

## *Retraction*

# **Retracted: Enterprise Performance Management following Big Data Analysis Technology under Multisource Information Fusion**

## **Security and Communication Networks**

Received 8 January 2024; Accepted 8 January 2024; Published 9 January 2024

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This article has been retracted by Hindawi, as publisher, following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of systematic manipulation of the publication and peer-review process. We cannot, therefore, vouch for the reliability or integrity of this article.

Please note that this notice is intended solely to alert readers that the peer-review process of this article has been compromised.

Wiley and Hindawi regret 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 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] Z. Qin, H. Liao, L. Chen, and L. Zhang, "Enterprise Performance Management following Big Data Analysis Technology under Multisource Information Fusion," *Security and Communication Networks*, vol. 2021, Article ID 7915670, 11 pages, 2021.

## Review Article

# Enterprise Performance Management following Big Data Analysis Technology under Multisource Information Fusion

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Received 27 September 2021; Revised 28 October 2021; Accepted 18 November 2021; Published 16 December 2021

Academic Editor: Xingsi Xue

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With the development of the Internet, big data collection, analysis, and processing are flourishing. The study aims to explore the performance management of power enterprises based on multisource information fusion and big data. First, the application of big data to enterprise management is analyzed. Second, the multisource information fusion method is introduced, and the multisource information fusion model is implemented. Finally, the fuzzy language algorithm is used to evaluate the performance management of power enterprises. The results show that the proposed multisource information fusion algorithm has high efficiency in evaluating enterprise performance management. The evaluation result is closer to the actual value than other algorithms, and the maximum acceleration ratio can reach 7, indicating that the algorithm is suitable for processing big data. The performance evaluation shows that enterprises pay most attention to the quality of their products; the weight reached 0.414; and the index weight difference is large. This study promotes the reform of the performance management mode and improves the management efficiency of enterprises through the proposed enterprise performance management strategy. It provides a great reference for the application of big data and information fusion technology.

## 1. Introduction

The multisource information fusion method is known as the multisensor information fusion method and also a data fusion method because it is a method mainly for data processing in early times [1]. At present, basic theoretical research develops very rapidly [2], and communication technology and efficient sensors develop quickly accordingly. This greatly promotes the development of information fusion technology. The pioneer of the information fusion theory is Professor Y. Bar-Shalom, an internationally renowned system scientist at the University of Connecticut [3]. He first proposes the concept of probabilistic data interconnect filter in the 1970s. The principle of multisource information fusion is that information processing is the same as that of the human brain. Human brains analyze and process information and data through multiple sensors and then optimize and complement them to generate a consistent interpretation of the observed object.

The ultimate goal of information fusion is to process the scattered information of multiple sensors in multiple levels and aspects and output useful information [4]. At present, information fusion is widely used in industries, transportation, environmental monitoring, finance, meteorology, and other fields [5].

Big data technology is a leading technology in the development of computer technology in the twenty-first century and plays an important role in promoting the fusion and innovation of the Internet and industries [6]. The development trend of big data requires traditional enterprises to analyze the development direction of big data, explore their potential values, and manage enterprises innovatively so that the management ability of enterprises is improved. In general, business managers and employees should integrate big data into corporate decision-making, management philosophy, working methods, and corporate culture [7]. The application of big data to enterprise management is the

assistance in enterprise decision-making to conduct regular research and analysis, judge the developing trend, provide important bases and means, increase the scientificity of decision-making, and avoid losses and risks caused by mistakes [8].

In short, the performance management of power enterprises is studied based on big data and the multisource information fusion method. First, the backgrounds of multisource information fusion and big data are introduced. Second, the management of power enterprises and the traditional method of the multisource information fusion method are introduced, and the multisource information fusion model is implemented. And the enterprise performance evaluation method is studied. Third, the experimental results are analyzed and discussed. The simulation experiment of the fusion algorithm and the enterprise performance evaluation results under multisource information fusion can help enterprises save performance evaluation costs. Finally, the experimental conclusion is drawn. The study aims to improve the efficiency of performance management of power enterprises through the multisource information fusion model. The main contribution of the research is that a management fusion model is implemented through the multisource information fusion method and big data. At the same time, the data collected by the power system in the wind field are used for experimental simulation. The research helps promote the reform of enterprise performance management mode and improve the management efficiency of enterprises.

