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Energy management system design for high energy consuming enterprises integrating the Internet of Things and neural networks

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Abstract

INTRODUCTION: High energy consuming enterprises continue to pay increasing attention to energy consumption. Therefore, designing an energy management system is significant.
OBJECTIVES: To improve the management level and economic benefits of enterprises, a high energy consuming enterprise energy management system design based on Internet of Things technology and neural network algorithms is proposed.
METHODS: Internet of Things devices are used for data collection and transmission. The combination of neural network model prediction and optimization algorithms can achieve real-time monitoring, prediction, and optimization control of energy consumption.
RESULTS: The research results indicated that the response time of the high energy consuming enterprise energy management system proposed in the study was 80.2 ms when the number of people was 600. The fluctuation range of CPU usage within 24 hours was 14% to 45%.
CONCLUSION: A high energy consuming enterprise energy management system that integrates the Internet of Things and neural networks can manage energy more efficiently and intelligently, thereby improving the production efficiency and economic benefits of the enterprise. This helps companies gain greater advantages in fierce market competition.

Keywords: Internet of Things technology, Neural networks, Energy management, High energy consuming enterprises, Prediction and optimization control

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1. Introduction

With the continuous progress of the economy, the proportion of high energy consuming enterprises in global energy consumption is gradually increasing, which not only exacerbates the energy crisis but also puts enormous cost pressure on enterprises [1]. To address this challenge, numerous researchers and enterprises have devoted themselves to exploring efficient and sustainable energy management solutions. High energy consuming enterprises require a large amount of energy supply during the production process. However, traditional energy management methods have some problems, such as inaccurate data collection, difficulties in predicting and optimizing energy consumption, etc [2-3]. The integration of the Internet of Things (IoT) and neural network technology has brought new research and application prospects for energy management in high energy consuming enterprises. The energy management system that integrates the IoT and neural networks can achieve precise management and optimization of enterprise energy consumption through real-time data collection, model prediction, and optimization control. The IoT technology can achieve interconnection and interoperability of various devices, providing real-time energy consumption data. Neural network algorithms can predict and optimize energy consumption by learning historical data [4-5]. Therefore, an energy management system that integrates the IoT and neural networks has become an important tool for high energy consuming enterprises to achieve sustainable development. A high energy consuming enterprise energy management system based on IoT technology and neural network algorithms is proposed, aiming to provide an advanced solution to achieve the sustainable development goals of the enterprise. This study provides an innovative energy management solution for high energy consuming enterprises, which helps to promote sustainable development. The article has four parts. The first part is the literature review section, which discusses the current research status about IoT technology, neural networks, and energy management systems for high energy consuming enterprises both domestically and internationally. The second part proposes an energy management system for high energy consuming enterprises that integrates the IoT and neural networks. The third part verifies the effectiveness and performance of the system through experiments. The fourth part is the summary section, which summarizes the research results.

2. Related works

With the advances in deep learning, the application of neural networks in various fields is also constantly expanding. To improve agricultural production efficiency and quality, Lv et al. proposed an intelligent agricultural system based on IoT. The research results indicated that the system could monitor the environmental parameters and crop growth of farmland in real-time, and automatically adjust irrigation, fertilization, and pest control operations, achieving refined agricultural management and improving yield and quality [6]. To achieve sustainable development of smart cities, Wu et al. proposed a smart transportation system based on IoT technology. The research results indicated that the system could monitor traffic flow in real-time and optimize traffic signal control. It provided real-time traffic information and intelligent navigation for drivers and city managers, reduced congestion and traffic accidents, and improved the efficiency and safety of the transportation system [7]. To improve the production efficiency and quality of the manufacturing industry, Nauman et al. proposed an intelligent manufacturing system based on IoT technology. The research results indicated that the system could monitor various parameters and quality indicators of the production process in real time. This method automatically adjusted production parameters and control strategies to achieve intelligent manufacturing process management, and improved production efficiency and product quality [8]. To solve complex image recognition problems, Liu et al. proposed an image classification method based on deep neural networks. The research results indicated that this method could accurately classify and recognize various complex images, with high recognition accuracy and generalization ability [9]. To achieve automation and intelligence in natural language processing, Priyadarshi et al. proposed a language model based on recurrent neural networks. The research results indicate that the model could understand and generate natural language texts, achieving tasks such as machine translation, text generation, and sentiment analysis [10].

The enterprise energy management system design is an important research field, providing important support for enterprises to achieve energy conservation, emission reduction, and sustainable development. To improve the energy efficiency of enterprises, Zhang et al. proposed a data analysis and optimization based enterprise energy management system. The research results indicated that the system could monitor energy usage in real-time. Through data analysis and optimization algorithms, this method automatically adjusted the operating strategy of the energy system, effectively reducing energy consumption and costs [11]. To achieve intelligence and automation in enterprise energy management, Ji et al. proposed an enterprise energy management system based on artificial intelligence and IoT technology. The research results indicated that the system could monitor energy usage in real-time and predict energy demand. This method could automatically adjust the energy system operation, achieving the efficient energy management [12]. To reduce energy consumption and environmental pollution, Bahmanyar et al. proposed an enterprise energy management system based on energy optimization and renewable energy. The research results indicated that the system could maximize the renewable energy utilization and reduce dependence on traditional energy. It achieved a balance between energy supply and use, thereby achieving sustainable energy management [13]. To improve the operational efficiency of enterprise energy management, Drobayazko et al. proposed an enterprise energy management system based on the IoT and big data analysis. The research results indicated that the system could monitor energy usage in real-time, predict energy demand, and automatically adjust the operation of the energy system, achieving intelligent and efficient energy management [14]. To reduce the energy consumption in enterprises, Wozniak et al. proposed an enterprise energy management system based on energy monitoring and feedback. The research results indicated that the system could help enterprises identify energy consumption issues and take measures to improve them, thereby reducing energy consumption [15]. To achieve informatization and intensification of enterprise energy management, Lai et al. proposed an enterprise energy management system based on cloud computing and big data. The research results indicated that the system could achieve real-time monitoring and analysis of energy usage. It provided personalized energy management solutions to help businesses optimize energy consumption and reduce energy costs [16].

