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Optimization of Power Indicator Benchmarking Assessment Based on Cloud Computing and Big Data Technology

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ABSTRACT

This paper constructs the key business index system of electric power system consisting of electric power supply, electric power transmission, electric power distribution, electric power equipment and electric power system management. By evaluating the validity optimization, reliability optimization, and redundant indicator removal based on the neural network analysis method of the indicator system, a new power system key business indicator system is formed, and the weights of the optimized indicators are calculated. The power system key business indicator control program is designed based on the weight parameters, and a new power system key business indicator control platform is developed. Extract power data using the weighted FCM clustering algorithm, and classify user power data on the cloud platform. Resource utilization and performance response analysis are performed on the power system key business index control platform. The power system key business index control platform designed by index weights developed in this paper is able to meet the transaction demand under different concurrent user numbers, and always maintains a memory utilization rate within 10, with good operating conditions.

Keywords: neural network analysis, weighted FCM clustering, resource utilization, cloud platform, power data

1. Introduction

The good or bad business environment will directly interfere with the situation of investment attraction, and it will also interfere with the business enterprises in the region, which has a key role in the emergency development situation, social employment and tax revenues. For enterprises, efficient power services, stable power supply is more related to the production and operation and efficiency, which directly affects the enterprise to create economic value [1-2]. In order to make the business environment in the power assessment aspects to play a more efficient performance, the need to use

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better indicators in the assessment.

Optimizing the business environment is to liberate productive forces, improve comprehensive competitiveness, increase the sense of urgency from the point of view of international competition, reduce the cost of market operation and improve operational efficiency [3]. In recent years, China's power companies have been conscientiously working to optimize the power business environment, and through a series of major measures such as simplifying the procedures for handling electricity and optimizing the business expansion process, they have gradually realized online power operation, the average time for customers to receive electricity has been reduced, and the "access to electricity" indicator has begun to improve, and power customers have felt the benefits brought by the optimization of the power business environment [4-6]. Establish and use the "access to electricity" evaluation system to truly understand the evaluation and feedback of power customers, fully understand the shortcomings and deficiencies in current services, find out the needs of customers and the reasons for dissatisfaction, quantitatively evaluate the satisfaction status of current power customers, and discover the key service factors and service content that affect customer satisfaction, so as to promote the continuous improvement and improvement of service quality and help the continuous optimization of the business environment of power enterprises [7-8].

In the field of electric power evaluation index system, scholars have already carried out relevant researches to put the comprehensive evaluation index system of electric power market, starting from four dimensions of fairness, security, economy and environmental protection, and constructing it in a hierarchical and graded manner.Zhao, Y. et al. established an evaluation system of resources of the cloud training system of electric power dispatch, which helps the cloud training system of electric power dispatch to carry out the resource recommendation, improvement and deletion, and effectively improves the system's training quality to maintain the fairness of power dispatching [9]. Wu, J. et al. investigated the method of constructing a comprehensive evaluation system to maintain voltage stability, and used a combination of subjective and objective methods to optimize the power indexes, which can effectively determine the weakest bus in the power system to avoid the occurrence of large-scale voltage collapse events [10]. ZHANG, L. et al. showed that improving the efficiency of coal power conversion is an important measure for most of the important measures for electric power enterprises to develop circular economy, and the use of fuzzy comprehensive evaluation method to establish an evaluation model can fully understand the level of circular economic development of electric power enterprises [11]. Tan, Z. et al. use multi-level fuzzy comprehensive evaluation method to construct the evaluation index system of green development of distribution network, which can correctly reflect the level of green development of distribution network in the region, and put forward relevant improvement measures based on the analysis results [12].

For the principle of the construction of evaluation index system of multi-dc feeder grid, some scholars have also carried out relevant research. JIANG, X. et al. proposed a multidimensional evaluation index system for the main grid carrying capacity of multi-feed-in HVDC transmission system, which provides an optimization path for improving the grid carrying capacity by analyzing the grid strength of the transmission system under different operation scenarios [13]. Zhang, W. et al. used multi-feeder effective short-circuit ratio, multi-feeder interaction coefficient and immunity index of converter failure as indexes to establish the safety and stability evaluation index system of multi-feeder HVDC network, which provides an important guarantee for the safe and stable operation of the power grid [14]. Jiang, S. et al. constructed a renewable energy access assessment method based on the improved fully pure embedding method for the stability and safety of multi-feeder high-voltage dc receiver systems, which effectively solved the voltage stability and multi-feeder short-circuit problems that existed in the circuit system [15].

In addition to this, there exists a system of indicators for assessing power system transitions. Tziogas, C. et al. identified metrics for monitoring and evaluating the sustainability performance of the power system at the strategic, tactical, and operational levels of the organization, and integrating them with the physical system can help power utilities to make decisions that are consistent with the requirements of transitioning the power system to sustainability and energy security [16]. Wen, Y. et al. quantitatively assessed the transition strategies of the power sector in the pair of countries through a dynamic simulation model, and this assessment system developed a series of feasible low-carbon energy transition paths for power enterprises [17]. Nie, Y. et al. pointed out that a comprehensive assessment of the trajectory of low-carbon power generation system changes can facilitate the transition of power generation to sustainable green development, proposing a system of metrics for assessing the transition of the power system, which is effective in contributing to climate change mitigation and adaptation to China's resource constraints [18]. The above three evaluation index systems all carry out the construction of the assessment system of multiple indicators of the electric power system, but the lack of the process of eliminating redundant related indicators leads to the insufficiently high performance of the assessment indicators. For this reason, cloud computing as well as big data and other technologies can be used to optimize the electric power indicator system in order to achieve the purpose of optimizing the electric power business environment.

This paper introduces the concept of benchmarking management, analyzes the process of implementing benchmarking management in electric power enterprises, and draws the application model of benchmarking management in electric power enterprises. Analyze the main power data types in the power market trading system. Use the weighted FCM clustering algorithm to extract the power transaction data, and the cloud platform to classify the electricity consumption data. Establish the key business indicator system of the electric power system consisting of five first-level indicators: electric power supply indicators, electric power transmission indicators, electric power distribution indicators, electric power equipment indicators, and electric power system management indicators. The evaluation index system optimization method is used to eliminate the indicators with the lowest contribution rate and weight in the original evaluation system. The optimized indicator weights are used to design the power system key business indicator control scheme. Analyze the operation performance of the designed power system key business index control platform.