## 2. Enterprise Management Fusion Model Based on the Multisource Information Fusion Model and Big Data

*2.1. Key Technologies of Big Data Management in Power Enterprises.* The application of big data technology to enterprise management mainly has four difficulties, namely, information fusion, effective data extraction, data visualization, and massive data storage [9]. In the management of power enterprises, the efficiency of enterprise management, information acquisition, communication, and efficient data analysis are very important [10], and this needs to fuse massive data. Therefore, based on big data technology, the data are fused, and the fusion model is designed. At present, the methods of multisource information fusion mainly include unified identification, data comparison, heterogeneous weighting, and analysis modeling [11]. Big data about enterprise management can be generally divided into three categories, as shown in Figure 1.

Big data about the management of power enterprises have the characteristics of huge quantity, multiple types, fast speed, and high density, which are in line with those of big data [12]. Therefore, the fused management technology is one of the important technologies in the application of big data technology. It can reduce the complex dimension of data and prevent information silo. It includes data cleaning, information aggregation, and databases [13]. Since the sources of enterprise management data are various and

extensive, the data are very complex. Therefore, these data must be first organically fused before they are processed, and then a unified structure is used to store these data to ensure their quality and effectiveness. Another key technology is big data visualization, which is to simplify the display of multisource information contained in complex data, including data visualization, spatial data flow, and historical data flow [14]. The visualization technology can be used to obtain the hidden value behind the enterprise operation data and detect the state of enterprise operation intuitively.

*2.2. Traditional Method of Multisource Information Fusion.* The principle of multisource information fusion is the same as that of the human brain and processes information comprehensively. Human brains analyze and process information from multiple sensors and then optimize and complement them to generate a consistent interpretation of the object. The ultimate goal of information fusion is to process the scattered information of multiple sensors in multiple levels and aspects and then output the useful information [15], making the system have better performance than its components. Multisource information fusion falls into the following levels, as shown in Figure 2.

The role of information fusion is to fuse the data perceived by the information collection point in a specific range to avoid data redundancy because redundant data may occupy limited broadband resources. Then, the data transmission performed by many acquisition points from a single channel at the same time indirectly causes data blockage, which will delay the time of data processing. Moreover, if the sensor fails, simply relying on the sensor to transmit data will increase data errors and failures. Based on the above, the data processing based on information fusion will solve these problems, and it can reduce data redundancy and data congestion and improve the efficiency of data processing. Typical information fusion methods are the centralized processing method and the distributed processing method [16], and the process of the centralized processing method is shown in Figure 3.

The traditional method of information fusion is mainly based on the backpropagation neural network (BPNN), which is divided into the input layer, the hidden layer, and the output layer [17]. In the model based on the BPNN,  $Y = (y_1, y_2, \dots, y_m)^T$  is obtained if  $X = (x_1, x_2, \dots, x_n)^T$  is input, and  $m, n$  are the numbers of neurons in the input layer and the output layer, respectively. Concerning the  $i$ -th neuron of the  $K$  layer, its input value is as follows:

$$X_i^k = \sum_{j=1}^{n+1} w_{ij} X_j^{k-1}. \quad (1)$$

The output of this neuron can be expressed as follows:

$$Y_i^k = f(x_i^k). \quad (2)$$

When the error is reversed, the expected input is  $Y_j$ ,  $j \in [1, N]$ , and the error can be calculated by the following equation:

