Hindawi
Journal of Function Spaces
Volume 2023, Article ID 9805725, 1 page
https://doi.org/10.1155/2023/9805725

Retraction

Retracted: Application of Internet of Things Based on Big Data Ecosystem in Factory Energy Consumption Analysis Model

Journal of Function Spaces

Received 17 October 2023; Accepted 17 October 2023; Published 18 October 2023

This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope

(2) Discrepancies in the description of the research reported

(3) Discrepancies between the availability of data and the research described

(4) Inappropriate citations

(5) Incoherent, meaningless and/or irrelevant content included in the article

(6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] A. Li, C. Zhang, and L. Li, "Application of Internet of Things Based on Big Data Ecosystem in Factory Energy Consumption Analysis Model," *Journal of Function Spaces*, vol. 2022, Article ID 7631323, 10 pages, 2022.

Hindawi
Journal of Function Spaces
Volume 2022, Article ID 7631323, 10 pages
https://doi.org/10.1155/2022/7631323

Research Article

Application of Internet of Things Based on Big Data Ecosystem in Factory Energy Consumption Analysis Model

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Received 10 May 2022; Revised 24 June 2022; Accepted 28 June 2022; Published 12 July 2022

Academic Editor: Miaochao Chen

The demand for energy in factories is huge. With abundant energy supply, factories can raise their production capacity to a new height. Energy is the material basis of domestic economic development. As the largest developing country in the world, energy shortage has become an urgent problem for China. In this paper, an Internet of Things based on big data ecosystem is proposed to analyze the energy consumption of the factory and build a model. The Internet of Things technology of big data ecosystem can be summarized as a technology that uses information sensing devices to complete the transaction and network connection according to the protocol content. A total of 853,000 power distribution operations were carried out in the power grid. In 2019, the average ratio of decision tree algorithm, machine learning algorithm, and machine learning algorithm was 36.8%, 37.4%, and 43.5%, respectively. Compared with the three methods, the method in this paper increased by 37.9% year-on-year and reduced the power outage by 2.63 million households, which is equivalent to a corresponding reduction of 35 users per operation. The functional requirements of the IoT energy consumption analysis system in factories based on big data ecosystem are reflected in three aspects: energy consumption monitoring and management, power control and management, and energy consumption supervision and analysis. Based on the management of energy consumption monitoring and power control through the software platform, the functional requirements of the system are analyzed.

1. Introduction

After the founding of New China, especially since the reform and opening up, China's manufacturing industry has developed rapidly and continuously, and a complete and independent industrial system has been built, which has effectively promoted the process of industrialization and modernization and significantly enhanced the overall national strength. Panfactory electric power pays more attention to how to mine the value of collected data; that is, through the analysis and mining of data, it can achieve the optimal management of the whole power system of the factory and then promote energy conservation and consumption reduction on the energy consumption side and use energy intelligently, thus providing important support for the transformation and upgrading of the energy system [1, 2]. At present, factories are playing an extremely important role. Uninterrupted operation refers to the operation in which factory personnel directly contact live lines or equipment, or factory personnel use special tools, equipment, or devices to work on live lines or equipment, so as to carry out maintenance and testing on uninterrupted power lines or equipment [3, 4]. The demand for energy in factories is huge. With abundant energy supply, factories can raise their production capacity to a new height. Energy is the material basis of domestic economic development. As the largest developing country in the world, energy shortage has become an urgent problem to be solved in China [5]. In this case, it is necessary to supervise the energy and further help the factory to reduce costs and increase efficiency, so as to build a more perfect smart factory.

This paper proposes an Internet of Things based on big data ecosystem, analyzes the energy consumption of factories, and constructs a model. The Internet of Things technology of big data ecosystem can be summarized as a technology that uses information sensing equipment to complete the connection between transactions and networks according to the protocol content [6, 7]. In this technology, things mainly use information sensing media to promote information data exchange, sorting, adjustment, and optimization and then complete the optimization, identification, positioning, tracking, supervision, and other functions of intelligent system [8]. The Internet of Things of big data ecosystem is the application extension and business expansion based on the Internet. The composition and operation of the Internet of Things can achieve the connection between things and networks. The Internet of Things is regarded as a great opportunity for development and change in the information field. The Internet of Things of big data ecosystem is a network with self-configuration capability. Similar to the Internet, the Internet of Things must also operate according to the communication protocol [9, 10]. Internet of Things technology has been extended to all aspects of people's life. It can be said that driven by Internet of Things technology, it has played an important role in both social and economic development and the improvement of people's quality of life [11]. The rapid development of the Internet has led to a sharp increase in the number of users and data of various Internet applications. Only increasing the storage capacity of single point devices cannot solve the massive data processing needs of users and enterprises. At the same time, the big data ecosystem gradually developed on the basis of distributed file system to meet the storage and calculation of massive data has been gradually improved [12].