2. Indicator benchmarking and electricity data processing

2.1. Benchmarking

Benchmarking management can also be called pole aiming, benchmarking system and fixed-point transcendence. Benchmarking is mainly to promote the significant improvement of enterprise competitiveness by means of measurement and comparison, and it mainly emphasizes to take the excellent company as the main object of learning, and to make its own competitive advantage be further strengthened by means of continuous improvement. Earlier, benchmarking mainly refers to the reference mark made by surveyors or craftsmen during the relevant content measurement. Later, along with the gradual widening of its application, it was gradually extended to a kind of datum or reference point. During the adoption of benchmarking management, imitation and innovation are its essence, which mainly refers to the learning process with purpose and goal. Through the method of continuous learning, enterprises can redesign and rethink their own business model. And through the advanced concepts and modes of reference, make their own enterprises for transformation, innovation. And then create a new business model suitable for their own development. The above process is actually a continuous imitation and innovation process.

2.1.1. The role of benchmarking. In the process of enterprise development, the method of benchmarking management can provide it with relatively high feasibility and credibility of the business objectives. At the same time, it can provide enterprises with the idea of surpassing themselves, in addition, it can also use benchmarking management to discover the shortcomings between themselves and the target enterprises, and then discover the methods and tools that can be used to narrow the gap.

The ultimate goal of the implementation of benchmarking management is to enhance the operational performance of the enterprise through its own continuous pursuit of excellence and to strengthen the continuous improvement of itself in order to promote the core competitiveness of the enterprise and the significant improvement of competitive advantage. During the period of benchmarking management, operability and rationality are its main characteristics, through the adoption of benchmarking management program helps to establish a learning organization, thus making the enterprise in the correction of their own behavior, the long-term development of the enterprise has a positive role in promoting.

2.1.2. Implementation of benchmarking in electric power enterprises. The implementation of benchmarking management in electric power enterprises, is through the enterprise internal and external data analysis, to clarify “what”, “how to do”, “who is the best” and other issues, and finally Gap analysis, put forward proposals and plans to implement measures for continuous improvement of a management approach.
1) Phase I. Selecting the target of benchmarking, i.e. identifying the key success factors and the processes to be benchmarked for management change. In this stage, enterprise managers should have a comprehensive understanding of the enterprise's operating conditions, examine and speculate on the enterprise's strategies and tactics, draw management process maps and business process maps, analyze and diagnose whether the key business processes are reasonable, set up the necessary standards and bases, and screen out the contents or areas that need to be benchmarked.
2) Second stage. Investigate the internal workflow, i.e., understand the operation status of the benchmarking target within the enterprise, and the in-depth investigation of the internal operation status is the basis for the implementation of benchmarking management.
3) Third stage. The implementation of benchmarking management in electric power enterprises must choose an object that can be compared and learned, i.e., to specify a target enterprise, as the benchmarking target enterprise can be the advantageous enterprise in the country and the industry, or the international leading enterprise with global competitiveness.
4) Fourth stage. Analyze the specific practices of the target object, after determining the benchmarking enterprise should make efforts to collect various data and information of the target object through various channels.
5) Fifth stage. Analyze the obtained information and make an all-round benchmark comparison with the benchmark enterprise, which is an important part of whether the benchmark management can achieve significant results.

2.1.3. Benchmarking Application Model in Electricity Enterprises. In order to avoid the implementation of benchmarking management enterprises into the above misunderstanding, this paper puts forward the following benchmarking management application model applicable to electric power enterprises, the application model of benchmarking management in electric power enterprises is shown in Figure 1.

The core idea of benchmarking management emphasizes a kind of transcendence and innovation. Only by selectively absorbing and having independent innovation of benchmarking management can we avoid going into the wrong zone, give full play to the role of benchmarking management, and improve the competitiveness of enterprises from the fundamental basic management. Power enterprises to implement benchmarking management, it is necessary to learn the benchmarking enterprise management concepts, technological advantages, cultural advantages on the basis of innovative thinking, to establish a set of their own mode of operation.
1) Learning benchmarking management concepts and innovating their own management concepts. Requirements for the implementation of benchmarking management of enterprise managers

combined with the enterprise's own characteristics, the development of management methods suitable for their own, in the study of advanced benchmarking enterprises on the basis of excellent management concepts continue to innovate, so as to establish their own management system. Only with this kind of management concept of continuous learning and innovation can each enterprise obtain long-term sustainable development.

2) Learning the technological advantages of the benchmark and improving the technological innovation ability. In the learning and implementation of the management concept of the benchmark enterprise at the same time, but also on their own business technology innovation, not only to realize the “for my use”, but also “for all of me”, the use of the transformation into their own core technological competitiveness. For electric power enterprises, technological innovation is mostly dependent on grass-roots front-line staff, only to effectively stimulate the enthusiasm of grass-roots employees, the work practice will be directed to improve the ability to innovate, the use of new technologies, in order to effectively promote the technological progress of enterprises.

3) Learning the cultural advantages of the benchmark and shaping the enterprise's own culture. From the perspective of the strategic development of enterprises, corporate culture has a decisive role in the long-term business performance of enterprises, so when learning the corporate culture of the benchmark enterprise can not be completely imitated, but should be combined with their own cultural heritage to learn selectively.

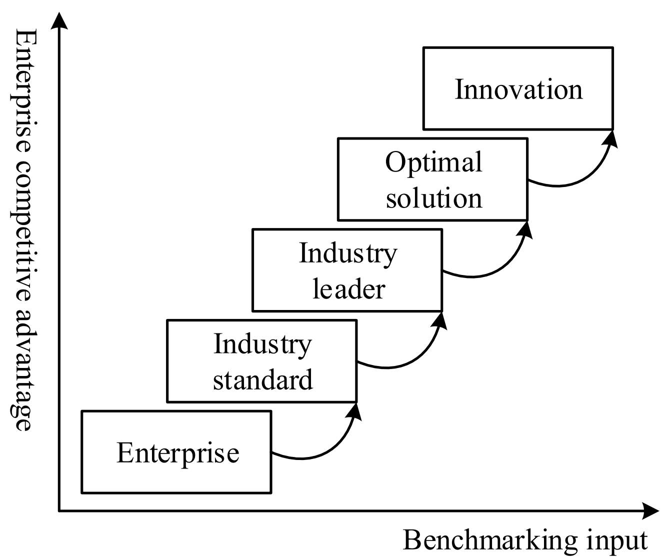

Fig. 1. The application model of benchmarking in power enterprises

2.2. Power Transaction Data Processing

2.2.1. Main types of data in electricity market trading systems:

1) Basic data. In the power market trading system, the basic data mainly refers to the most fundamental data to maintain the normal operation of the overall trading system, including power plant units, user identity information, user trading qualification, electricity price, hydropower plant operation, power sales company and other basic information, which is the prerequisite for the normal development of all the business work of the power company.

2) Business data. Business data is mainly reflected in the trading module of the power market trading system, including the basic data information of business creation, declaration, calibration, execution and other business processes. At the same time, it contains part of the market information, such as market participants, market declaration parameters, market trading parameters, market constraints information, market trading results information and so on.

