Modeling and Optimization of Data Center Energy Consumption

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Abstract*—In this era of high-speed data development, the demand for computing that data centers(DC) need to process is rapidly increasing, and its high energy consumption problem is also becoming increasingly prominent. Currently, the total energy consumption of DC has occupied about 2.7% of the whole energy consumption of society, and optimizing the energy consumption of DC has been a research hotspot of concern in last several years. However, the current study ignores the start-stop relationship and climbing constraints of information technology (IT) equipment between different time periods, and the optimization strategy given by it may lead to frequent start-up and shutdown of IT equipment in actual operation when the arithmetic power demand changes greatly in a short period of time, resulting in excessive IT equipment loss. Based on this, the optimization model of data center energy consumption is established by considering the energy consumption characteristics of IT equipment and the heat exchange relationship of air conditioning equipment, as well as the start-stop relationship and the climbing constraint of IT equipment. For the dynamic and nonlinear characteristics of the temperature exchange process between IT equipment and the air conditioner, the DDPG algorithm is proposed for solving. Finally, the practicality and efficiency of the method are verified by a large-scale data center simulation example with 100,000 IT equipment.

***Keywords*—Data center; IT equipment; Optimization of energy consumption; Heat exchange; DDPG algorithm**

I. Introduction

Domestic data centers consumed more than 200 billion kilowatt-hours of power in 2020, making up 2.7% of all electricity consumed. By 2023, it's anticipated that data centers would use more energy than 250 billion kwh of electricity, and by 2030, it will exceed 400 billion kilowatt-hours, with the proportion of electricity consumption rising to 3.7%. The "Three-Year Action Plan for the Development of New Data Centers (2021-2023)" by the Ministry of Industrial Development and Information Technology, in response to this issue, specifies the PUE of data centers: the PUE of newly constructed big data centers and higher ought to be reduced to below 1.35 by the end of 2021 and below 1.3 by 2023. Beijing and Shenzhen are two cities that have harsher regulations for newly constructed data centers, with Shenzhen encouraging the construction of data centers with PUE values under 1.25. "Green computing" with low PUE has become a trend for sustainable development. Data centers also need to upgrade to new components with high computing power, space-saving, and low carbon emissions to solve energy consumption problems.

The energy usage of data centers has been under more and more scrutiny recently due to the Internet's and cloud computing's fast expansion. By 2025, it is anticipated that data centers will rank among the world's top energy consumers since their yearly energy consumption has surpassed that of the Three Gorges Dam. Data centers have also developed into a crucial DR resource for consumers as a platform for offering computing and data storage services. However, due to the uncertainty of data loads, electricity prices, and renewable energy output, ensuring the operational economy of data centers in real-time operation is an urgent problem to be solved. Optimizing data center energy use is a crucial way for operators to increase their competitiveness in the market.

TAOS algorithm was proposed for reducing hotspots and thermal gradients in data centers ultimately reducing energy consumption[1]. Data center energy consumption optimization method based on active hibernation was proposed[2]. A new scheduling strategy was proposed for virtualized data centers[3]. A data center server energy consumption optimization (ECOXG) algorithm incorporating extreme gradient boosting (XG Boost) and multiple gated cyclic units (Multi -GRU) algorithm was proposed for data center server energy optimization (ECOXG)[4]. The total energy consumption of the system was reduced by performing digital twin modeling of the data center and its iterative interaction with deep reinforcement learning models[5].

However, the temperature-aware scheduling algorithms proposed in the above studies, while able to significantly reduce hotspots, data center temperature, and energy consumption, also degrade system performance.

The deep learning algorithm DDPG proposed in this paper is able to capture the dynamic and nonlinear characteristics of the temperature exchange process between IT equipment and air conditioners, reflecting the advantages of model-free, adaptive and online learning, and ensuring high system operation performance.