In recent years, the application of IoT and neural networks in the field of energy management has become increasingly widespread, and they provide powerful technical support for improving energy efficiency and reducing costs. By applying artificial neural networks (ANN), Momeni et al. successfully developed an accurate model for predicting energy consumption in office buildings. This study confirms that the trained neural network can effectively enhance the energy planning and optimization process and achieve high efficiency of energy management [17]. Yankson et al. investigated the role of intelligent investment in improving the resilience of power systems and proposed a vulnerability assessment framework based on the N-1 emergency criteria. This framework can identify the weakest links in the power system and provide key guidance for investment decisions, thus significantly enhancing the system's shock resistance [18]. For battery-free iot devices, Schieber et al. consider a scheduling problem that involves completing a job in n time units, each with a specific release time, due date, energy requirement, and weight. They assume that time is preset and that the time parameters for all jobs are fixed. The goal of the research is to find a scheduling scheme that maximizes the total weight of the job while ensuring that the energy requirements of each job are met [19]. In the drinking water supply chain and its pricing management, Zarreh et al. applied game theory to construct a mathematical model to analyze competitive pricing strategies between public water systems (PWS) and bottled water plants (BWP) under government intervention. The model uses a dynamic approach to deal with temporal changes in precipitation and water demand, and takes into account uncertainties in water supply. The study found that by adjusting incentives, PWS can significantly improve the earnings, and the adjustment of price sensitivity can also significantly improve the profits of PWS and BWP [20]. Karkehabadi et al. adopted the fuzzy SWARA decision method, combined with network characteristics, to identify the optimal parent nodes of each sensor in the sensor network, aiming to improve network performance, reduce resource consumption, and accurately determine the weight of network components to ensure the provision of high-quality services. The research results show that the proposed method has achieved significant improvement in network performance compared with the prior art [21].

In summary, IoT technology can monitor and collect enterprise energy consumption data in real-time, while neural networks can optimize energy management by learning and predicting models. However, there is still relatively little research on integrating the two methods. Therefore, a design scheme combining the IoT and neural networks is proposed. This plan has potential and advantages in energy utilization efficiency and energy-saving effects. Further research and practice will further promote the development and application of this field.

3. Design of energy management system for high energy consuming enterprises

A high energy consuming enterprise energy management system that integrates the IoT and neural networks is proposed. The IoT technology collects and transmits real-time energy consumption data of high energy consuming enterprises. By combining ANN learning and prediction models, the energy management system is optimized.

3.1 Data collection and transmission based on IoT devices

Enterprise Energy Management System (EEMS) is a system that monitors, analyzes, optimizes, and manages energy consumption in enterprises. It helps enterprises reduce energy consumption, improve energy efficiency, and control energy costs by integrating energy data collection, processing, and control technologies [22]. The enterprise energy management system has three layers, acquisition layer, network layer, and system layer. The overall architecture is displayed in Figure 1.

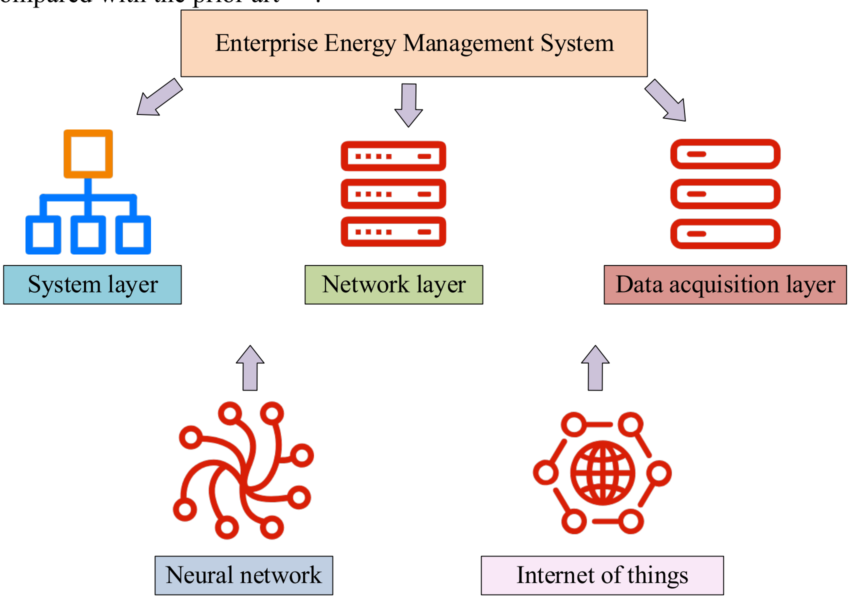

Fig. 1 Main architecture of enterprise energy management system

The data collection and transmission of energy management systems for high energy consuming enterprises based on IoT devices are the foundation for achieving real-time energy monitoring and analysis. In this system, IoT devices are deployed at various energy usage points of the enterprise to collect energy consumption data. Some devices such as sensors and smart meters are applied to complete the task. These devices and sensors include smart meters with remote communication capabilities that accurately measure and record power consumption, providing detailed energy consumption data including real-time power, total energy consumption and power factor. Temperature and humidity sensors are deployed in critical areas to monitor ambient temperature and humidity. Flow meters are installed on water, steam and gas lines to measure the flow of fluids. Pressure sensors are used to monitor the pressure of equipment and piping systems, ensuring safe system operation while providing data to optimize energy distribution. Vibration and sound sensors are installed on critical mechanical equipment to detect abnormal vibrations and sounds. The light intensity sensor is used to monitor the light intensity and cooperate with the intelligent lighting system to automatically adjust the lighting intensity according to the actual lighting demand and save energy. Gas concentration sensors are used to monitor the concentration of harmful gases that may be produced during the production process, ensuring employee safety while optimizing energy use and reducing emissions. Environmental monitoring sensors integrate multiple sensor devices that can simultaneously monitor multiple environmental parameters such as temperature, humidity, pressure, light and air quality, providing comprehensive data support for energy management. The collected energy consumption data needs to be transmitted to the enterprise energy management system for analysis and processing. Data transmission can be achieved through various communication technologies, including wired and wireless connections. The appropriate data transmission method should consider factors such as data transmission speed, stability, and security. To ensure smooth data transmission between IoT devices and energy management systems, appropriate communication protocols need to be adopted. For energy management systems of high energy consuming enterprises, data security is crucial. Therefore, in the data collection and transmission, security measures need to be taken, such as encrypted transmission, identity verification, etc., to prevent data leakage or tampering. Once energy consumption data is transmitted to the energy management system, it can be processed and analyzed. Message Queuing Telemetry Transport (MQTT) is a lightweight publish/subscribe message transmission protocol that is particularly suitable for communication between IoT devices. Due to its lightweight, flexibility, and reliability, MQTT is widely used for communication between IoT devices, especially in low bandwidth, high latency, and resource limited environments [23]. It is widely used in various IoT applications, as shown in Figure 2.