3) Settlement data. Settlement data is mainly distributed in the final link in the power market trading system, mainly refers to the data for final settlement of power cost according to the actual trading link transaction power information. In addition, the settlement data also includes the power plant's electricity consumption, outstanding fee information, power plant's monthly clearing data, account data, power plant's deviation power information, etc.

2.2.2. Mechanisms for applying big data technology in power trading. A large amount of data is generated in the process of power trading. And big data technology has the advantages of fast processing speed and a wide range of data types. The establishment of a power trading platform on the basis of this technology is conducive to the accurate extraction of structured and unstructured transaction data. The power trading platform, supported by big data technology, can standardize all types of data within the platform in accordance with the unified data specification. And combined with the calculation of different timeliness to realize the storage, circulation and management of data. The role of big data technology in power trading mechanism is shown in Figure 2.

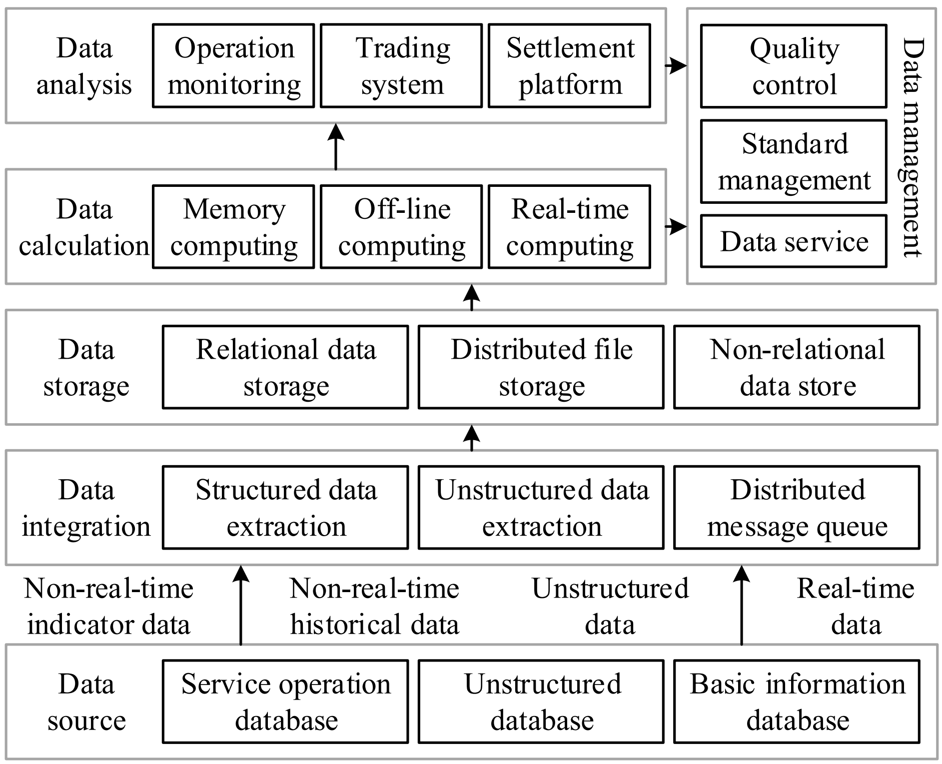

Fig. 2. The large number is the mechanism of technology in power trading

2.2.3. Dynamic extraction of power transaction data. The large amount of power transaction data restricts the data extraction process to a certain extent, making it difficult to cluster and extract data at once and time-consuming. Therefore, the aggregation of power transaction data is preprocessed to realize the compression of power transaction data, which lays a solid foundation for the final data extraction.

Set d -dimensional data $A(x_1,x_2,\cdots,x_d)$, given a parameter point noted as $P(\delta_1,\delta_2,\cdots,\delta_d)$, the parameter point does not run the data computation task, and subsequent downstream nodes can be directly hung under the parameter node. Focus a piece of data A to a particular data point by aggregation preprocessing $B(X_1,X_2,\ldots,X_d)$. The power trading data aggregation preprocessing expression is:

$$\begin{cases} X_i = \delta_i \left(\left\lfloor \dfrac{x_i}{\delta_i} \right\rfloor + \dfrac{1}{2} \right) \\ i = 1, 2, \cdots, d \end{cases} \tag{1}$$

In Eq. (1), X_i denotes the ind data point after convergent preprocessing. δ_i denotes the given ith parameter point, each of which is different. x_i denotes the original ith power transaction data point.

Conventionally, the given parameter points of each power transaction data are different, which affects the clustering extraction of power transaction data and causes clustering bias. Therefore, in this paper, parameter σ is added in the aggregation preprocessing process, which is used as the basis for adaptively adjusting the metric size and transforming the power transaction data aggregation preprocessing expression into:

$$\begin{cases} X_i = \dfrac{\delta_i}{\sigma_i} \left(\left\lfloor \dfrac{x_i \delta_i}{\delta_i} \right\rfloor + \dfrac{1}{2} \right) \\ i = 1, 2, \cdots, d \end{cases} \tag{2}$$

Equation (2) does not intuitively show the effect of convergence preprocessing of power transaction data, so the two-dimensional power transaction data as an example, the convergence preprocessing effect of the graphical display, for the subsequent power transaction data sorting process to provide convenience.

Based on the aggregated preprocessed power transaction data, combined with the needs of data extraction, the power transaction data is sorted based on the full alignment theory, which facilitates the acquisition of the characteristics of the subsequent power transaction data.

Take the sorted and processed power transaction data as the basis to obtain the power transaction data features, and provide weighted support for the subsequent clustering extraction of power transaction data. Power transaction data is a kind of information coupling, which has a close connection with time.

Therefore, the power transaction data can be regarded as a time series $X'(t)$ (after convergence preprocessing and sorting), and t represents the moment of power transaction data generation, with a value range of [1, n]. Feature extraction can provide the basis for power transaction data clustering and improve the accuracy of data clustering. In this paper, power transaction data features are extracted in three dimensions: volatility, trend and variability.

Among them, the volatility features mainly include the extreme deviation, the dispersion coefficient and the geometric mean, calculated as:

$$\begin{cases} \alpha = \max[X'(t)] - \min[X' \\ \beta = \dfrac{\sum_{t=1}^{n} \left[X'(t) - \bar{X}'(t) \right]}{nX'(t)} \\ \chi = n\sqrt{\prod_{t=1}^{n} X'(t)} \end{cases} \tag{3}$$

In Eq. (3), α, β and χ denote the extreme deviation, dispersion coefficient and geometric mean of the power transaction data, respectively. max[·] and min[·] denote the maximum and minimum values of [·], respectively, and $\bar{X}'(t)$ denotes the arithmetic mean of the power transaction data. η denotes the total number of power transaction data.