II. THE OPERATING CHARACTERISTICS OF MAJOR EQUIPMENT IN DATA CENTERS.

A. EquipmentOperational Characteristics and Modeling of IT Equipment

1) Computational Power Consumption of IT Equipment

Existing studies[6] had shown that the dynamic power consumption of IT equipment was approximately linearly related to the resource utilization rate of the equipment. The computational power consumption $P_{IT\mathrm{cal}}$ can be expressed as[7]:

$$P_{IT\mathrm{cal}} = \left(P_{fl} - P_{\mathrm{idle}}\right)U + P_{\mathrm{idle}} \tag{1}$$

where $P_{IT\mathrm{cal}}$ represents static power; P_{fl} represents full load power; $U \in [0,1]$ represents the resource utilization rate of IT equipment; $\left(P_{fl} - P_{\mathrm{idle}}\right)U$ represents dynamic power consumption.

2) The leakage power consumption of IT equipment.

Existing research has simplified it using a first-order linear function $f(\cdot)$:

$$f\left(T_{\mathrm{IT}}\right) = a_1 + a_2 T_{\mathrm{IT}} \tag{2}$$

where a_1 and a_2 are constants, reference [8] takes a_1=0.75 and a_2 =0.003125; T_{IT} represents the chip temperature of IT equipment.

The energy consumption of IT equipment P_{ITlp} is expressed as the calculated power consumption after correcting for leakage power consumption:

$$P_{\mathrm{ITlp}} = P_{\mathrm{ITcal}} f\left(T_{\mathrm{IT}}\right) \tag{3}$$

Therefore, the energy consumption model of IT equipment during startup and operation can be obtained as follows:

$$P_{\mathrm{ITlp}} = \left[\left(P_{fl} - P_{\mathrm{idle}}\right)U + P_{\mathrm{idle}}\right]\left(a_1 + a_2 T_{\mathrm{IT}}\right) \tag{4}$$

Specifically, IT equipment has a standby state in addition to the on and off states. When IT equipment is in standby/sleep mode, it automatically reduces voltage and frequency to achieve energy-saving effects, and the power consumption at this time is a small constant value P_{standby} , typically around 20W[9]. Let $S_i(t)$ be the state variable of IT equipment i during time period t, where $S_i(t)$ takes on 2, 1, or 0, representing the three states of on, standby, and off, respectively. Then the energy consumption of IT equipment i during time period t can be expressed as:

$$P_{\mathrm{ITlp},i}(t) = \begin{cases} P_{\mathrm{ITlp}} & S_i(t) = 2 \\ P_{\mathrm{standby}} & S_i(t) = 1 \\ 0 & S_i(t) = 0 \end{cases} \tag{5}$$

Let N be the total number of IT equipment. Let O be the number of IT equipment on. The total energy consumption of IT equipment during time period t is $\sum_{i=1}^{N} P_{\mathrm{ITlp},i}(t)$. When an IT equipment is switched from off to on, a self-check of the internal hardware is performed, and the instantaneous current of each internal hardware will reach its peak. This process will cause a certain loss to the IT equipment, which is called the start-up cost. The cost caused by this loss is called start-up cost, while the changes between other states usually do not cause any loss[10]. Let $C_i(t)$ be the start-up cost of IT equipment i during time period t. If IT equipment i is switched from off to on during this time period, then $C_i(t)$ takes on a non-zero value, otherwise it is 0. The total start-up cost of all IT equipment during time period t is $\sum_{i=1}^{N} C_i(t)$.