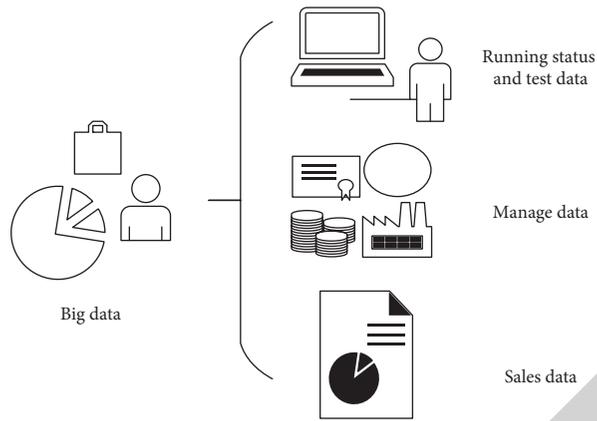


FIGURE 1: Categories of the big data about enterprise management.

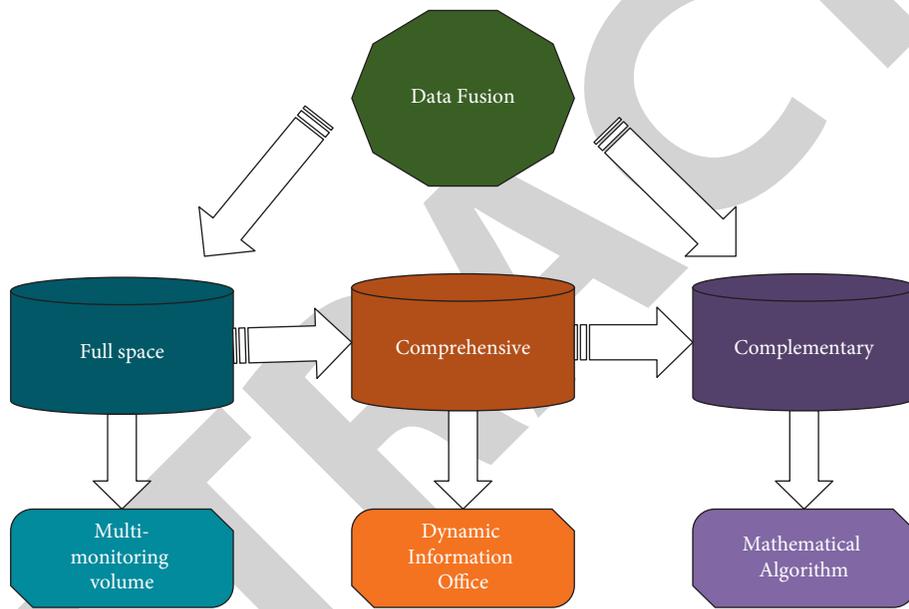


FIGURE 2: Levels of multisource information fusion.

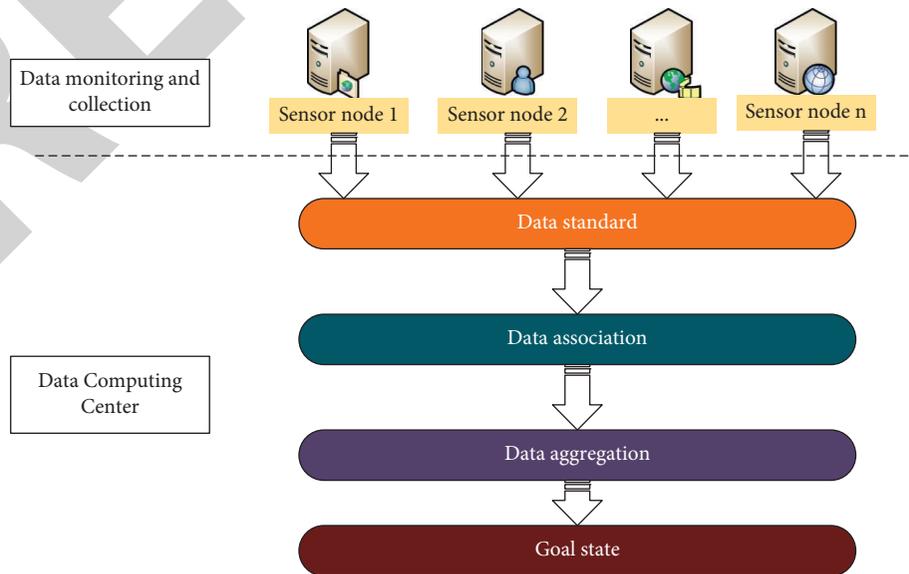


FIGURE 3: Process of the centralized processing method.