The trend characteristics mainly include correlation coefficient, center of mass, median difference, etc., and the expression is:

$$\varepsilon = \frac{\sum_{t=1}^{n/2}\left[X'(t)-\bar{X}'(t)\right]\cdot\sum_{t=n/2+1}^{n}\left[X'(t)-\bar{X}'(t)\right]}{\sqrt{\sum_{t=1}^{n/2}\left[X'(t)-\bar{X}'(t)\right]^2\cdot\sum_{t=n/2+1}^{n}\left[X'(t)-\bar{X}'(t)\right]^2}} \tag{4}$$

$$\phi = \frac{1}{n}\sum_{t=1}^{n} p_i X'(t) \tag{5}$$

$$\varphi = X'_{\text{mean1}}(t) - X'_{\text{mean2}}(t) \tag{6}$$

In Eqs. (4) to (6), ε, ϕ and φ represent the correlation coefficient, center of mass and median difference of the power trading data, respectively. p_i represents the characterization energy of the power trading data, and $X'_{mean1}(t)$ and $X'_{mean2}(t)$ represent the median values of the two time series (before $n/2$ and after $n/2$), respectively.

The variability characteristics mainly include waveform entropy, center distance, etc., which are calculated as:

$$\begin{cases} \gamma = -\dfrac{1}{n}\displaystyle\sum_{i=1}^{n} p_i \lg(p_i) \\ \eta = \displaystyle\sum_{i=1}^{n} (t-t)^2 p_i \end{cases} \tag{7}$$

In Eq. (7), γ and η denote the waveform entropy and center distance of the power transaction data, respectively. t represents the center value of moment t. The above extracted features of power transaction data are integrated and recorded as $Y_i = \langle \alpha, \beta, \chi, \varepsilon, \phi, \varphi, \gamma, \eta \rangle$, which provides data basis for subsequent dynamic extraction of power transaction data.

Based on the above acquired power transaction data features, the weighted FCM clustering algorithm is applied to dynamically cluster and extract the power transaction data to meet the data needs of different market members and provide support for the correct formulation of power transaction decisions [19-20].

The weighted FCM clustering algorithm takes into account the different factors of feature vectors affecting clustering, which can greatly improve the accuracy of data clustering, i.e., improve the accuracy of data extraction.

The set of power trading data samples is set to $Z = \{z_1, z_2, \ldots, z_n\}$ and the set of data features is set to $Y_i = \{\alpha, \beta, \chi, \varepsilon, \phi, \varphi, \gamma, \eta\}$. Using the weights to indicate the magnitude of their contribution to the clustering, which is denoted as $\omega_1, \omega_2, \ldots, \omega_8$, the weighting matrix is expressed as:

$$\kappa = \begin{Bmatrix} \omega_1 & 0 & \cdots & 0 \\ 0 & \omega_2 & \cdots & 0 \\ \vdots & \vdots & & \vdots \\ 0 & 0 & \cdots & \omega_8 \end{Bmatrix}_{8\times 8} \tag{8}$$

The partition matrix in the weighted FCM clustering algorithm is calculated as:

$$U^{(t)} = \left[\mu_{ij}^{(t)}\right]_{n\times c} \left\{ \mu_{ij}^{(t)} = \left[\sum_{k=1}^{c} \left(\frac{d^{(t)}(z_i, z_j)}{d^{(t)}(z_i, z_k)}\right)^{\frac{2}{m-1}}\right]^{-1} \right. \tag{9}$$

In Eq. (9), $U^{(t)}$ denotes the partition matrix. $\mu_{ij}^{(t)}$ denotes the affiliation value, c denotes the number of clustering categories. $d^{(t)}$ represents the Euclidean distance, m represents the total number of clustering categories. (z_i, z_j) denotes the low weight division interval of the power transaction data sample, and (z_i, z_k) denotes the high weight division interval of the power transaction data sample. The obtained division matrix information updates the clustering center until $\| Z^{t+1} - Z^{t} \| < \zeta$ (Z represents the clustering center, ζ represents the given threshold), terminates the weighted FCM clustering algorithm iteration, and outputs the clustering result that is the dynamic extraction of power transaction data.

2.2.4. Classification Algorithm for Electricity Consumption Data Based on Cloud Platforms. Changes in electricity consumption data over a period of time often reflect the demand for electricity by users or the operation of electrical equipment. If the electricity record at each point in time is regarded as a dimension, the longer the time period, the higher the dimension of the electricity consumption data and the more information it contains. Distinguishing between normal and abnormal conditions of high-dimensional electricity consumption data is of great significance to electric power enterprises.

In the problem described in this chapter, the power data to be processed is a series of multidimensional vectors $v1, v2 \cdots vi$. vi corresponds to the power data of a certain device for a number of days (which may be 100 days, 200 days, or a year), such that the dimensions of the vectors are 100, 200, or 365 accordingly, and c_m represents the columns of the vectors, and a column, which is also a feature, is denoted as t_m .

Unlike traditional logistic regression classification, the algorithm in this paper first preprocesses the data to find representative columns as predictive features (i.e., input features) for logistic regression. Feature selection is based on the relevant theory of information theory, comparing the information content of each feature, and then selecting the informative features as the predictive features for the subsequent classification work, and the input features are denoted as $t_m^{'}$.

The model of the logistic regression algorithm can be expressed as equation (10):

$$p(Y = 1 \mid x) = \pi(x) = \frac{1}{1 + e^{-g(x)}} \tag{10}$$

where $g(x)$ has the form shown in Eq. (11):

$$g(x) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_\rho x_\rho \tag{11}$$

Obviously, the process of determining the model is then the process of determining $\beta_0, \beta_1, \beta_2 \cdots \beta_\rho$. How to determine these coefficients is the key to the algorithm. The maximum likelihood function can be expressed as equation (12):

$$L(\beta) = \sum_{i=1}^{n} \left\{ y_i \ln\left[\pi(x_i)\right] + (1 - y_i) \ln\left[1 - \pi(x_i)\right] \right\} \tag{12}$$

The optimal solution is obtained when $L(\beta)$ is maximized.

In the analysis of power consumption data, abnormal data refers to those power consumption records with large fluctuation amplitude and frequency, because the cause of such data may be the failure of metering equipment, which requires targeted investigation.