Based on the Internet of Things technology of big data ecosystem and the sensor nodes of Internet of Things that monitor the factory energy consumption analysis data of actual production equipment in factories as specific data sources, this paper puts forward an innovative design concept for the overall architecture of the factory energy consumption analysis system based on the Internet of Things of big data ecosystem, adapts the characteristics of big data of factory energy consumption analysis, designs and implements a complete factory big data processing system, and puts forward energy-saving strategies according to the analysis of big data of factory energy consumption by this system [13, 14]. The research and development of processing technology and system architecture of massive data generated in the analysis of energy consumption in factories are still in its infancy. Because of its many differences with Internet big data, a set of processing methods and tools that directly copy Internet big data cannot meet the demand of Wang Ye production for big data processing [15]. However, due to insufficient investment in information technology in traditional industries, relatively backward technology, and lack of rational use of data, the big data ecosystem of factory energy consumption analysis is still far from perfect.

The innovation of this paper is to propose an Internet of Things based on big data ecosystem, analyze the energy consumption of factories, and establish a model. Compared with the traditional three methods, the outage time of the proposed method is reduced by 15.3% year-on-year, which is equivalent to reducing the downtime of 35 users by 2.33 h each time. In the future, the Internet of Things must face the realistic problem of the proliferation of Internet of Things devices. At the same time, mobile communication itself has high requirements for the reliability and immediacy of communication. Therefore, on the premise of meeting the needs of all parties, mature dynamic spectrum management in the Internet of Things can be realized. And correctly use the spectrum sensing technology to realize the content of spectrum sharing in the Internet of Things.

Based on the big data ecosystem, the application of the Internet of Things in the factory energy consumption analysis model is analyzed. The Section 1 describes the background of industrialization and modernization. The Section 2 analyzes the research status of related work. The energy consumption of the Internet of Things in the factory is analyzed. Section 3 analyzes the principle and model of the Internet of Things big data ecosystem. Section 4 implements the plant energy consumption analysis model and designs the IoT plant energy consumption analysis system. Section 5 summarizes the full text. The research will gradually increase data types and design more targeted algorithms to process and analyze data, so as to further optimize energy-saving strategies and verify the energy-saving effects of relevant strategies.

2. Related Work

2.1. Research Status at Home and Abroad. Ulusoy et al. proposed that in most factories, due to the failure to coordinate the energy distribution among various production departments, the comprehensive utilization rate of factory energy is still high, and it is difficult to achieve the energy-saving goal, so it is impossible to achieve the statistical analysis of energy consumption of the whole factory, and there is no data support for whether the energy consumption is saved [16]. Gutierrez-Osorio et al. proposed that the energy consumption system uses information technology to promote energy conservation and consumption reduction, which is an important measure to improve the fine management level of enterprises, and provides technical support for enterprises to accurately grasp and analyze the development trend of energy conservation and consumption reduction and make scientific use of energy [17]. Li et al. put forward that the factory still records and manages energy information in a manual way, which wastes a lot of labor costs. The data stays on paper, which cannot guarantee the accuracy of the data and provide data basis for leaders' decision-making quickly and accurately. At the same time, there is a lack of statistics on the operation of equipment startup and shutdown, resulting in low efficiency of energy information processing and lack of decision-making mechanism to effectively use energy consumption data and deeply analyze the operation status of energy system, and the control of energy consumption cost always lags behind the occurrence of cost [18]. Mumtaz et al. Proposed the acquisition method of node preprocessing, which means that the acquisition node preprocesses the sensor data to a certain extent. For example, aggregate multiple data to a certain extent, and then transmit. After preprocessing, the bandwidth required for the transmission of collected data will be greatly reduced, which will lead to the corresponding reduction of energy consumption [19]. Orenga-Rogla et al. proposed that for factories, in order to directly or indirectly reduce the total amount of greenhouse gas emissions and achieve "zero emission" of carbon dioxide, it is necessary to implement staggered peak power consumption; that is, according to the load characteristics of the power grid, transfer part of the load during the peak period of power grid to the low period of power consumption through administrative, technical, and economic means, so as to reduce the peak and valley load difference of the power grid and optimize the allocation of resources and improve the security and economy of power grid [20]. Ahad and Biswas proposed to establish a perfect energy consumption monitoring and energy management system; realize the informationization, visualization, and controllability of the dynamic process of energy consumption; and monitor and manage the energy consumed in the factory production process, which can greatly improve the energy efficiency [21]. Sánchez et al. put forward that nearly 50% of the energy saving in California comes from the energy efficiency services of public utilities. Applying accurate electricity metering data can directly provide users with the basis for energy-saving decisions and, at the same time, improve and change the current electricity consumption mode to improve the energy efficiency. As electricity involves all users, the energy saving generated by energy efficiency services will account for 50% of the total energy saving in the whole state [22]. Broring et al. put forward that in order to ensure that the carbon emissions reach the standard without affecting the realization of the enterprise's production objectives, the factory should realize automatic meter reading by the Internet of Things, remote control, and other technologies, and the computer should monitor the energy consumption data in real time and make corresponding adjustments to help enterprises save costs, reduce carbon emissions, and achieve green production [23]. Asch et al. put forward a model-based approach combining the advantages of preprocessing, further abstracting the data collection model, selecting a reasonable algorithm according to the characteristics of data, calculating the collected data to a certain degree, and finally sending information such as a certain coefficient or weight of the relevant data, thus reducing the traffic volume and greatly reducing the energy consumption [24]. The central air conditioner produced by Jan et al. is the key energy-consuming equipment, which usually accounts for more than 50% of the total energy consumption of the enterprise. Compared with other energy-consuming equipment, the cost of energy consumption control and renovation of central air-conditioning is small, and it will not affect production [25].