B. Air conditioning equipment operation characteristics and modeling

1) Computational Power Consumption of IT Equipment

IT equipment generates the majority of the heat in a data center, which accounts for around 90% of the cooling load on the air conditioning system. It makes sense to just take into account the heat produced by IT equipment[9]. This can be expressed as follows:

$$Q_{AC} = Q_{IT} + Q_{ENV} \tag{6}$$

where Q_{AC} is the total cooling load of the air conditioning system, and Q_{IT} is the heat generated by IT equipment. (Most IT equipment manufacturers provide information on power consumption and heat dissipation, with heat dissipation being about 97% of power consumption.[11]) Q_{ENV} represents the environmental heat, and can be expressed as follows[11]:

$$Q_{IT} = 97\% P_{\mathrm{ITlp}} \tag{7}$$

$$Q_{ENV} = m_T S_{IT} \tag{8}$$

The equation (8) includes the environmental temperature coefficient m_T , which increases with the ambient temperature. In southern China, a value of approximately 0.18 can be chosen, while northern China can choose a value of around 0.10. For other regions, the value can be determined based on actual conditions between 0.10 and 0.18. S_{IT} refers to the sum of IT equipment's projected areas.

2) The performance coefficient of air conditioning equipment.

The ratio of the cooling load Q_{AC} to the power consumption of the air conditioning equipment P_{AC} is known as the coefficient of performance (COP) of air conditioning equipment.

$$m_{COP} = \frac{Q_{AC}}{P_{AC}} \tag{9}$$

Better energy efficiency of the air conditioning system is indicated by a higher coefficient of performance (m_{COP}). The following table shows the relationship between T_{AC} and the air supply temperature of the air conditioning system[11]:

$$m_{COP} = 0.0068T_{AC}^2 + 0.0008T_{AC} + 0.458 \tag{10}$$

In summary, the energy consumption of air conditioning equipment can be expressed as:

$$P_{AC} = \frac{Q_{AC}}{m_{COP}} = \frac{97\%P_{\mathrm{ITlp}} + m_T S_{IT}}{m_{COP}} \tag{11}$$

3) Heat exchange model between IT equipment and air conditioning equipment.

IT equipment generates heat during operation, and air conditioning equipment is needed to absorb the heat to ensure that IT equipment operates within a safe temperature range. The relationship between the energy consumption models of IT equipment and air conditioning equipment is based on convective heat transfer, which can be described by an equivalent thermal resistance model.

$$T_{\mathrm{IT}} = P_{\mathrm{ITlp}} R_{in} + T_{in} \tag{12}$$

where T_{in} is the inlet airflow temperature. R_{in} is the inlet convective heat transfer coefficient, which depends on the heat transfer area, relative velocity between the heat transfer surface and air flow, as well as physical properties of gas and solid. During the convective heat transfer process between cooling airflow and IT equipment, R_{in} is only a function of relative velocity between heat transfer surface and air. In this study, the airflow passing through the server is assumed to be constant, and R_{in} can be regarded as a constant with the value of $R_{in} =$ 0.0147 K/W .

The relationship between the supply air temperature of the air conditioning system and the inlet air temperature of IT equipment can be stated as follows[7]:

$$T_{in} = T_{AC} + 97\%GP_{\mathrm{ITlp}} \tag{13}$$

where G is the heat transfer coefficient, which only affects how the equipment is arranged and can be roughly regarded as a constant in this study assuming the equipment is distributed uniformly.

The rule of energy conservation, which states that when IT equipment reaches a state of thermal equilibrium, the heat produced by the IT equipment plus the heat of the cold air coming in equals the heat produced by the hot air exiting the equipment, is the fundamental tenet of this approach.

In conclusion, the sum of the energy P_{SUM} used by IT equipment both while it is in use and when it is in standby, as well as the energy used by air conditioning equipment when it is in use, may roughly represent the total energy used by a data center. As a result, we have:

$$P_{SUM} = P_{ITlp,sum} + P_{AC,sum} = \sum_{i=1}^{N} P_{\mathrm{ITlp},i} + \sum_{j=1}^{M} P_{AC,j} \tag{14}$$

where P_{SUM} is the total energy consumed by a data center, which may be calculated as the sum of the energy consumed by IT equipment when it is in use ($P_{ITlp,sum}$). The energy used by IT equipment when it is in standby mode and the energy used by air conditioning equipment when it is in use ($P_{AC,sum}$). The energy consumption of the air conditioning equipment j and the IT equipment i is represented by $P_{\mathrm{ITlp},i}$ and $P_{AC,j}$, respectively. The data center's whole inventory of air cooling units is represented by the number M.