In the process of feature selection, the concept of “information” is defined for each anomaly feature. In the category of anomalies, if the value of a feature is larger, the probability of the occurrence of the eigenvalue of that value is smaller, and according to the information theory, it should represent a greater amount of information. Meanwhile, in order to fit with the theory of probability theory, the probability of occurrence of all abnormal feature values in the same anomaly category should be 1. Based on the above two points, the information content of anomalous features in the anomaly category is defined as shown in equation (13):

$$h(m) = \log_2 \left[1 / p(m) \right] \tag{13}$$

where the value of $p(m)$ is shown in equation (14):

$$p(m) = (\frac{1}{v_m}) / sum(\frac{1}{v_m}) \tag{14}$$

The so-called feature selection is to calculate the "information" of each anomalous feature, and select the predictive features for subsequent Logistic Regression among all the anomalous features according to certain selection rules, so as to reduce the computational complexity of Logistic Regression. The process of feature selection is as follows. The process of feature selection is as follows:

1) Judge whether it is an abnormal power. For each record, first determine whether it is anomalous data (maximum value > 100 * average value), and if it is not anomalous data, then feature selection is not performed.

2) Initialization. For anomalous data, initialize the information quantity $map_m(k,v)=(m,0)$.

3) Calculate the amount of information about the anomalous feature and update map. Calculate $h(m)$, if $h(m) > map_m(k,v)$, then $map_m(k,v)=(m,h(m))$, otherwise do nothing.

4) Output the result. Iterate through the whole map, find the serial numbers of the first n features with maximum value and output them as the selected features.

Through the above four steps, all the anomalous features are examined from the perspective of the whole test set, and the structure of the map that saves the information of the anomalous features is constantly updated to avoid the individual data from affecting the results too much. The algorithm finally outputs n features, and compared with other features, these n features are the most able to represent the characteristics of abnormal data to distinguish normal data, and can provide more information for the subsequent Logistic Regression.

3. Power system key business indicator control platform design

3.1. *Power system key business indicator system*

In order to realize the design of the power system key business index control platform, it is necessary to construct the power system key business index system first. The power system key business indicator system can truly reflect the operating status and performance of the power system, and analyze and deal with its potential problems.

When constructing the power system key business indicator system, it needs to follow the principles of scientificity, comprehensiveness, importance, operability and dynamics. Among them, the principle of scientific refers to the selected indicators must be able to objectively reflect the operating status and performance of the power system, the principle of comprehensiveness refers to the selected indicators need to cover a number of aspects of the power system, the principle of importance refers to the selected indicators to have a certain degree of representativeness, reflecting the characteristics of the power system in a certain aspect, the principle of operability refers to the selected indicators to have a certain degree of feasibility, the principle of dynamics The principle of operability means that the selected indicators should be feasible, and the principle of dynamism means that the selected indicators can be adjusted and optimized according to the changes of the power system to ensure the real-time nature of the indicators. On the basis of the above principles, the key business index system of the power system is constructed.

The key business indicator system of the electric power system is shown in Table 1. The first-level indicators are, in order, electric power supply indicators $B1$, electric power transmission indicators $B2$, electric power distribution indicators $B3$, electric power equipment indicators $B4$, electric power system management indicators $B5$, and 14 second-level indicators.

Table 1. Key business index system of power system

Index system	Primary indicator	Secondary indicator	Specific description

Key business index system of power system A	Power supply indicator $B1$	Power reliability $C1$	Power failure
			Failure duration
		Power quality $C2$	Voltage fluctuation
			Frequency fluctuation
			Harmonic
		Power abundance $C3$	Balance of power demand and supply
		Transmission capacity $C4$	The rated power of the transmission line
			Actual transmission power
	Power transmission index $B2$	Transmission efficiency $C5$	Line loss
			Power loss
	Power distribution index $B3$	Transmission reliability $C6$	Transmission interrupt times
			Interrupt duration
		Distribution efficiency $C7$	Distribution margin
			Power loss
		User satisfaction $C8$	The complaint is timely
			User satisfaction survey
	Electrical equipment indicator $B4$	Device reliability $C9$	Equipment failure rate
			Maintenance cycle
		Equipment performance $C10$	Equipment utilization
			Production efficiency
		Equipment safety $C11$	Equipment safety hazard
			Accident incidence
	Power system management indicators $B5$	Management effectiveness $C12$	Management process standardization
			Decision accuracy
		Personnel quality $C13$	Training rate
			Skill mastery
		Information system application level $C14$	System stability
			Data accuracy

3.2. *Optimization of the assessment indicator system*

3.2.1. Optimizing the effectiveness of the indicator system. The validity coefficient in statistics provides a measure of the degree of cognitive deviation that occurs when people make assessments with a particular assessment indicator or indicator system. If the degree of cognitive deviation is smaller when assessment experts assess the subject of assessment with a particular indicator system, the smaller the differences in the assessment results produced, indicating that there is a more consistent understanding of the assessment role provided by the indicator system, the stronger the validity of the indicator system.

Assuming that the indicator system is $C=\{c_1,c_2,\ldots,c_n\}$ and the number of experts participating in the assessment of the indicator system is S, the formula for calculating the validity coefficient a_i of an indicator is if the set of ratings given by experts j for each indicator is $X_j=(x_1 j,x_2 j,\ldots,x_{nj})$:

$$a_i=\sum_{j=1}^{n}\sqrt{(\overline{x_i}-x_{ij})^2}\,/\,sq \tag{15}$$

The validity coefficient a of the indicator system is calculated by the formula:

$$a = \sum_{i=1}^{n} a_i / n \tag{16}$$

where $\overline{x_i} = \sum_{j=1}^{n} x_{ij} / s$, q are the optimal values of the ratings in the rubric set for Indicator c_i.

The validity coefficient method reflects the degree of deviation of different experts' perceptions when using the same indicator system for assessment. The smaller the value of the validity coefficient, the higher the validity of the indicator system.

3.2.2. Optimization of the reliability of the indicator system. The test of stability and reliability of an indicator system focuses on the "degree of difference" between the results of multiple assessments of an indicator system, or the "closeness" of the assessment results to the ideal value. If the assessment data obtained by using a certain indicator system are closer to the "ideal data", it indicates that the indicator system is more capable of reflecting the assessment object, i.e., the stability of the indicator system is higher.

Setting the average data set of expert group ratings at $Y = \{y_1, y_2, ..., y_n\}$, the formula for calculating the reliability coefficient of the indicator system ρ is:

$$\rho = \sum_{j=1}^{S} \left(\frac{\sum_{i=1}^{n} (x_{ij} - \overline{x_j})(y_i - \overline{y})}{\sqrt{\sum_{i=1}^{n} (x_{ij} - \overline{x_j})^2 \sum_{i=1}^{n} \left(y_i - \overline{y} \right)^2}} \right) / S \tag{17}$$

Among them:

$$\overline{x_j} = \sum_{i=1}^{n} x_{ij} / n \tag{18}$$

$$\overline{y} = \sum_{i=1}^{n} y_i / n \tag{19}$$

$$y_i = \sum_{j=1}^{s} x_{ij} / S \tag{20}$$

Taking the mean value of the results of the S assessments of c_i as the ideal value, the degree of difference between the data of the S assessments and their mean values can be calculated, which can reflect the variability of the data of the S assessments using the same indicator system. The larger the reliability coefficient ρ of the indicator system, the smaller the variability of the assessment results and the higher the reliability of the indicator system.