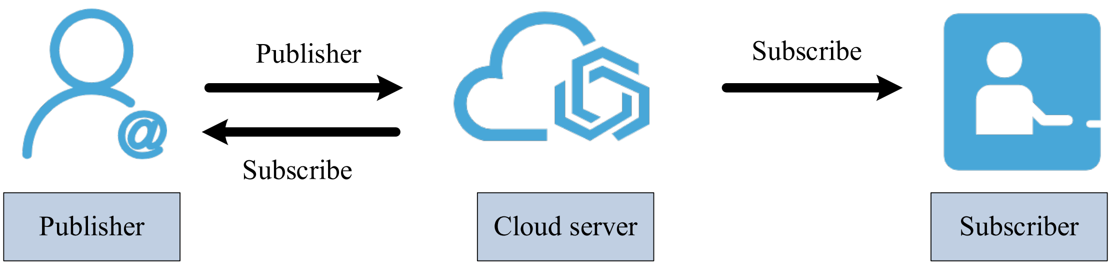

Fig. 2 MQTT technical data transfer mode

The MQTT protocol is designed with simplicity and low resource consumption and bandwidth usage. Therefore, it is very suitable for use in IoT environments with limited bandwidth and resources. MQTT adopts a publish/subscribe messaging model. Devices can send data to specific topics by publishing messages. Other devices can receive data by subscribing to corresponding topics. This asynchronous communication model makes communication between devices more flexible and decoupled. Radio Frequency Identification (RFID) is a technology that uses radio signals to automatically identify target objects and read relevant data. The RFID system mainly consists of reading and writing devices and electronic tags. Reading and writing devices are used to send signals to electronic tags and read data from the electronic tags. RFID technology has long reading distance, strong penetration ability, anti-interference, high efficiency, and large information content. It can recognize a single specific object and process multiple labels simultaneously. The anti-collision algorithm for RFID tags is mainly used to solve the conflict problem that occurs when multiple RFID tags send signals simultaneously. The steps of the RFID tag anti-collision algorithm are shown in Figure 3.

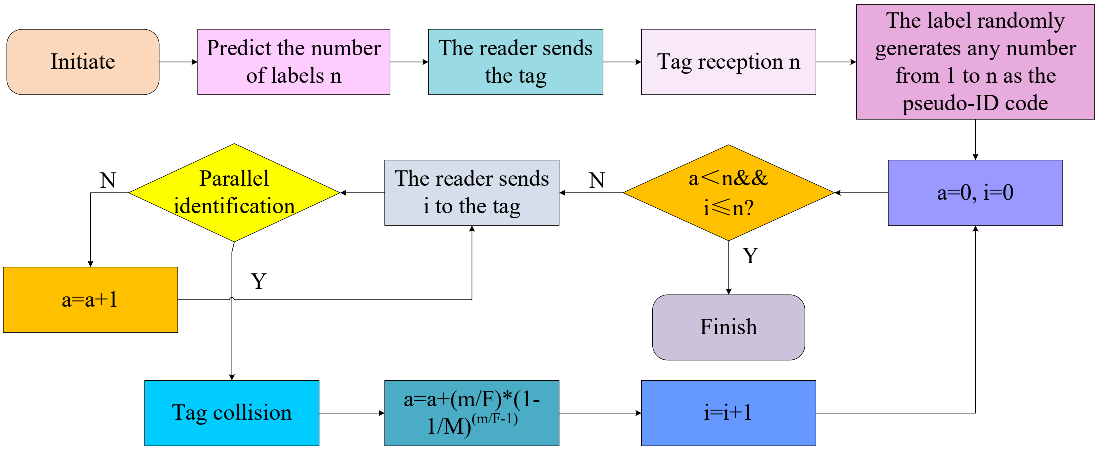

Fig. 3 The steps of RFID tag anti-collision algorithm

A parallel identification technology combining pseudo ID code grouping and tags is proposed to improve the throughput of RFID tag identification transmission. Under the condition of occupying the same transmission band, the transmission performance of RFID multi tag identification system can be improved [24]. The reader generates a series of pseudo labels based on the estimated labels. Within the range of values for this label, one is randomly selected as its own identification symbol. The possibility of selecting a pseudo ID code simultaneously by m markers is shown in equation (1).

$$P(L,n,m)=C_n^m\cdot(\frac{1}{L})^m\cdot(1-\frac{1}{L})^{n-m} \quad (1)$$

In equation (1), L represents the number of pseudo ID codes generated by the reader. n refers to the total tags to be identified within the recognition range. m is the number of tags selected for the current pseudo ID code. The ratio of the expected number of successful pseudo ID codes to the total number of pseudo ID codes is taken as the limit value, as shown in equation (2).

$$P(L,n,m)=C_n^m\cdot(\frac{1}{L})^m\cdot(1-\frac{1}{L})^{n-m} \quad (2)$$

In equation (2), the number of successfully identified pseudocodes has reached its maximum value. In fact, the number of n in the equation is very large, so 1 can be ignored, $L=n$. Before recognizing the label, the reader first estimates the total number of labels n within the recognition range. Then, the reader sends n to the label. The random number generator of the label generates a number between $1\sim n$ as a pseudoID code. At this point, there are several scenarios for pseudo ID codes. The pseudo ID code has no label selection, i.e. $m=0$. There is one tag that selects the pseudo ID code, which is $m=1$. The number of labels for selecting this pseudo ID code is greater than or equal to 2, that is, $m\geq 2$. At this point, the collision phenomenon in ordinary algorithms occurred. When $m=0$ is reached, the probability of an empty ID code appearing during the recognition process is shown in equation (3).

$$P_{(m=0)}=(1-\frac{1}{L})^n \quad (3)$$

When m=1, the probability of successfully identifying the pseudo ID code can be obtained, as shown in equation (4).