III. DATA CENTER ENERGY CONSUMPTION OPTIMIZATION MODEL

The main goal of the energy optimization challenge in data centers is to achieve maximum energy effectiveness while making sure that the facility's overall processing power is sufficient to satisfy the demand at hand and that the cooling capacity allows IT equipment to function normally.

The operational costs of the data center and the start-up and shutdown costs of IT equipment are combined to form the objective function of the optimization model proposed in this study. The supply air temperature of the air conditioning system, resource usage levels, and the operational state (on, off, or standby) of each IT device are among the decision variables. The constraints include computing demand, air supply temperature range, chip temperature limit, inlet air temperature range, IT equipment ramping constraints, and IT equipment downtime constraints.

A. Objection Function

The objective function includes two parts: operating cost and start-stop cost.

$$\min \sum_{t=1}^{T} \left\{ CP_{SUM}(t)\Delta t + \sum_{i=1}^{N} C_i(t) \right\} \tag{15}$$

where *t* is the current time period. T is the total number of time periods. Δt is the time interval, C is the running cost coefficient. $P_{SUM}(t)$ is the total energy consumption of the data center in period t. $CP_{SUM}(t)\Delta t$ is the running cost of the data center. And $\sum_{i=1}^{N} C_i(t)$ is the total start-stop cost of IT equipment in period t.

This model considers three states for IT equipment: on, off, and standby. Compared to directly turning off, the standby state avoids the damage caused by start-stop cycles, significantly reducing start-stop costs. Therefore, if the standby power cost is less than the start-stop cost, standby is preferred to reduce the total cost, and vice versa.

B. Constraint Condition

1) Computational resource demand constraint.

$$\sum_{i=1}^{N} B_{cp,i} = B_{sum}(t) = D_{IT}(t) \tag{16}$$

Equation (16) limits the total computing capacity of the data center, where $B_{cp,i}$ is the total computing capacity of the IT equipment i , $B_{sum}(t)$ is the computing capacity provided by the data center at time t, and $D_{IT}(t)$ is the computing demand at time t.

2) Air conditioning supply air temperature range constraint.

$$T_{\mathrm{AC,min}} \le T_{\mathrm{AC}}(t) \le T_{\mathrm{AC,max}} \tag{17}$$

where $T_{\mathrm{AC}}(t)$ is the temperature of the air supplied by the air conditioning equipment, and $T_{\mathrm{AC,min}}$ and $T_{\mathrm{AC,max}}$ are the minimum and maximum allowable temperatures, respectively. Equation (17) represents the constraint on the temperature range of the air supplied by the air conditioning equipment:

3) The constraint on the range of inlet air temperature.

$$T_{\mathrm{IT}}(t) \le T_{\mathrm{IT,max}} \tag{18}$$

where $T_{\mathrm{IT}}(t)$ represents the chip temperature of IT equipment in time period t, and $T_{\mathrm{IT,max}}$ is the upper limit of the chip temperature of IT equipment. Formula (18) constrains the upper limit of the chip temperature $T_{\mathrm{IT,min}}$ for normal operation of IT equipment, which is usually 80 ℃.

4) The leakage power consumption of IT equipment.

$$18℃ \le T_{in} \le 27℃ \tag{19}$$

The airflow range restrictions provided by the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE), a recognized international standard for the construction of data centers, are represented by equation (19).