3.2.3. Optimization of redundancy in the indicator system:

1) Neural network analysis method. The purpose of neural network training is to determine the degree of importance or relevance of the assessment indicators relative to the assessment results, which is referred to here as the contribution of the indicators. The result obtained by neural network training is only the relationship between neurons of each neural network, and if we want to get the real relationship between input factors and output factors, that is, the contribution of assessment indexes to the assessment results, we also need to analyze and process the weighting information between neurons.

The relationship between the neural network input factors and output factors can be described by the following formula:

Correlation significance coefficient:

$$r_{ij}=\sum_{k=1}^{p}W_{ki}(1-e^{-x})/(1+e^{-x}) \qquad x=w_{jk} \tag{21}$$

Related Index:

$$R_{ij}=|(1-e^{-y})/(1+e^{-y})| \qquad y=r_{ij} \tag{22}$$

Absolute impact factor:

$$S_{ij}=R_{ij}/\sum_{i=1}^{m}R_{ij} \tag{23}$$

Where, i is the neural network input unit, i.e., the assessment index, $i=1,2,\dots,m$. j is the neural network output unit, i.e., the assessment result, $j=1,2,\dots,n$. k is the implied unit of the neural network, $k=1,2,\dots,P$. w_{ki} is the weight coefficient between the input layer neuron i and the implied layer neuron k. w_{jk} is the weight coefficient between the output layer neuron j and the hidden layer neuron k. Where the absolute influence coefficient S is the required indicator contribution. 2) Elimination of redundant indicators. The first step is to train the neural network by taking the assessment indicator sample data as the network input and the comprehensive assessment result data as the network output. The neural network analysis function of SPSS Statistic software can be used to complete the network training and find out the contribution of indicators. The neural network parameters and training information are shown in Table 2. Among them, the number of implied layer units is the optimal number adapted by the neural network training, and the number of implied layer units is 10.

Table 2. Neural network parameters and training information

Parameter name	Parameter value
Input layer number	137
Implicit layer number	10
Output layer number	2
Squares and errors	5.518E-33
Relative error	1.744E-33
Training time	0.036s

Indicators with a lower indicator contribution have less influence on the assessment results, i.e., they play a lesser role in the assessment and should be eliminated. However, considering that the indicator weight is an important reflection of the importance of an indicator itself, the size of the indicator weight value should be fully taken into account while removing redundant indicators based on the indicator contribution. Therefore, indicator weight and indicator contribution should be taken as screening conditions at the same time, and indicators with lower weight and contribution should be eliminated.

Partial calculations of the contribution of key business indicators for the power system are shown in Table 3. Indicators with low weights and contributions include power sufficiency $C3$, so it is appropriate to exclude them.

Table 3. The results of the contribution of key business indicators of the power system

Index	Weighting	Contribution degree	Index	Weighting	Contribution degree
$C1$	0.081	0.2321	$C8$	0.056	0.0331

$C2$	0.056	0.0448	$C9$	0.082	0.0254
$C3$	0.052	0.0001	$C10$	0.066	0.0129
$C4$	0.096	0.1524	$C11$	0.064	0.0137
$C5$	0.098	0.0110	$C12$	0.085	0.0365
$C6$	0.075	0.0576	$C13$	0.072	0.0259
$C7$	0.039	0.0563	$C14$	0.078	0.0397

3.3. *Post-optimization assessment indicators*

Through the above work, the power system key business indicator system and indicator weight information are obtained. The optimized key business index system of power system is shown in Table 4.

Table 4. The optimized power system key business index system

Index system	Primary indicator	Secondary indicator	Weighting
Key business index system of power system A	Power supply indicator $B1$	Power reliability $C1$	0.075
			0.059
		Power quality $C2$	0.056
			0.062
			0.043
		Transmission capacity $C4$	0.056
			0.068
	Power transmission index $B2$	Transmission efficiency $C5$	0.075
			0.061
	Power distribution index $B3$	Transmission reliability $C6$	0.072
			0.059
		Distribution efficiency $C7$	0.063
			0.075
		User satisfaction $C8$	0.056
			0.042
	Electrical equipment indicator $B4$	Device reliability $C9$	0.076
			0.048
		Equipment performance $C10$	0.069
			0.054
		Equipment safety $C11$	0.025
			0.064
	Power system management indicators $B5$	Management effectiveness $C12$	0.048
			0.063
		Personnel quality $C13$	0.054
			0.059
		Information system application level $C14$	0.065
			0.077

3.4. *Power system key business indicator control program*

On the basis of the above design, utilizing the constructed power system key business indicators system, combined with the calculated weight parameters of each indicator, the corresponding power system key business indicators control program is designed.

The design process of the power system key business indicators control program is shown in Figure 3. In the above design process, according to the actual situation of the power system, the corresponding control objectives are determined, and the corresponding power system key business indicator system is constructed. Calculate the weight parameters of different indicators, analyze the current situation of the power system, and thus develop relevant control measures. Such as strengthening the maintenance and overhaul of power equipment, improving equipment reliability and stability, reducing the number of failures and downtime. Optimize the load distribution of transmission lines, avoid line overload and light load, and improve the utilization rate and operational efficiency of transmission lines. Promote intelligent distribution grid technology, realize remote monitoring and intelligent dispatching of distribution grids, improve the operational efficiency and management level of distribution grids, etc., so as to guarantee the stable operation of the power system. So far, the design of the power system key business index control platform is completed.