$$P_{(m=1)}=C_n^1\cdot(\frac{1}{L})\cdot(1-\frac{1}{L})^{n-1}=\frac{n}{L}\cdot(1-\frac{1}{L})^{n-1} \quad (4)$$

At $m\geq 2$, the pseudo ID code is the usual collision ID code. The probability of label collision P_m when m≥2 is shown in equation (5).

$$P_m=1-P_{(m=0)}-P_{(m=1)}=C_n^m\cdot(\frac{1}{n})^m\cdot(1-\frac{1}{n})^{n-m} \quad (5)$$

3.2 Model prediction and optimization based on ANN

ANN is a computational model developed inspired by biological neural systems. It is used to simulate complex nonlinear relationships and implement machine learning tasks. It is composed of multiple neurons (or nodes), which are connected to each other by connecting weights, forming a network structure. ANN simulates the working principle of biological neurons. Each neuron receives an input signal and calculates its output based on the weight and activation function. Multiple neurons are interconnected through hierarchical structures, forming a multi-layer neural network. The input layer (IL) receives raw data. The output layer (OL) produces the final prediction or classification result. The hidden layer (HL) in the middle is used for processing and extracting features [25]. The training process of ANN is achieved by adjusting the connection weights. The connection weights of the ANN are shown in Figure 4.

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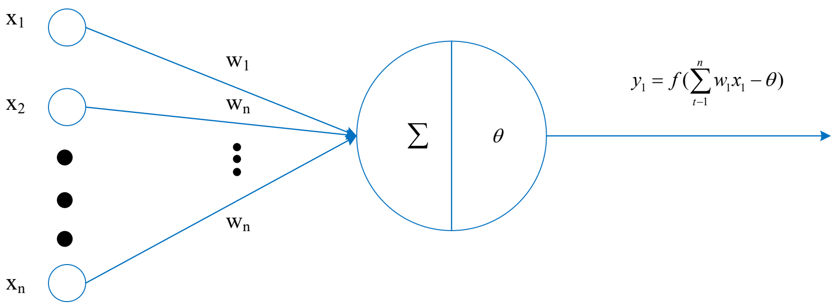


Fig. 4 The connection weight of ANN

ANN can be applied to energy management systems of high energy consuming enterprises, achieving optimization and conservation of energy consumption. By collecting historical energy usage data and other related parameters, a neural network model can be trained to predict future energy demand. This helps companies develop more accurate energy procurement plans and energy allocation strategies to minimize energy waste and costs. Neural network models can predict and optimize the energy load of enterprises. This can help enterprises adjust energy consumption reasonably to reduce energy load during peak demand periods, reduce excessive use of high energy consuming equipment, and achieve an improve energy efficiency. Neural networks can learn and recognize the normal usage patterns of high energy consuming devices, and issue alerts when abnormal situations occur. Energy usage is monitored in real-time. When energy consumption exceeds the normal range, the system can detect it in a timely manner and take corresponding measures to reduce energy waste and losses. Usually, backpropagation (BP) algorithm is used for training. During the training process, the output of the network is compared with the expected results. The error is reduced by fine-tuning the weights. This process is iterated multiple times until the network can produce expected results. The flowchart of the BP is displayed in Figure 5.

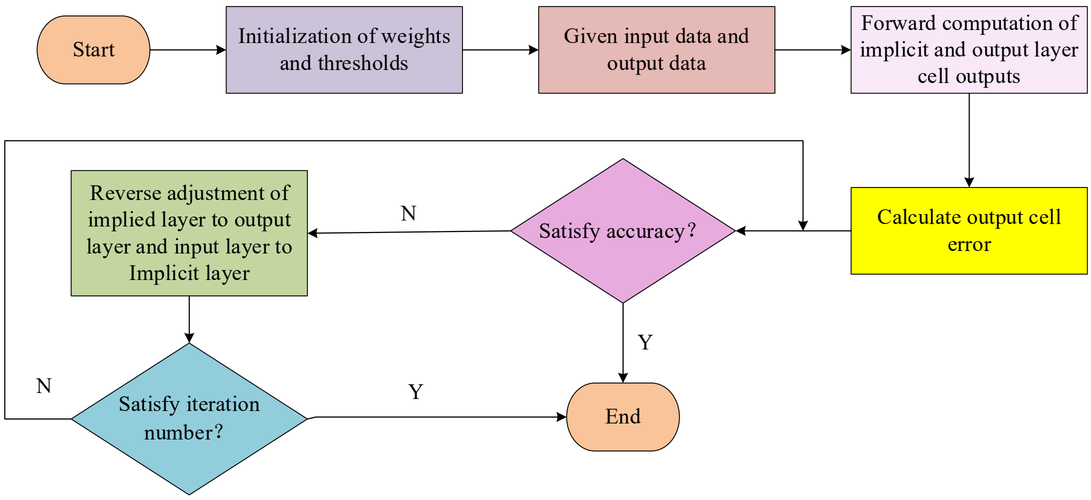


Fig. 5 Flow chart of BP

In Figure 5, the input data is propagated through the network. The output values of the HL and OL are calculated. By comparing the predicted and actual values of the OL, the error is calculated. The weights and bias values are updated using gradient descent. Forward propagation and backpropagation are repeated until the stopping condition is reached. The IL nodes depend on the dimension of the input vector. The optimal HL node quantity can be determined using the trial and error method, as displayed in equation (6).

$$m = \sqrt{n+l} + a \quad (6)$$

In equation (2), m refers to the HL node quantity. n is the IL node quantity. l is the OL node quantity. a is a constant from 1 to 10. The OL node quantity depends on the dimension of the target variable. Nonlinear transfer functions are used. The hyperbolic function is used commonly, as displayed in equation (7).

$$f(x) = \frac{1}{1+e^{x}} \quad (7)$$

There is a positive correlation between the experimental sample and the accuracy. However, when the sample size reaches a certain level, the accuracy will remain stable within a range and there will be no significant changes. A larger network size indicates that the mapping relationship of the network is also more complex. There are two common methods for selecting initial weights. One way is to choose an initial weight that is small enough. Another approach is to make the number of initial weights +1 and -1 equal. Multiple networks can be trained. The most suitable network can be selected based on the analysis results. The performance of the single HL vector model in MATLAB used in the study is shown in Figure 6.