5) The leakage power consumption of IT equipment.

$$P_{\mathrm{ITlp},i}(t)\,|_{S_i(t)=1} - P_{\mathrm{ITlp},i}(t-1)\,|_{S_i(t)=1} \le R_{IT}(t=2,3...,T) \tag{20}$$

where $P_{\mathrm{ITlp},i}(t)\,|_{S_i(t)=1}$ denotes the power use of the computer hardware I at time t while it is in the starting stage. T is the total number of time periods, and R_{IT} is the ramp-up coefficient. IT equipment's ramp-up rate is limited by equation (20).

IV. Deep Reinforcement Learning Method

A. Preliminaries of Markov Decision Process

The MDP equation is fixed as a 5-tuple such that (S, O, A, r, γ). Sris the state set, represents the current condition of the environment, O=is the connected observation set of the agent, A=represents the connected action set of the agent， r refers to a global reward which measures the agent choices, whereas $\gamma \in (0,1]$ is a reduction ratio which can be utilized to manage short-term and long-term objective. At time t, the connected action A^{t} is chosen and conversed with the environment that focuses on the state set $S^{t}$and the observation set O^{t}. Then, the receive global reward r^{t} along with the following condition set S^{t+1} are delivered to the agent to pile up experience. The objective of the agent is to find the best connected policy π, which maximizes:

$$J(\pi) = \max_{\pi} \mathrm{E}_{\pi}\left[\sum_{t=0}^{\infty} \gamma^{t} r^{t}\right] \tag{21}$$

B. The DDPG algorithm

The DDPG algorithm, which is a deep reinforcement learning (DRL) algorithm based on the performer structure, could achieve a superior scheduler even though only demanding local dimensions for the agent, which is suitable for the separated optimization and management of large shared generation in today's large-scale ADS. In order to resolve the suggested multi-objective scheduling issue within the MDP structure, the DDPG algorithm is used. The systematic training set of the DDPG algorithm is fully explained following the introduction of the DDPG's preliminary steps in this part. The following is how the deep reinforcement learning horse choice process is set up:

1) State space.

This paper designs 7 state variables, including the number of IT equipment turned on $O(t)$,resource utilization of IT equipment $U(t)$, power of IT equipment $P_{\mathrm{ITlp}}(t)$, chip temperature of IT equipment $T_{\mathrm{IT}}(t)$, the inlet airflow temperature $T_{in}(t)$, the temperature of the air condition supplied $T_{\mathrm{AC}}(t)$, the power consumption of the air conditioning equipment $P_{AC}(t)$.

2) Action space.

It can be inferred from the energy consumption model that the energy consumption of IT equipment is correlated with the number of IT devices active and the rate of resource utilization, and that the energy consumption of air conditioning cooling is correlated with the temperature of the system's air supply.

The strategy for improving the energy effectiveness of multi-time period data centers is suggested in this research. Therefore, the number of IT equipment on $O(t)$, resource utilization rate $U(t)$ and air supply temperature of air conditioner $T_{\mathrm{AC}}(t)$ are selected as control actions.

3) Reward functions

According to the optimization objective, the design reward function is shown in (22).

$$r = \begin{cases} -\left[\mathrm{CP}_{SUM} + \sum_{i=1}^{N_{off-on}} C_i(t)\right], & if\ eqs.(16)-(20) satisfied \\ r_{done}, & \text{else} \end{cases} \tag{22}$$

where r is the reward function and N_{off-on} denotes the number of IT equipment that are turned on from off to on. In the case of satisfying Equations (16)-(20), the value of r is the sum of the operating cost and the start-up and shutdown cost taken as the opposite number. After taking the opposite number, the smaller the cost, the larger the value of the reward function will be. In other cases, the value of the reward function takes r_{done}.

V. Example Analysis

A. Parameter setting

To validate the practicality and efficiency of the proposed method, Python software was used to simulate energy optimization using real operating data from a large-scale data center of a domestic internet company. The data center is equipped with 100,000 uniformly distributed IT equipment and a central air conditioning system. The optimization step size is 15 minutes and the total optimization time is 24 hours. The computing demand curve is sourced from reference[12].The equipment parameters as shown in Table Ⅰ.