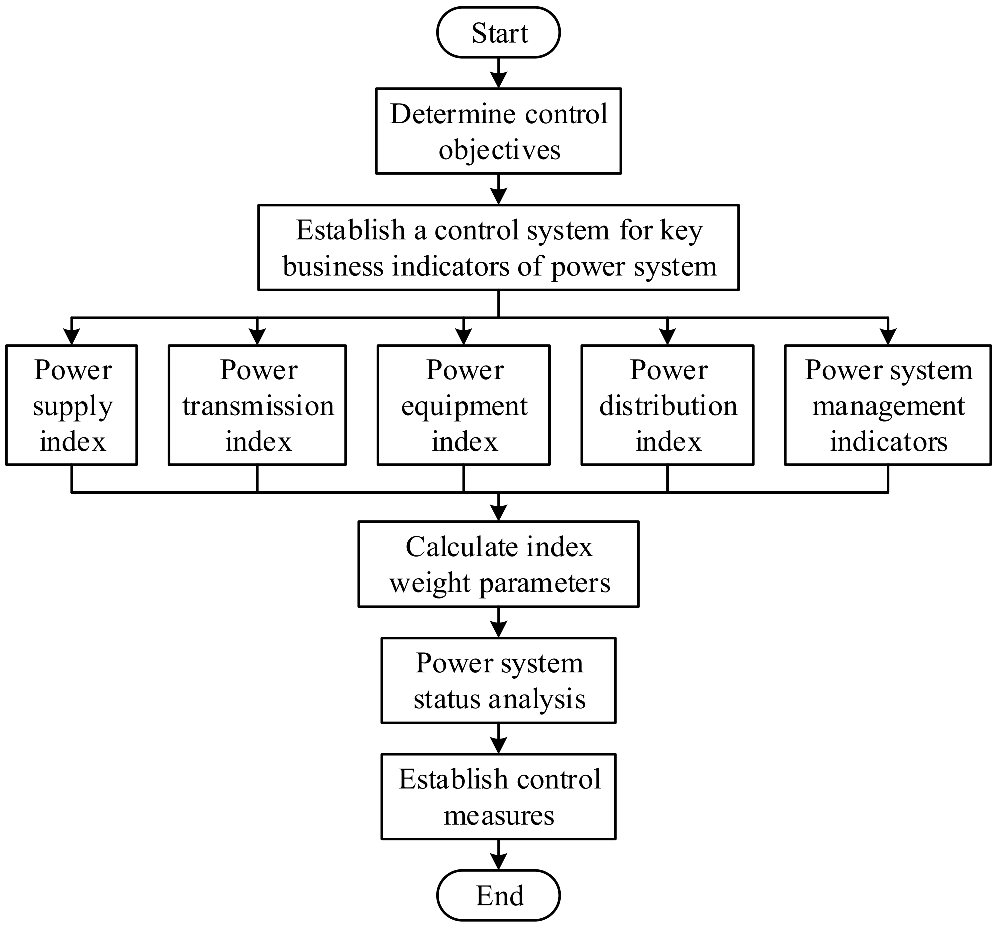

Fig. 3. Design process of key business index control scheme for power system

4. Testing of a business control platform based on power metrics

4.1. Power Data Extraction and Classification

The object of the study is the electricity consumption data of 30 users in a region for the whole year of 2024, and the sampling setting of the electricity data is 24h sampling, which obtains a total of 6512 electricity consumption curves. In order to reduce the workload of data calculation, the annual average is processed to obtain 26 electricity consumption curves.

The user's power data contains numerous power information, and for the convenience of the experimental narrative, the load data in the power consumption data is taken as a representative. In order to obtain accurate experimental results, the load data is processed in a standardized manner and the standardized load is used as the user's electricity data. The technology of this paper is used to detect outliers in the standardized electricity data in order to analyze the effect of the application of the technology of this paper.

The technology of this paper is used to mine the above 26 electricity consumption curves, which are divided into five classes by clustering. Among them, the first class of electricity consumption curves are the 5th, 7th, 10th, 14th and 25th. The second category of power usage curves are 1st, 3rd, 17th, 19th, 21st and 23rd. The third category of power consumption curves are 2, 9, 11, 15 and 20. The fourth type of power consumption curve is Articles 6, 8, 13, 16, and 24. The fifth type of electricity consumption curve is the 4th, 12th, 18th, 22nd and 26th. The characteristic curves of electricity consumption of the above five categories of users are shown in Fig. 4.

It can be seen that the first category of curves is smoother, with higher electricity consumption, which has been maintained at a high level, and the peak of electricity consumption is about 20:00 hours.

The second curve shows a sharp increase in electricity consumption from 0:00 to 2:00, a sharp decrease from 4:00 to 6:00, a rising trend from 6:00 to 12:00, and a peak at 12:00, a decrease from 12:00 to 15:00, a rising trend from 15:00 to 18:00, and a gradual decrease after 18:00.

The third type of curve is from 0:00 to 5:00 hours when electricity consumption decreases, and from 5:00 to 12:00 hours when electricity consumption increases and reaches its peak at 12:00 hours.

The fourth curve maintains an increase in electricity consumption from 0:00 to 12:00 hours, and electricity consumption rises rapidly from 11:00 to 12:00 hours and reaches its peak at 12:00 hours.

The fifth curve shows a small fluctuation of power consumption from 0:00 to 9:00, and an increasing trend from 9:00 to 13:00. 13:00 to 18:00 the power consumption stays relatively stable. 19:00 to 21:00 the power consumption increases and reaches the peak at 20:00, and then 21:00 to 24:00 shows a decreasing trend.

The experimental results show that the technique in this paper can successfully cluster 26 curves into 5 classes based on the curve similarity characteristics. The potential relationship between the unused load curves can be mined, which realizes the requirement of mining power big data, and the mined power data has certain similar characteristics.

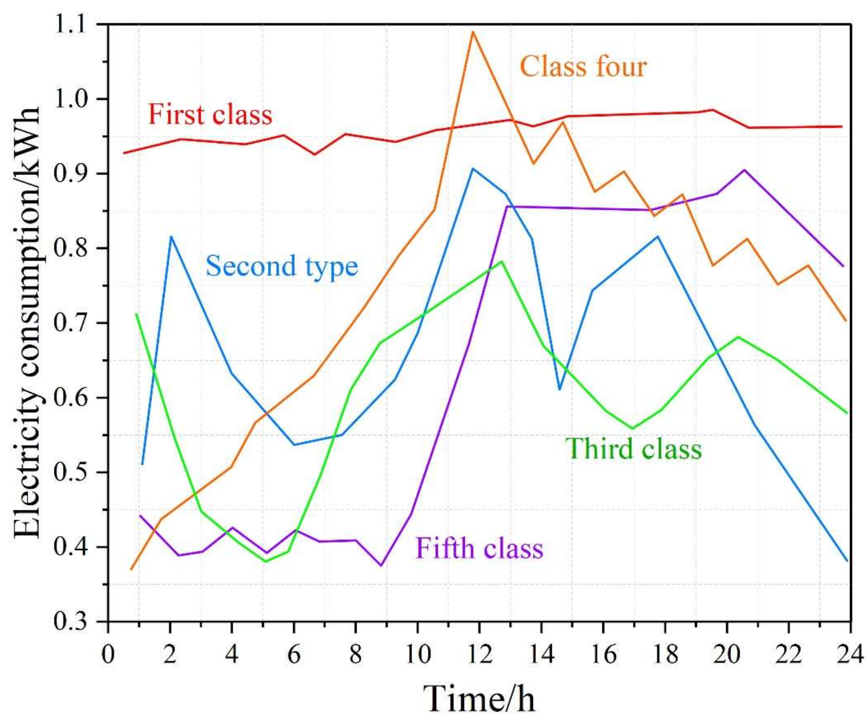

Fig. 4. Five types of user electrical characteristics curve

4.2. Power System Key Business Indicator Control Platform Testing

4.2.1. Cloud-based data processing. The traditional power data analysis system is unable to adapt to the new trend of smart grid data towards sea quantization because of the limitation of hardware and software resources, low data access and computation efficiency.