2.2. Research Status of Internet of Things in Factory Energy Consumption Analysis. The above open-source technologies and frameworks have been widely used in the field of Internet, but there are still many improvements and adaptations for plant energy consumption analysis. Therefore, the Internet of Things based on big data ecosystem is studied in the factory energy consumption analysis in this paper. The factory energy consumption analysis platform designed in this paper is also designed and implemented on the basis mentioned above. Energy consumption is divided into two parts: energy consumption online monitoring system and energy consumption management system. It can provide some energy consumption statistics for enterprises and summarize them into the local total energy. The other is to help enterprises save energy fundamentally. According to the annual and quarterly comprehensive energy consumption of the products, the energy consumption at the plant level is managed in a multiangle and multilatitude manner. From the aspects of energy use type, monitoring area, production process/section time, sub items, etc., the energy consumption statistics of enterprises, year-on-year and month-on-month analysis of energy consumption per unit product, and energy consumption per unit output value are carried out by means of curves and digital tables. Find out the loopholes and unreasonable places in the process of energy use, so as to adjust the energy distribution strategy and reduce the waste in the process of energy use. In the field of Internet of Things of big data ecosystem, embedded system is also widely used. It is a place for embedded system technology in the system development of all kinds of Internet of Things terminals. Based on the big data ecosystem, the Internet of Things faces the total power consumption, total water consumption, total incoming line, and other elements in the process of plant energy consumption analysis. The enterprise integrated energy consumption management system is an integrated management and control system. It is aimed at the energy instruments such as water, electricity, gas, and steam in industrial enterprises and carries out remote data acquisition and control through networking, integrating wired and wireless measurement and control and computer LAN. Form a network system with multiple transmission media to monitor the operation status of on-site energy media in real time. The parameters of each instrument can be remotely collected and set through the network, and the running status of the instrument can be monitored in real time through the computer terminal. The results of energy consumption monitoring are reflected in the form of histogram and data, in which the histogram faces each cycle such as day, month, and year. In the process of querying factory energy consumption analysis, you can freely filter indicators and set the energy consumption data range, time range, and indicator type required in the query.

3. Internet of Things Principle and Model of Big Data Ecosystem

At present, the related technologies of big data are mainly used in the Internet environment, which is used to process the device data and massive media data generated in the network. The Internet of Things technology of big data ecosystem mainly uses communication radio frequency identification technology and data communication technology to form an integrated network. Its main feature is to realize information sharing and provide convenient conditions for information exchange and development in various industries. With the maturity of technologies in the field of big data processing, the demand for data mining has become more and more obvious, and related machine learning algorithms have been applied to big data ecosystems, and a series of open-source machine learning frameworks for big data ecosystems, represented by Mahout and MLiib, have emerged. The function realization of the factory energy consumption analysis model is based on the Internet of Things of big data ecosystem. Using the query tool script of the Internet of Things of big data ecosystem can enable nontechnical personnel to query and count the data in the massive data scene like relational database, which is a very reasonable solution. The database language provided by the plant energy consumption analysis model and the data statistics requirements of the platform realized in this paper that are not strong in real-time requirements use the plant energy consumption analysis model. The IoT flow chart of big data ecosystem is shown in Figure 1.

The real-time data query processing of Internet of Things based on big data ecosystem can meet the needs of users for fast data query and can quickly locate energy consumption information and equipment information in massive data. Making use of the advantages of the Internet of Things of the pan-big data ecosystem in comprehensive state perception and efficient information processing to carry out pioneering changes in the analysis and management of factory energy consumption can effectively change the defects of long energy consumption and low efficiency. This paper presents an energy consumption analysis model of Internet of Things in factories based on big data ecosystem. The overall structure of the model is shown in Figure 2.

The model is mainly based on the data acquisition system, and the function analysis module realizes the establishment and management of uninterrupted power operation scheme. The data acquisition system mainly collects relevant data from the electricity acquisition system, PMS2.0 system, marketing system, GIS system, and SCADA system. The PMS2.0 system takes asset life cycle management as the main line, condition maintenance as the core, realizes the integration of drawings and numbers, and has the linkage mechanism of "account-card-object." The real condition of equipment can be collected through the PMS system.

