When utilizing energy, users should consider not only the operational requirements of equipment, but also the carbon emissions resulting from the energy consumption, and should try to use renewable energy. As the core of data exchange, the DC must control the energy consumption of all equipment to ensure the efficiency of data exchange and the operating efficiency of the system.

5. CONCLUSIONS

AI technology is becoming more and more widely used for the energy management and optimization of CC data centers. Increasingly, it is being used for equipment and system energy consumption and performance modeling, task and resource scheduling, operation parameter optimization, and the selection of energy-saving measures, achieving good results. However, during the actual application process, many complex factors may be encountered, which would affect the management. Therefore, in the follow-up research, the start time, end time and constraints of specific management tasks will be studied in depth so as to further optimize the management method proposed in this paper and achieve the ideal outcome.

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