In order to verify whether the performance of the cloud computing-based massive power data analysis system is better than the existing system, this section simulates the development of a traditional type of power data analysis system. The two are tested in comparison under the same test environment. The simulation system mentioned in the following section refers to the system developed by simulating the traditional power data analysis system, while this system refers to the cloud computing-based massive power data analysis system.

1) Test environment. Hardware environment: Servers: 6, 24 cores each. Memory: 60GB. Hard disk: 1TB.
Software environment: Operating system platform: Linux CentOS. Server platform: Tommcat.
Database: 2 install Mysql, 4 build HBase cluster.
Software platform: Java Web project. Hadoop distributed system.

2) Insertion Performance Test. In order to ensure database consistency, data insertion was set as a single-threaded execution. The data insertion comparison data is shown in Table 5.

The table shows the efficiency statistics of importing 10,000, 50,000, 500,000, 5,000,000 and 50,000,000 pieces of battery data using the two systems respectively. From the table, it can be visualized that the insertion time of this system is much less than that of the simulation system for the same amount of data. And with the increase of data volume, the efficiency gap becomes more and more obvious. So for the import of massive data, this system has better performance.

When the power data increases to 50 million, the insertion time of this system is 200.45s, and the efficiency ratio between the insertion time and the simulation system is 11.84, which is smaller than the efficiency ratio when the power data is 5 million. The power data affects the insertion time of the system.

Table 5. Data insertion comparison data

Data volume(10000)	Analog system insertion time(s)	This system inserts time(s)	Efficiency ratio
1	4.53	0.96	4.72
5	12.47	1.55	8.05
50	95.08	6.31	15.07
500	991.26	64.93	15.27
5000	2374.24	200.45	11.84

3) Query Performance Test. This part simulates the simultaneous reading of data by multiple users by using multi-threaded concurrent access to the Mysql database of the simulation system and the distributed HBase database of this system, and the test comparison is shown in Table 6. The query time of the system designed in this paper is always controlled within 1s, and the response is rapid.

Through this table, it can be clearly seen that despite the index optimization of Mysql database, there is still a gap between the query performance and HBase. The gap is even more obvious as the amount of query data and the number of concurrent threads increase. For the HBase database in this cluster, the data volume of 10 million is still far from the processing limit. The query time has stabilized with the change of data volume and the number of concurrent thread accesses.

Table 6. Test comparison

Data volume(10000)	Mysql Query time(s)	HBase Query time(s)

Single line query 100	1.39	0.71
10 thread queries 100	2.31	0.78
Single line query 1000	3.55	0.75
10 thread queries 1000	4.02	0.82
100 thread queries 1000	29.46	0.89

4) Calculation Performance Test. This part compares the data calculation capability of the two systems by using the simulation system and this system to test the power data variance calculation for a specified level of data volume respectively, and the data calculation comparison is shown in Table 7.

The comparison table shows that the computation time of this system is much less than that of the simulation system. Although the processing efficiency of the cluster cannot reach six times that of a single server due to aspects such as task initiation, file reading and inter-cluster communication network latency, this has greatly improved the processing performance.

Table 7. Data calculation contrast

Data volume(10000)	Analog system (s)	This system (s)	Efficiency ratio
3	120	65	1.85
5	403	122	3.30
30	965	274	3.52
50	1021	533	1.92
500	2973	1002	2.97
1000	4866	1565	3.11
5000	7218	3017	2.39
100000	9035	3184	2.84

4.2.2. System business processing performance. In a provincial power company 3 district network environment by an office computer for remote desktop connection, the Huawei U2000 and ZTE U31 network management end of the actual device configuration issued by the tuning test, test host information shown in Table 8.

Table 8. Test host information

R&d workstation	Remote network end	Remote desktop connection permissions
178.14.55.115	178.14.55.331	userName: passWord:
233.233.255.0	233.233.255.0	
175.11.55.10	175.11.55.10	

The efficiency test of the key business index control platform of the power system is shown in Table 9, and the transaction passage rate of the index-optimized power business index control platform is 100 under different numbers of concurrent users, which meets the user requirements.

Table 9. Efficiency test of key business index control platform of power system

Test item	Concurrent number	Mean response time(s)	TPS(pen/s)	Transaction rate
User login average response time	30	0.741	30.52	100
	40	1.009	32.46	100
	50	1.322	45.21	100
Alarm table	30	0.459	40.96	100
	40	0.528	50.33	100
	50	0.769	54.78	100
System configuration	30	0.312	40.12	100

	40	0.439	45.24	100
	50	0.455	50.16	100

The resource utilization rate of the power system key business index control platform is shown in Table 10. The data show that under different concurrent users, the CPU utilization rate of the power system key business indicators control platform designed in this paper is lower than 55, and the memory utilization rate is lower than 10. The power system key business indicators control platform designed in this paper can run well.

Table 10. System key business index control platform resource utilization

Test content	Concurrent number	CPU utilization	Memory utilization	IO
User login average response time	30	13.221	5.26	30.221
	40	15.767	5.41	34.518
	50	25.338	4.787	40.269
Alarm table	30	36.247	7.339	18.234
	40	39.564	8.644	19.643
	50	33.559	6.553	14.119
System configuration	30	46.919	7.552	15.216
	40	40.423	7.609	15.998
	50	53.171	6.334	23.334

5. Conclusion

This paper combines the application of benchmarking management in electric power enterprises, and by selecting and optimizing the key business index system of electric power system, designs a key business index control scheme of electric power system corresponding to the weights of the indexes. Establish the system operating environment and develop the power system key business index control platform. Analyze the processing of electric power data by cloud computing and big data technology, and test the application of electric power system business platform.

Utilizing the enhanced FCM clustering algorithm to divide the user power data, the algorithm successfully clusters 26 curves into 5 classes by basing on the curve similarity characteristics, effectively mining the similarity characteristics of the power data to meet the requirements of power big data mining. The power data analysis system based on cloud computing is able to improve the insertion time, query time and calculation time compared with the traditional system.

Initially build the key business indicator system of electric power system by the principle of electric power system indicator screening. Using the optimization method of indicator system validity, reliability and redundancy, the power sufficiency in the original indicator system is eliminated $C3$. The power system key business indicator management platform designed by the new assessment indicators can run well with a memory usage rate of less than 10 under different concurrent user numbers.

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