The application of energy detection method in the local detection of secondary users is the most common, because its implementation difficulty is relatively low, the calculation cost is low, and the judgment method is direct. A binary detection model can be used to simulate whether the received main user signal exists. The sampling signal $e(t)$ of the secondary user at time t is as follows:

$$\begin{cases} H_1 : e(t) = s(t)h(t) + w(t), \\ H_0 : e(t) = w(t), \end{cases} \tag{1}$$

where H_1 represents the busy channel, that is, the primary user is using the channel; H_0 is the opposite; $s(t)$ represents the signal of the primary user; $w(t)$ is the additive white Gaussian noise (AWGN) existing in the channel; and $h(t)$ is the channel gain between the secondary user and the primary user. Assuming $s(t)$ and $w(t)$ are independent of each other, using the energy detection method, when the secondary user samples S times on a channel, the energy calculated by the secondary user for the received signal is

$$E = \sum_{n=1}^{S} \frac{|e(n)|^2}{S}. \tag{2}$$

Because when n changes, E follows the standard normal distribution, E constitutes a chi-square distribution. γ is the instantaneous signal-to-noise ratio of the received signal. When the main user does not exist, E follows the central chi-square distribution with degree of freedom $2S$. When the main user exists, E follows the noncentral chi-square distribution with $2S$ degree of freedom and 2γ noncentral parameter

$$\begin{cases} H_1 : E \sim \chi^2_{2S}(2\gamma), \\ H_0 : E \sim \chi^2_{2S}. \end{cases} \tag{3}$$

Assuming that the number of sampling points S is large enough and that the signal and noise are zero-mean circularly symmetric Gaussian random distributions and they are independent of each other, according to the central limit theorem, E conforms to Gaussian distribution.

$$\begin{cases} H_1 : E \sim N\left(\sigma_w^2(1+\gamma), \dfrac{2\sigma_w^2(1+\gamma)^2}{S}\right), \\ H_0 : E \sim N\left(\sigma_w^2, \dfrac{2\sigma_w^4}{S}\right). \end{cases} \tag{4}$$

The detection probability and false alarm probability in single energy detection are

$$P_{\mathrm{d}} = P\{E \geq \lambda | H_1\} = Q\left(\frac{\lambda}{\sqrt{(2/S)}\sigma_w^2(\gamma+1)} - \sqrt{\frac{S}{2}}\right), \tag{5}$$

$$P_{\mathrm{f}} = P\{E \geq \lambda | H_0\} = Q\left(\frac{\lambda - \sigma_w^2}{\sqrt{(2/S)}\sigma_w^2}\right), \tag{6}$$

$Q(x) = (1/\sqrt{2\pi})\int_x^{+\infty} e^{-(t^2/2)}dt$ is the right tail function of the standard normal distribution, which decreases with the increase of x, and is a decreasing function. Therefore, it can be seen from formula (5) that the higher the signal-to-noise ratio, the greater the detection probability. It can be seen from formula (6) that the larger the sampling point S is, the smaller the false alarm probability is.

By analyzing the characteristics of the noise energy of the signal, the high and low thresholds λ_{H} and λ_{L} are set. The noise uncertainty parameters of wireless environment are the ratio of actual noise power to Gaussian white noise

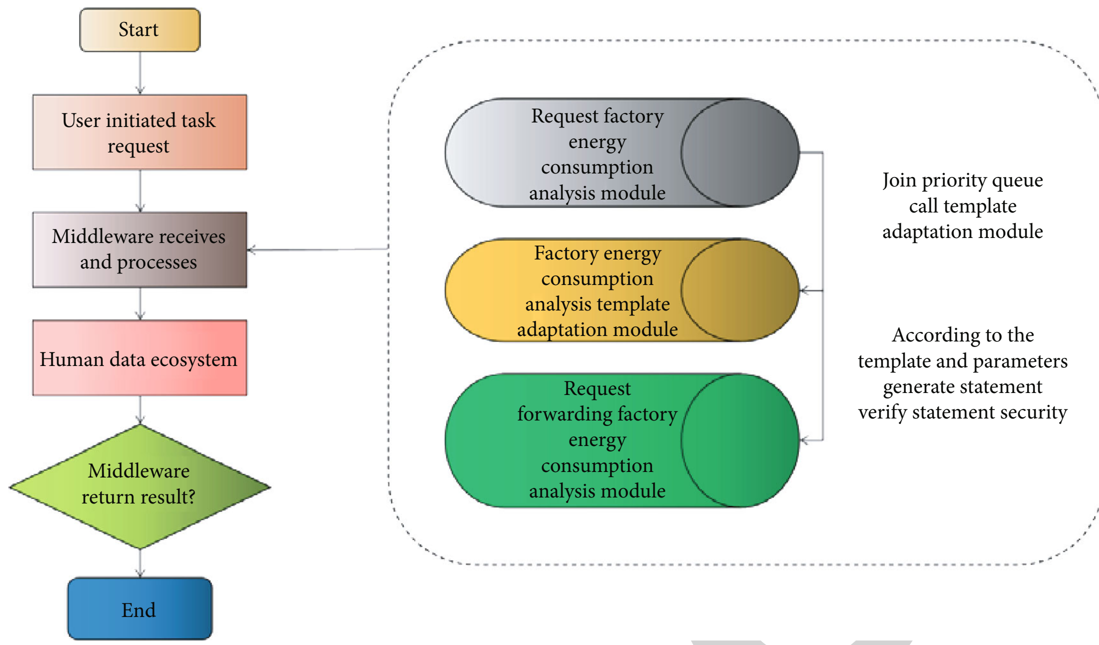

Figure 1: Internet of Things flow chart of big data ecosystem.