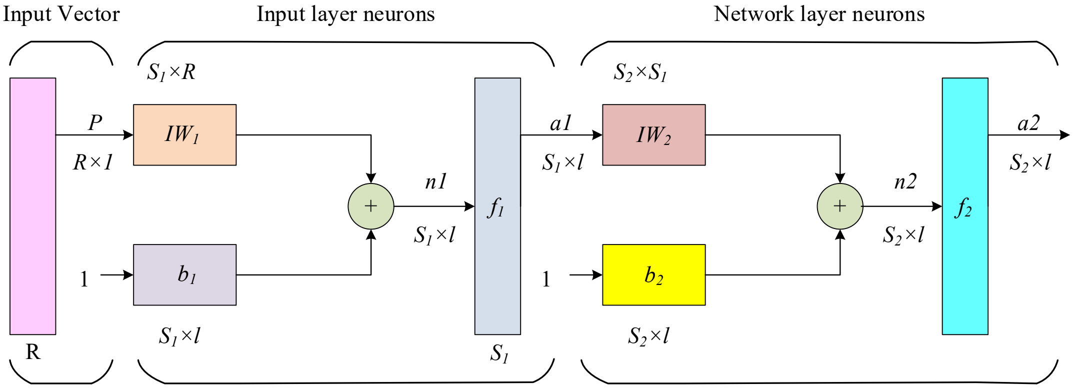


Fig. 6 The vector model of multi-layer neural network in MATLAB

In Figure 6, P is the input vector, with a size of $R \times 1$, as displayed in equation (8).

$$P = [P_1, P_2, ..., P_R] \quad (8)$$

b_1 is the threshold vector of the IL neurons, with a size of $S_1 \times 1$, as displayed in equation (9).

$$b_1 = [b_1, b_2, ..., b_{S_1,1}] \quad (9)$$

IW_1 is the connection weight vector between the IL neuron and the input vector, with a size of $S_1 \times R$, as shown in equation (10).

$$IW_1 = \begin{bmatrix} iw_{1,1}^{1,1} & iw_{1,2}^{1,1} & \dots & iw_{1,R}^{1,1} \\ iw_{2,1}^{1,1} & iw_{2,2}^{1,1} & \dots & iw_{2,R}^{1,1} \\ \dots & \dots & \dots & \dots \\ iw_{S_1,1}^{1,1} & iw_{S_1,2}^{1,1} & \dots & iw_{S_1,R}^{1,1} \end{bmatrix} \quad (10)$$

n_1 is the intermediate calculation result of the first layer neuron, which is the weighted sum of the connection weight vector and threshold vector, with a size of $S_1 \times 1$, as shown in equation (11).

$$n_1 = IW_1 p + b_1 \quad (11)$$

a_1 is the output direction of the first layer neuron, with a size of $S_1 \times 1$, as illustrated in equation (12).

$$a_1 = f_1(IW_1 p + b_1) \quad (12)$$

The IoT technology is used to collect datasets and normalize the data, as shown in equation (13).

$$pn = 2 \times (\frac{p - p_{\min}}{p_{\max} - p_{\min}}) - 1 \quad (13)$$

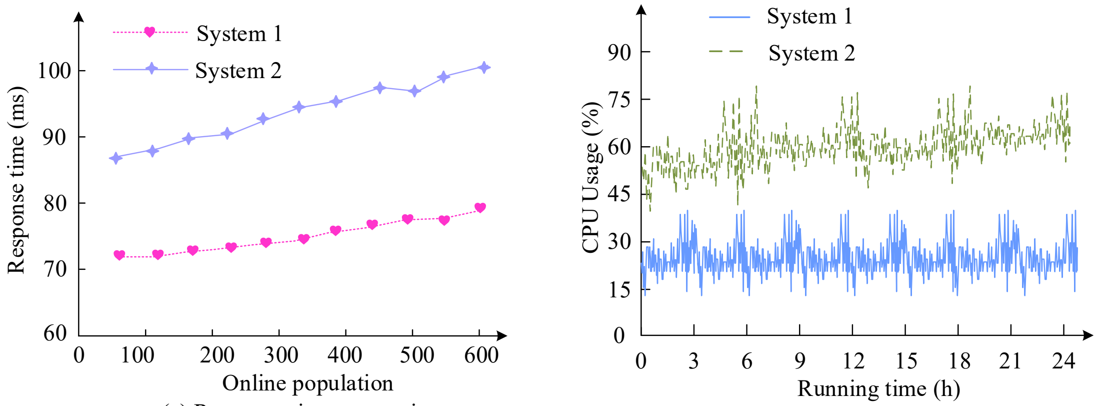
In equation (13), pn represents the processed data. p represents the data to be processed. $p_{\min}$ represents the minimum value of the dataset. $p_{\max}$ represents the maximum value of the dataset. The neural network architecture is as follows, with the input layer receiving data from iot devices, including real-time energy consumption data and environmental parameters. The first hidden layer maps the input data to the feature space through weights and biasing for preliminary feature extraction and nonlinear transformation. The second hidden layer further processes the output of the first hidden layer to extract deeper features that provide support for energy consumption predictions. The output layer converts the output of the second hidden layer into the predicted energy consumption value, and each node of the output layer corresponds to the predicted consumption of an energy type. In order to further optimize the decision-making process of energy management system, reinforcement learning algorithm Deep Q Network (DQN) is introduced. By combining the learning ability of deep neural network and the decision process of Q learning, DQN algorithm automatically learns the energy consumption pattern and predicts the optimal energy management strategy. Specifically, the study designed a DQN model that receives real-time energy consumption data from iot devices as state inputs and is trained to learn to map these states to optimal energy management actions, such as adjusting device operating parameters or purchasing additional energy. The DQN model utilizes experiential replay and target networks to stabilize the learning process and uses a reward mechanism to encourage energy efficiency gains and cost reductions. In this way, the energy management system can continuously optimize itself to adapt to changing energy demand and market conditions, resulting in more efficient and economical energy use. In order to achieve more comprehensive and synergistic benefits, the energy management system proposed in the study will work closely with other management systems such as production planning, supply chain optimization and financial management of the enterprise through integration and interface design. This integrated approach will allow energy management systems to access and analyze a broader set of data, including production demand, supply chain dynamics, and financial metrics, enabling optimization at multiple levels. For example, energy management systems can be integrated with production planning systems to adjust energy purchase and use plans based on production demand and energy price forecasts to reduce energy costs and increase production efficiency. At the same time, by integrating with the supply chain management system, the energy management system can take into account the transportation energy consumption of raw materials and products, optimize the logistics path and transportation mode to reduce the overall energy consumption and environmental impact. In addition, the combination of energy management systems with financial management systems will enable companies to more accurately forecast energy costs, optimize budget allocations, and assess the return on investment of energy efficiency improvement measures. This integration across systems will facilitate data sharing and process automation, improving the consistency and efficiency of decision making.