TABLE I. EQUIPMENT PARAMETERS

Type	***Parameter name***	***value***	***unit***
IT equipment	Static power	200	W
	Standby power	20	W
	Full power	500	W
	Climbing rate	26	W/s
	Start-Stop Cost	0.0149	RMB/time
	Running Costs	1.2	RMB/kW·h
Air condition	Projected area of single equipment	5	m^2
	Equivalent heat resistance	0.0147	K/W
	Heat transmission coefficient	0.0326	K/W
Server room environment	Total area of server room	500000	m²
	Ambient temperature coefficient	0.18	-

Table Ⅱ contains a list of the suggested algorithm's parameters. The agent in the actor-network has the same neural network architecture, which consists of one input layer, two hidden layers, and one output layer. Each hidden layer contains 64 neurons, and the Re LU and Sigmoid functions are chosen as the activation functions. The actor-input network's is a 1×105 state vector. A 1×4 action vector is the result of the actor-network. A 1×109 vector that concatenates the status and action vectors serves as the critic network's input. With a learning rate of 1e-4, RMS Prop[13] is utilized as the optimizer for updating the policy and critic networks.

TABLE II. PARAMETERS OF THE PROPOSED ALGORITHM

Param-eters	r_{done}	Discount factor	Replay buffer	Batch	Maxim-um time steps	Maximum episodes
Value	-500	0.99	5000	64	96	10000

B. *Traning Performance*

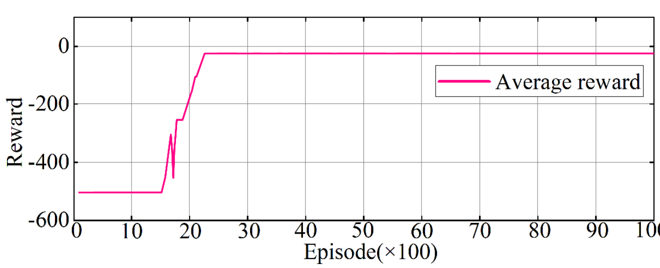
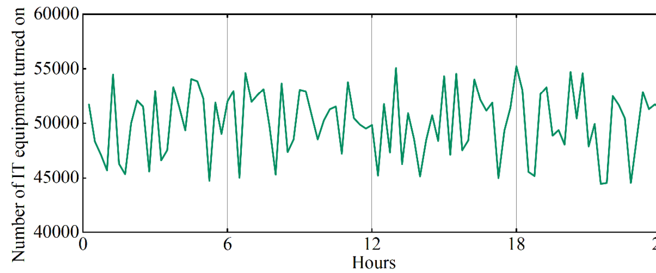


Fig. 1 Average reward

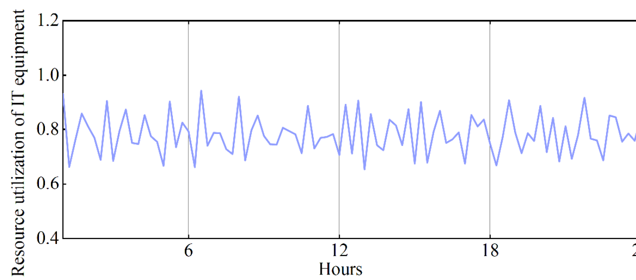
As shown in Fig. 1, the reward function is trained for 100 times, and in the first 16 times of training, the reward function obtains the value of r_{done}, indicating that the conditions of Eq. (16)-(20) are not satisfied. In the 17th-22nd training, the conditions of Eq. (16)-(20) have been satisfied, and the value of the reward function is changing and fluctuating wildly, but the overall trend is increasing, indicating that the agent gradually evolves and learns the optimization strategy for data center energy consumption. Until the start of the 23rd training, the value of the reward function is stable and no longer changes, indicating that the optimal value has been taken and the training results are satisfied.