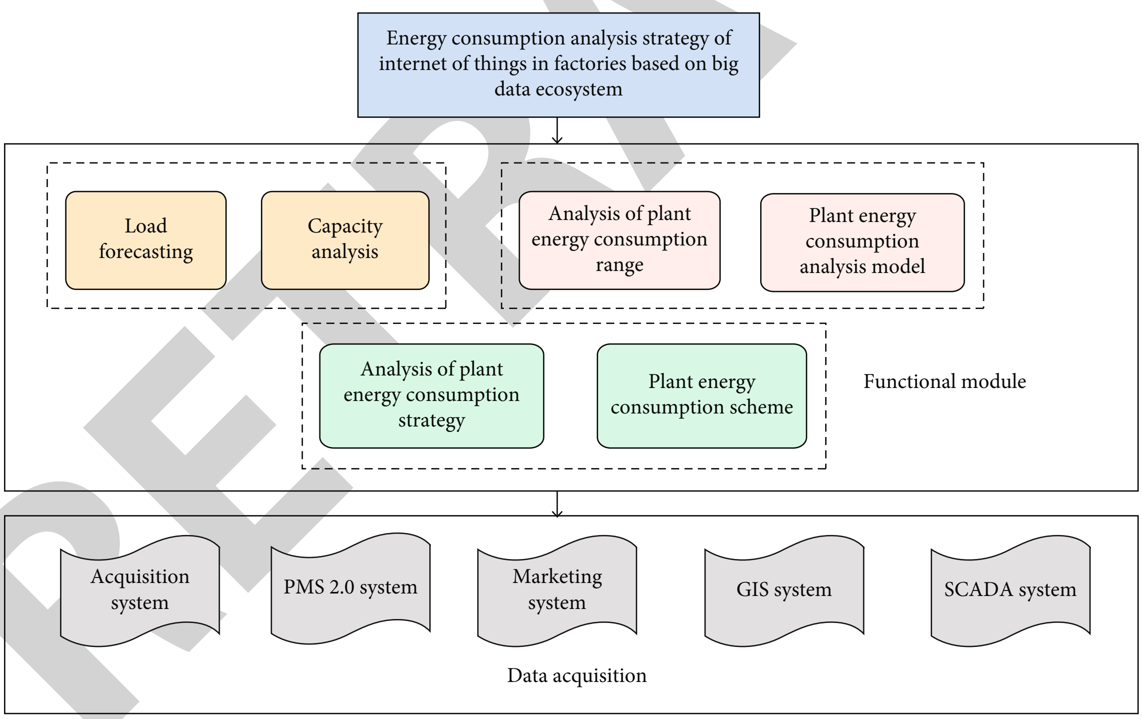

Figure 2: Analysis model diagram of IoT energy consumption in factory based on big data ecosystem.

power ρ, $\rho = \sigma^{\wedge 2}_{w}/\sigma^2_w$. The high and low thresholds of double-threshold energy detection method are

$$\lambda_{\mathrm{H}} = \rho\lambda = \rho\sigma_w^2\left(\sqrt{\frac{2}{S}}Q^{-1}(P_{\mathrm{f}}) + 1\right),$$
$$\lambda_{\mathrm{L}} = \frac{\lambda}{\rho} = \frac{\sigma_w^2}{\rho}\left(\sqrt{\frac{2}{S}}Q^{-1}(P_{\mathrm{f}}) + 1\right). \tag{7}$$

When $E \geq \lambda_{\mathrm{H}}$, it is determined that the main user exists. If $E \leq \lambda_{\mathrm{L}}$, it is determined that the main user does not exist. If it is between two threshold values, the result is considered unreliable and no definite conclusion is given for the time being. The high and low thresholds are related to the channel state and can be adjusted adaptively according to the channel state. When the noise power in the channel is large, the difference between the high and low thresholds can be increased when the value increases. When the channel quality is good, the difference between high and low thresholds can be reduced by reducing the value to make the determination more accurate. If the ρ value in the channel is 1, the high and low thresholds of $\lambda_L = \lambda_H = \lambda$ are equal, which is equivalent to single threshold detection.

When the energy observation value E_i is in the middle of the high and low thresholds λ_H and λ_L, the secondary user thinks that the subchannel result is unreliable and will temporarily store the data locally. If FC wants to make a second round of judgment, it will upload the value to FC. Secondary user's decision D_i for i subchannel can be expressed as

$$\begin{cases} 0 \le E_i \le \lambda_L : D_i = 0, \\ E_i \ge \lambda_H : D_i = 1. \end{cases} \quad (8)$$

In the local decision of secondary users, among the$K$ subchannels detected by secondary users, K_1 get the decision result 1 and K_2 get the decision result 0. In addition, the subchannels with no definite conclusion of $(K - K_1 - K_2)$ are considered unreliable, and the energy data of these "unreliable channels" are stored locally. Then, the secondary user will conclude the channel state according to the "m-out-of-k" rule above, and the conclusion D_l is

$$\begin{cases} K_1 < A : D_l = 0, \\ K_1 \ge A : D_l = 1. \end{cases} \quad (9)$$

In this formula, $l \in [1, N_A]$ represents the l secondary user, and $A \in [1, K]$ is the threshold value when the secondary user locally fuses the results of each subchannel; that is, the secondary user will judge that there is a primary user signal on the measured subchannel when the judgment result of at least A subchannel in K subchannel is 1. Then, the secondary user whose local judgment D_l is 1 will send the local judgment result to FC, and the secondary user whose local judgment is 0 will not send the local judgment.