4. Performance and application analysis of energy management system for high energy consuming enterprises integrating IoT and neural networks

The performance and application effectiveness of energy management systems for high energy consuming enterprises that integrate the IoT and neural networks are analyzed. The overall performance of the energy management system for high energy consuming enterprise is evaluated.

4.1 Performance analysis of energy management systems for high energy consuming enterprises

Firstly, the neural network is configured and trained. The input layer nodes of the neural network are determined based on the number of sensors and the type of energy monitored and contain 10 nodes. The hidden layer employs two hidden layers, each containing 15 neurons, to handle complex non-linear relationships. The output layer contains the predicted energy consumption value and has a node. The input layer to the hidden layer uses the ReLU activation function to increase the nonlinear representation of the network; The hidden layer to the output layer uses linear activation functions to maintain the continuity and interpretability of the output. The learning rate is set to 0.01 to ensure the stability and convergence speed of the training process. With the Adam optimizer, the learning rate is automatically adjusted for handling large data sets. The training program consists of the following steps, data preprocessing, including data cleaning, normalization processing, and data enhancement. The normalization process uses Min-Max Scaling to scale the data to between 0 and 1 to speed up the training and improve the generalization ability of the model. Randomly initialize the weights and biases of the neural network to break symmetry and ensure diversity of training. Computes the output of each layer from the input layer to the output layer, including the calculation of the activation function. The gradient is calculated based on the loss function, and the gradient is backpropagated to each layer of the network through the chain rule, updating the weights and biases. The forward propagation and backpropagation processes are repeated until the model's performance on the validation set no longer significantly improves, or a preset number of iterations is reached. Evaluate the performance of the model on the test set, including prediction accuracy, generalization ability, and stability. According to the performance of the model on the verification set, the learning rate, the number of layers, the number of neurons and other hyperparameters are adjusted to optimize the model performance. To analyze the performance of a high energy consuming enterprise energy management system that integrates the IoT and neural networks proposed in the study, the overall performance of a high energy consuming enterprise energy management system (System 1) that integrates the IoT and neural networks is compared with that of a traditional high energy consuming enterprise energy management system (System 2). The same testing conditions and data set are set. The response time and system occupancy rate of the two systems are recorded, as shown in Figure 7.

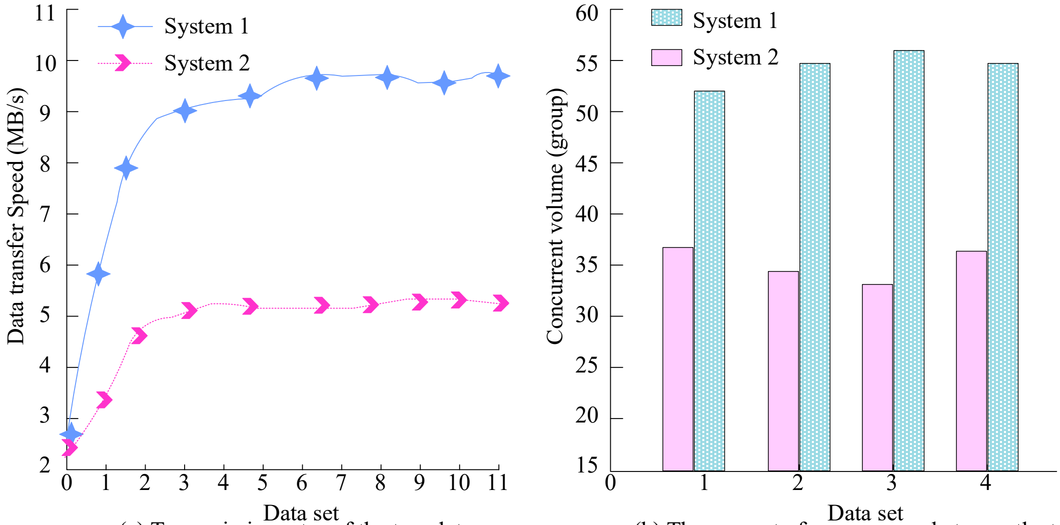


(a) Response time comparison

(b) Comparison of CPU usage

Fig. 7 Performance test comparison of the two systems

In Figure 7 (a), the response time of the high energy consuming enterprise energy management system proposed in the study was 80.2ms when the people were 600. The response time of System 2 was 99.8ms when the people were 600. The response time of the energy management system for high energy consuming enterprises was much lower than that of System 2. In Figure 7 (b), the fluctuation range of CPU usage in the energy management system of the high energy consuming enterprise proposed in the study within 24 hours was 14% to 45%. The CPU usage of System 2 fluctuated 45% to 76% within 24 hours. The CPU usage and response time of the high energy consuming enterprise energy management system constructed were better than those of System 2, fully meeting the requirements of enterprise management. To further analyze the performance of System 1 and System 2, the transmission rate and concurrency rate of the two systems are compared, as shown in Figure 8.



(a) Transmission rates of the two data integration methods

(b) The amount of concurrency between the two methods of data integration

Fig. 8 Comparison of transmission rate and concurrency rate between the two systems

In Figure 8 (a), when the number of data groups increased to 2, the transmission rates of System 1 and System 2 increased sharply. After participating in more than 5 data groups, the transmission speed values tended to flatten out. The final transmission speed of System 2 was about 5 MB/s, which was relatively low. The transmission rate of System 1 was about 10 MB/s, which was relatively high. In Figure 8 (b), the average number of concurrent data sets for System 2 was 34, indicating poor concurrency results. In contrast, System 1 could handle up to 54 concurrent tasks, which had good operational feasibility. It could handle most data sets. After verifying the superior performance of the high energy consuming enterprise energy management system proposed in the study, its economic benefits are analyzed. The main comparison indicators are total investment cost and return. The economic efficiency of the energy management system for high energy consuming enterprises is shown in Figure 9.