C. *Testing Performance*

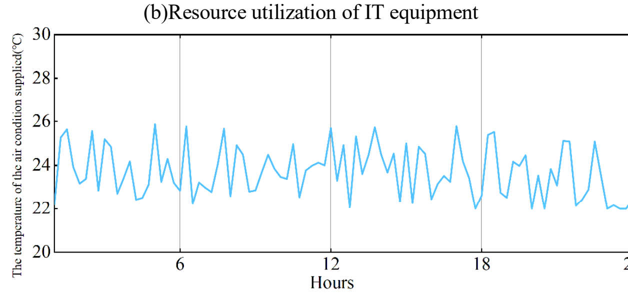
The well-trained agent is modified to real-time scheduling judgment during the real-time testing process. The topology is chosen from a prospective topology set different than the standard topologies, and the 1 day testing data is chosen at random from the test data set. Three test cases are created to show the proposed DDPG algorithm's superiority and generalizability.



(a)Number of IT equipment turned on



(b)Resource utilization of IT equipment



(c)The temperature of the air condition supplied

Fig. 2 Optimization results of method M1

M1: The method this paper proposed for optimizing the energy efficiency of multi-time period data centers.

M2: The scenario where no optimization of energy consumption is conducted. In this scenario, all IT equipment remains powered on without any operational management of their operational status and computing power allocation, and the air conditioning equipment is set to operate at a constant 25℃.

M3: Traditional single-hour data center energy consumption optimization approach[14].

The optimization effect of the method proposed in M1 is compared with the M2 and M3.

As shown in Fig. 2, (a) represents the number of IT equipment turned on. (b) represents resource utilization of IT equipment and (c) represents the temperature of the air condition supplied. When the amount of load to be processed in the data center increases, the number of IT equipment start-ups will increase accordingly, which makes the resource utilization of IT equipment increase in order to process the arithmetic power load as soon as possible in a short time.

The ambient temperature of the data center will rise as a result of the heat dissipation of IT equipment. Cooling is necessary to lower the temperature, ensuring the equipment's normal operation and the data center's safety. As a result, the air supply temperature of the air conditioning equipment must be lowered, increasing the energy required for cooling. However, when the load on the data center decreases, the situation is reversed.

Table III shows the comparison findings between the proposed methods M1 , M2 and M3. The proposed method M1 has a total cost that is 87.554million RMB while M2's is 110.253million RMB, and M3's is 99.856million RMB. In addition, the calculation time of the proposed method is 0.2s, which can realize real-time optimization of energy consumption. Since method M2 is not optimized, there is no optimized calculation time. While M3's calculation time is 0.4s.

The total cost and optimized computation time of Method M1 are lower than those of Method M3 under normal fluctuation of the arithmetic power demand curve. The total cost of both method M1 and method M3 is lower than the total cost of method M2. Thus, the energy consumption optimization method M1 based on DDPG algorithm proposed in this paper is better than the traditional optimization method M3 in optimizing the total cost of energy consumption in data centers.

TABLE III. COMPARISON RESULTS

Strategy	*Total Cost/M*	*Optimized calculation time*
M1	87.554	0.2s
M2	110.253	-
M3	99.856	0.4s

VI. CONCLUSION

This paper proposed a DDPG algorithm for optimizing energy consumption of data centers. The DDPG algorithm considers the respective energy consumption models of IT equipment and air conditioning equipment, as well as the heat exchange models of these components. Specifically, the proposed DDPG algorithm can optimize the energy efficiency of data centers, while ensuring that the total computing power meets current demand and that the air conditioning cooling capacity maintains the normal operation of IT equipment.

The method M1 proposed in this paper can serve as a valuable reference for energy-saving and consumption-reducing operations of data centers. It can control the number of IT equipment turned on and resource utilization of IT equipment , as well as the temperature of the air condition supplied and other related parameters. Furthermore, the method can provide theoretical support for modeling and optimizing the energy efficiency management system at the data center level.

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