As the Internet big data-related technology has experienced a long period of development, the technology has become mature, and many of its methods have been applied to many industries and environments outside the Internet. As a medium, the Internet of Things integrates everything in the world with the virtual Internet to form a unified integrated network. The operation of the world will carry out social and economic activities based on the integrated network.

4. Implementation of Plant Energy Consumption Analysis Model

4.1. Design of Energy Consumption Analysis System for Internet of Things Factory. With the popularization of the Internet of things infrastructure and the diversification of sensor information collection, the amount of data generated by the bottom information collection nodes of the Internet of Things based on the big data ecosystem is increasing exponentially. How to reasonably and effectively process and utilize these data and make them become the basis of industrial production and management is an urgent problem to be solved at present. The Internet of Things based on big data ecosystem has self-organization ability and generally requires low power consumption of nodes. Therefore, the ability of the Internet of Things equipment of the plant energy consumption analysis system is limited. For various optimization algorithms in cognitive radio, the main goal of optimization is to improve the accuracy of spectrum sensing. Once spectrum sensing is applied to the Internet of

Table 1: Real-time display page loading time of energy consumption test group.

Test group	Average loading time
Group 1	5.62 s
Group 2	5.25 s
Group 3	5.36 s
Group 4	5.57 s

Table 2: Cluster statistics query function select statement test.

Test group	Average loading time
Group 1	180.502 s
Group 2	182.608 s
Group 3	179.004 s
Group 4	188.553 s

Table 3: Test of count statement of statistical query function.

Test group	Average loading time
Group 1	30.677 s
Group 2	31.677 s
Group 3	31.522 s
Group 4	31.687 s

Table 4: KL divergence value when k is 3.

Clustering dimension	Cluster 1	Cluster 2	Cluster 3
Devld	0.448	0.156	0.024
Date	0.217	0.422	0.367
Time	0.271	0.487	0.517
Period	0.324	0.713	0.571

Table 5: KL divergence value when k is taken as 5.

Clustering dimension	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
Devld	0.725	0.131	0.612	0.598	0.758
Date	0.138	1.078	0.467	0.312	0.603
Time	0.222	1.395	0.648	0.352	0.976
Period	0.391	2.402	0.815	0.538	1.067

Table 6: KL divergence value when k is 6.

Clustering dimension	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6
Devld	0.597	0.832	0.456	0.604	0.844	0.607
Date	0.367	0.354	0.365	0.412	0.154	0.402
Time	0.454	0.575	0.388	0.495	0.264	0.595
Period	0.688	0.835	0.687	0.686	0.542	10.95

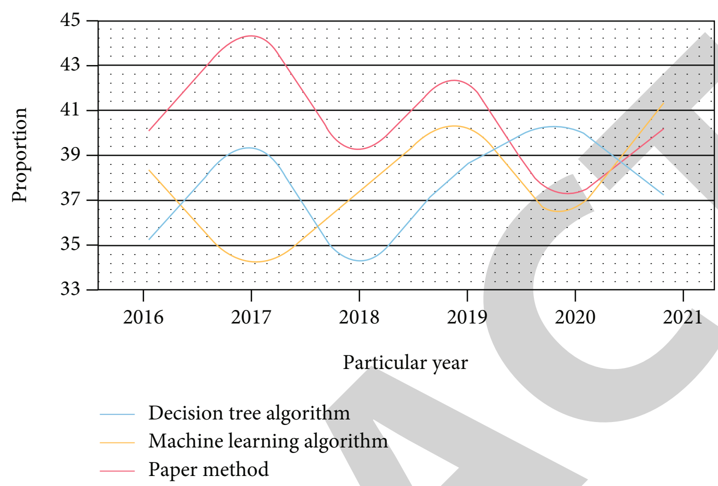

Figure 3: Number of times of live work in distribution network of power grid factory.

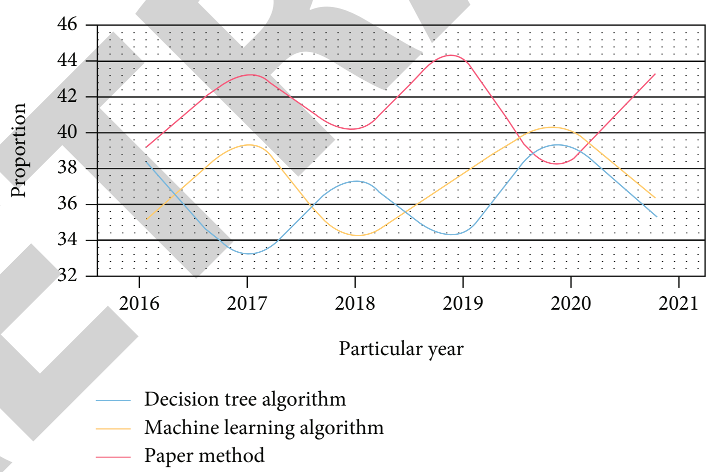

Figure 4: Number of times of live operation in distribution network of power grid factory.