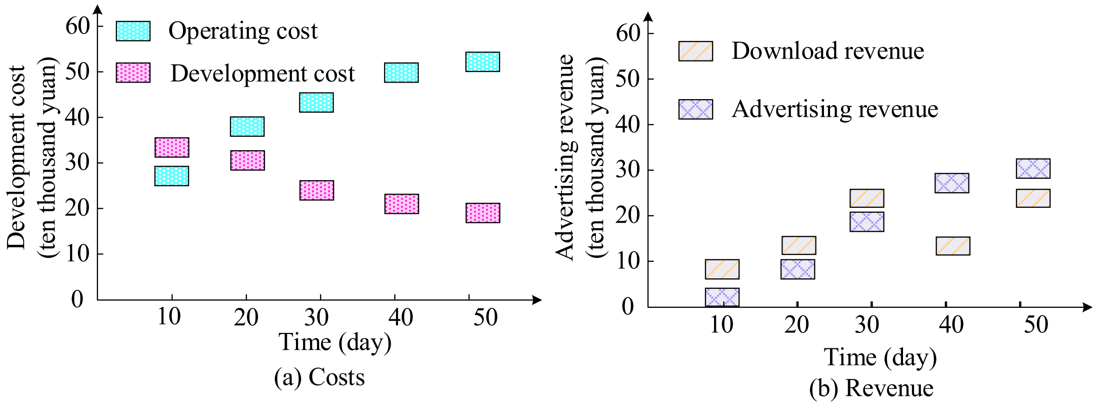


Fig. 9 Comparison of economic benefits of system 1

In Figure 9 (a), the development cost of the high energy consuming enterprise energy management system proposed in the study showed an increasing trend over time, reaching 600000 yuan. The operating costs showed a downward trend over time. In Figure 9 (b), the advertising revenue of the high energy consuming enterprise energy management system proposed in the study showed an upward trend over time, and gradually stabilized with traffic, leading to an increase in advertising revenue. The download revenue generally showed an upward trend over time. The advertising and download revenue of this system increased over time. It could achieve good cost-effectiveness. The proposed energy management system for high energy consuming enterprises was compared with existing energy management solutions, including enterprise resource planning systems (ERP), building energy management systems (BEMS), and rule-based energy management systems. Comparison indicators include economic benefit, energy efficiency, system stability, real-time performance, scalability, response time, and data accuracy. All indicators were normalized and the final results were shown in Table 1.

Table 1 Comparison of energy management schemes

Indicators	Study the proposed system	ERP system	BEMS system	A rule-based system
Economic benefit	0.95	0.85	0.88	0.80
Energy efficiency	0.92	0.78	0.84	0.75
System stability	0.94	0.82	0.86	0.79
Real time	0.93	0.80	0.87	0.77
Extensibility	0.91	0.86	0.89	0.83
Response time	0.90	0.81	0.85	0.78
Data accuracy	0.96	0.84	0.88	0.82

In Table 1, the system proposed in the study performs well on all key indicators, scoring above 0.9, significantly higher than other systems. Especially in terms of data accuracy, the system proposed in the study leads with a high score of 0.96, showing its high accuracy in data acquisition and processing. In addition, the system also shows strong advantages in economic benefits, system stability and real-time, which indicates that it cannot only provide accurate data support, but also ensure the stable operation and rapid response of the system, so as to bring higher economic benefits and better energy management experience for enterprises.

4.2 The application effect analysis of energy management system in high energy consuming enterprises

The proposed high energy consuming enterprise energy management system is applied to the energy supply system of a park in northern China. The load demand and power supply data of the park are used to verify the system. The study sets up 1000 iterations and 200 populations. The two typical working days of the summer and winter cooling, heating, and electricity load demand and photovoltaic power generation in the park are analyzed. The demand for cooling, heating and electricity load and photovoltaic power generation on a certain day in summer and in winter are shown in Figure 10.

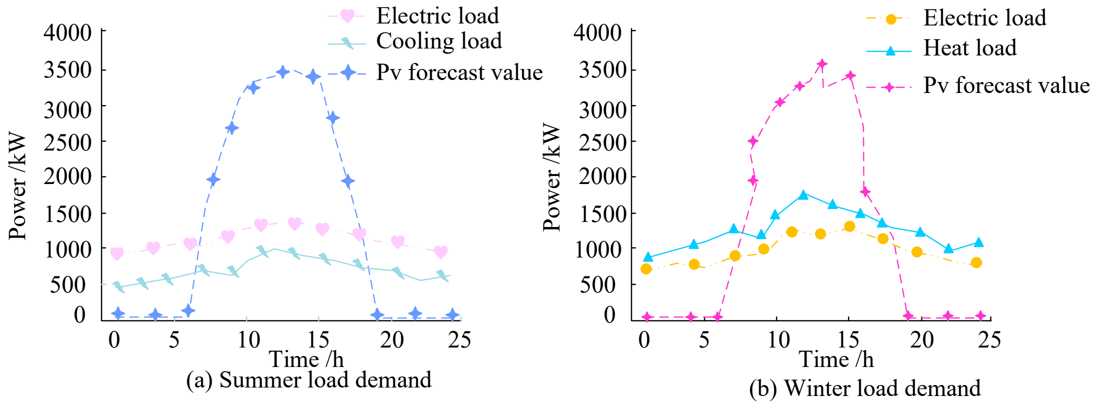


Fig. 10 Summer, winter cold and heat load demand and photovoltaic power generation

Figure 10 (a) shows the demand for cooling, heating, and electricity load and photovoltaic power generation on a certain day in summer. Figure 10 (b) shows the demand for cooling, heating, and electricity load and photovoltaic power generation on a certain day in winter. After applying the high energy consuming enterprise energy management system, the cold, heat and power load and photovoltaic power generation situation can be visually observed. The cooling load was stronger in summer and the heating load was stronger in winter. The predicted value of photovoltaics in summer was also higher. Further planning and analysis is conducted on the energy management system. The electrical balance of the increased photovoltaic power generation system equipment is shown in Figure 11