Things, it is necessary to consider the actual energy consumption factors. The functional requirements of the plant energy consumption analysis system of the Internet of Things based on the big data ecosystem are reflected in three aspects: energy consumption monitoring and management, power control management, and energy consumption supervision and analysis. The energy consumption supervision is analyzed on the basis of managing energy consumption monitoring and power control through the software platform, and the functional requirements of the system are analyzed here.

4.2. Experimental Results and Analysis. Aiming at the demand of real-time energy consumption information, this experiment uses real-time power information to represent real-time energy consumption information. The data display is accurate and has certain reference value. At the same time, the webpage loading time has been tested in 4 groups, 10 times in each group, and the average loading time of each group is shown in Table 1.

For the application scenario of statistical query, select the energy consumption data in a certain period of time. Import the energy consumption data into HDFS and create a table.

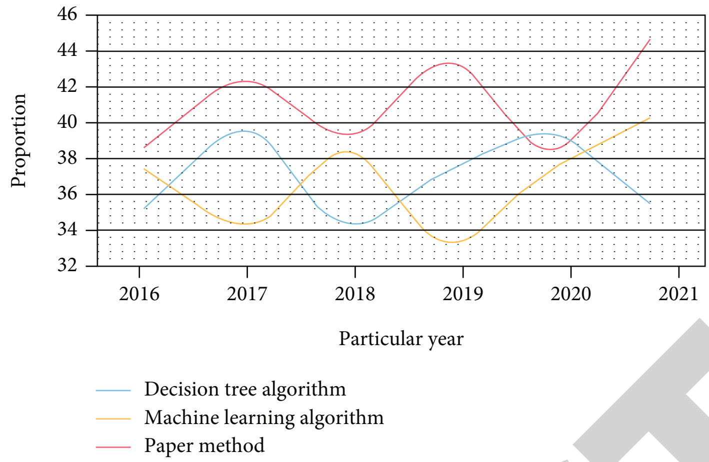

Figure 5: Number of times of live operation in distribution network of power grid factory.

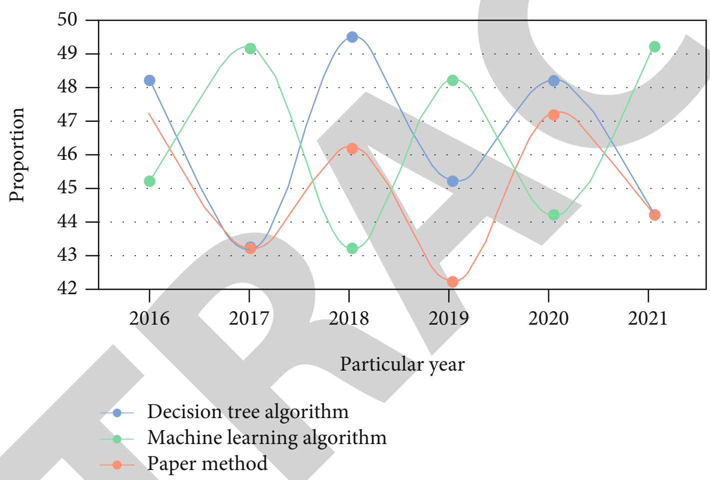

Figure 6: Average power outage time of plant users.

Here, the basic select and count statements are selected for testing. Each statement is divided into five groups for testing, and each group is tested ten times. The average query time is shown in Tables 2 and 3.

In cluster analysis, the selection of the number of clusters K has great influence on the results of cluster analysis. After many experiments, too many K values are selected, and only the most representative K values are selected into the following description; that is, K values of 3, 5, and 7 are selected for clustering. When the number of clusters K is 3, the results obtained according to the cluster analysis are shown in Table 4.

From the comparison in Table 4, it can be seen that the sensor network nodes represented by Devld have the highest correlation among clusters 1 and 3, and the sensor network nodes imply working areas. Different working areas in the actual factory are responsible for different groups, so the working groups have great influence on clustering. In cluster 2, the working time KL value of equipment period is the largest, which indicates that its correlation is high in cluster 2. Continue to analyze the KL value of the dimension of period employees' length of service which is in the second largest position in cluster 3, so the correlation of employees' length of service is larger in cluster 3, which is also the key index.

When the value of K is 5, the same experiment is carried out on the data, as shown in Table 5.

When the value of K is 6, repeat the above clustering process, as shown in Table 6.

It can be seen from Tables 5 and 6 that there is little difference in KL values of Devld in each cluster except cluster 2, and the KL values of each dimension in other clusters are relatively large in the two dimensions of period and time, indicating that they are highly correlated in each cluster. It can be concluded that when k is 6, the KL value of each dimension is basically similar to that when k is 5, and the dimension with the highest correlation in each cluster is the same. After many tests of taking a larger value of k, the distribution of KL value basically does not change much, so it is more appropriate to take a value of k of about 3 to 4.

With the rapid development of social economy, the traditional uninterrupted operation can no longer meet the power supply reliability requirements of people's demand

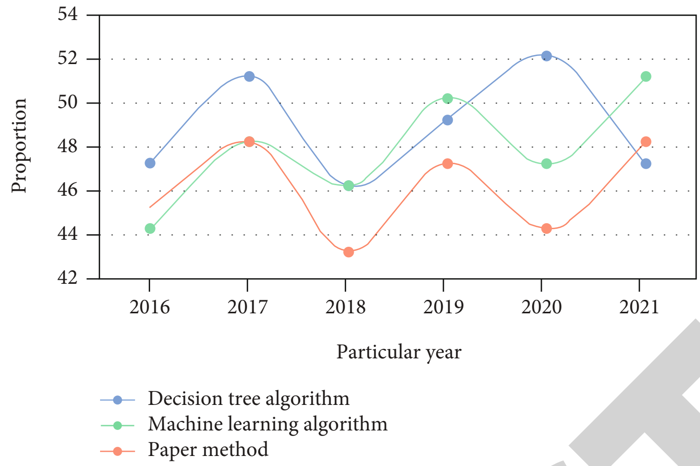

Figure 7: Average power outage time of plant users.

for a better life because of its long time-consuming and low efficiency. In this experiment, for the analysis of the effectiveness of live work in distribution network of a factory from 2016 to 2021, the decision tree algorithm, machine learning algorithm, and the method in this paper, including the completion times of live work, are used for three experimental comparisons. The experimental results are shown in Figures 3–5.

As can be seen from Figures 3–5, there are 853,000 times of uninterrupted power distribution in power grid factories. When the current year is 2019, the average percentage of decision tree algorithm, machine learning algorithm, and machine learning algorithm is 36.8%, 37.4%, and 43.5%, respectively. Compared with the three methods, the method in this paper increases by 37.9% year-on-year and reduces the power outage by 2.63 million h households. The excess power supply is about 748.59 million kW·h, which is equivalent to the power generation of 1.36 million kW installed power plant for about 2 years.

Similarly, this experiment is aimed at the analysis of the effect of reducing the average outage time of power outage users in power grid factories from 2016 to 2021 and adopts decision tree algorithm, respectively. The machine learning algorithm and the method in this paper, including the number of live-line operations, are compared twice. The experimental results are shown in Figures 6 and 7.

From Figures 6 and 7, it can be seen that the power grid factory reduces the average outage time of users. When the year is 2020, the average proportion of decision tree algorithm is 50.1%, the average proportion of machine learning algorithm is 45.5%, and the average proportion of this method is 30.5%. Compared with the three methods, the method in this paper reduces 15.3% year-on-year, which is equivalent to reducing the outage time of 35 users by 2.33 h each time. The future Internet of Things must face the realistic problem of the proliferation of Internet of Things devices. At the same time, mobile communication itself has high requirements for the reliability and immediacy of communication. Therefore, how to realize mature dynamic spectrum management in the Internet of Things and properly use spectrum sensing technology under the condition of meeting the requirements of all parties is the key to realize spectrum sharing in the Internet of Things.

5. Conclusions

With the development of large-scale data, modern personal data protection technology continues to develop. In principle, it cannot prevent the disclosure of personal data. At the same time, the current laws are imperfect and lack strong technical support. The IoT of big data ecosystem is studied in the factory energy consumption analysis model. The power grid plant has 853,000 times of uninterrupted power distribution. When this year is 2019, the average percentages of decision tree algorithm, machine learning algorithm, and machine learning algorithm are 36.8%, 37.4%, and 43.5%, respectively. Compared with the three methods, this method has a year-on-year increase of 37.9% and a reduction of 2.63 million hours of power failure. The energy consumption data collected by the system is not rich enough, and the analysis and mining of energy consumption data need to be further deepened. On the premise of meeting the needs of all parties, this paper can realize the mature dynamic spectrum management in the Internet of Things. And correctly use the spectrum sensing technology to realize the content of spectrum sharing in the Internet of Things. In the future work, data types will be gradually increased, and more targeted algorithms will be designed to process and analyze the data, so as to further optimize the energy-saving strategies and verify the energy-saving effects of relevant strategies.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This work was supported by the National Natural Science Foundation of China: Research on massive video intelligent transmission for MDMA terahertz system (No. 62071255); the talent project of "Blue Project" in Colleges and Universities of Jiangsu Province; Jiangsu University Natural Science Foundation Project: Research on video intelligent processing and protection based on saliency region and deep learning method (No. 21KJB510020); List of research and innovation projects of Academic Degree Postgraduates in Jiangsu Province: Research on video processing technology based on sparse low rank decomposition and saliency detection (No. KYLX16_0661).

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