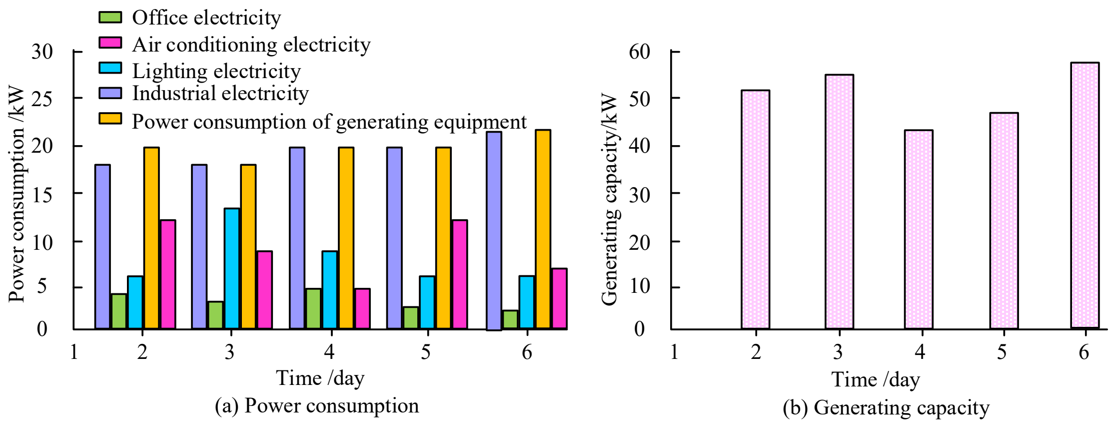


Fig. 11 Consider increasing the electrical balance of photovoltaic power system equipment

In Figure 11 (a), the industrial power consumption of this small energy park was the highest. The average daily power consumption was 20 kW. The average daily electricity consumption for lighting was 8kW. Air conditioning consumed an average of 10kW of electricity per day. The average daily electricity consumption for office was 3kW. The power generation equipment was 19kW. In Figure 11 (b), the average daily power generation of the park was 50kW, which met the park operation. The energy management system of high energy consuming enterprises could clearly analyze daily energy consumption, providing theoretical basis for enterprises. The energy management system is optimized with the goal of comprehensive cost. The results are shown in Table 1. To evaluate the application effectiveness of the energy management system proposed for high energy consuming enterprises, a comparative analysis is conducted on energy consumption rate, energy cost, energy utilization rate, energy consumption distribution, energy consumption to output ratio, carbon emissions, data accuracy, and real-time performance, as displayed in Table 2.

Table 2 Application effect of energy management system in high energy-consuming enterprises

Items	Statistical value	Actual value
Energy consumption rate (%)	32	33
Energy cost (Ten thousand yuan)	5530	5627
Energy efficiency (%)	86	86
Energy consumption distribution	Explicit	/
Ratio of energy consumption to output	0.98	0.96

value		
Carbon emission(t)	321	335
Data accuracy (%)	93	92
Real time performance (%)	97	97

In Table 2, the energy consumption rate of the energy management system in high energy consuming enterprises was 32%. The energy cost was 55.3 million yuan. The energy utilization rate was 86%. The energy consumption distribution was accurate. The ratio of energy consumption to output value was 0.98. The carbon emissions were 321 tons. The accuracy of the data was 93%. The real time performance was 97%. The statistical values of energy management systems in high energy consuming enterprises are not significantly different from the actual values, indicating that the application effect of energy management systems in high energy consuming enterprises is relatively good. In order to verify the effectiveness of the energy management system proposed in the study, a series of statistical tests were conducted, as shown in Table 3.

Table 3 Statistical test results

Inspection item	Energy consumption forecasting accuracy	System response time	Energy cost saving	System stability
Sample size	300	300	300	300
Mean variance	2.5	-0.15	5000	0.08
Standard deviation	1.2	0.5	1200	0.03
T-value	3.1	-3.0	4.2	2.7
Degree of freedom	298	298	298	298
p-value	<0.01	0.003	<0.01	0.007
95% confidence interval	(1.1, 3.9)	(-0.25, -0.05)	(4500, 5500)	(0.05, 0.11)

As shown in Table 3, the energy management system proposed in this study is significantly better than the existing system in terms of energy consumption prediction accuracy, system response time, energy cost saving and system stability. Specifically, the mean difference of energy consumption forecasts is 2.5, the standard deviation is 1.2, the T-value is 3.1, the P-value is less than 0.01, and the 95% confidence interval is (1.1, 3.9), showing a significant improvement in forecast accuracy. The mean difference of the system response time is -0.15, the standard deviation is 0.5, the T-value is -3.0, the P-value is 0.003, and the 95% confidence interval is (-0.25, -0.05), indicating that the system responds faster. In terms of energy cost saving, the mean difference is 5000, the standard deviation is 1200, the T-value is 4.2, the P-value is less than 0.01, and the 95% confidence interval is (4500, 5500), indicating that the system can effectively reduce energy cost. These data confirm the effectiveness of the system in improving energy management efficiency and reducing costs.

5. Conclusion

With the development of industrialization, the energy consumption problem of high energy consuming enterprises is becoming increasingly prominent. Energy management in high energy consuming enterprises is crucial for their development and sustainability. A high energy consuming enterprise energy management system based on IoT technology and neural network algorithms is designed. The practical application effect and feasibility are verified through experimental evaluation and data analysis. The research results indicated that the transmission rate of the system was about 10MB/s, which was relatively high. It could handle up to 54 concurrent tasks. It has good operational feasibility, which can handle most data sets. The practical significance of the proposed energy management system for high energy-consuming enterprises is that it can significantly improve energy efficiency and economic benefits, while reducing operating costs and environmental impact. In addition, the scalability of the system is reflected in its modular design and flexible architecture. As an enterprise grows in size or energy management needs change, the system can easily add new sensors, devices and users to suit a wider range of application scenarios. However, energy management systems that integrate the IoT and neural networks face compatibility issues. In the future, research should further strengthen the integration and compatibility with existing systems, and achieve data sharing and interaction. Explore more advanced neural network architectures, such as deep learning models and reinforcement learning algorithms, to improve the accuracy of energy consumption predictions and the adaptive capabilities of systems. Integrate a wider variety of IoT-based sensors and data sources for more comprehensive energy monitoring and finer energy consumption analysis.

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