$$e_i^k = Y_i^k (1 - Y_i^k) \sum W_{ij} e_j^{k-1}. \quad (3)$$

The mean square error of the whole BPNN can be expressed as follows:

$$E = \frac{\sum \sum (Y_q - Y_q')^2}{2R}. \quad (4)$$

The weight adjustment equation obtained from equation (4) is as follows:

$$W_{ij}(t+1) = W_{ij}(t) - \eta e_i^k Y_i^{k-1}. \quad (5)$$

Here,  $\mu$  is the learning rate. When the output value is inconsistent with the expected output value, the error is calculated according to equation (3). In the neural learning process, the main role of iterative step  $\eta$  is to adjust the degree of network oscillation and the search speed. In the forward propagation, the first output of the hidden layer is calculated by the following equation:

$$v_1 = f_1 \left( \sum_{m=1}^M \omega_m |X_m - V \right). \quad (6)$$

The  $j$ -th network output of the output layer is as follows:

$$y_j = f_2 \left( \sum_{l=1}^L \omega |jv_l - \theta_j \right), \quad j = 1, 2, 3, \dots, J. \quad (7)$$

For the  $i$ -th sample, the error function of neural network learning is calculated by the following equation:

$$E = \frac{1}{2} \sum_{j=1}^J (y_j - 0_{ij})^2. \quad (8)$$

In the network learning of the  $i$ -th sample, the error function of neural network learning is calculated by the following equation:

$$\begin{aligned} \Delta \omega_{1j} &= -\eta \frac{\partial E}{\partial \omega_{1j}} \\ &= -\eta \frac{\partial E}{\partial y_j} \cdot \eta \frac{\partial y_j}{\partial \omega_{1j}} \\ &= \eta (O_{ij} - y_j) \cdot f_2' \cdot v_1 \\ &= \eta \cdot \delta_{ij} \cdot v_1, \end{aligned} \quad (9)$$

where  $\delta_{ij} = (O_{ij} - y_j) \cdot f_2' = e_{ij} \cdot f_2'$ ,  $e_{ij} = O_{ij} - y_j$ , and  $f_2'$  are the derivatives of the time function  $f_2(u)$  to the independent variable ( $u$ ) when  $u = \sum_{l=1}^L \omega |jv_l - \theta_j$ .

In the process of calculating the training threshold and weights by using the BPNN, the transfer function of each neuron must have continuous derivability, which is a prerequisite for using the BPNN [18]. This is why Sigmoid is often used in systems based on the BPNN. The traditional algorithm is mainly based on the three-layer BPNN, and it may cause some problems in the selection of the convergence rate, the local minimum point, the network structure, and the

learning rate of the classical BPNN. For example, the local extreme value may appear by using the traditional BPNN algorithm when complex nonlinear problems are solved, and the learning rate that the algorithm can choose is not high. Therefore, the traditional algorithm needs to be optimized and improved [19]. In the BPNN, the learning rate and the derivative value of the correlation transfer function are two crucial factors that determine the convergence rate of the BPNN. When the error function is not a special standard concave function, the local minimum point at this time is not necessarily the minimum point globally, and an error is produced. The number of hidden layers and the number of neurons are two important factors to determine the network structure. And the changes in the number of hidden layers and neurons directly change the network structure.

*2.3. Implementation of the Multisource Information Fusion Model.* The basic structure of the information fusion model is shown in Figure 4.

Figure 4 shows that information fusion can exchange the information of  $n$  blocks of  $X$ .  $X$  is an entity whose value is unknown. The original data are input; the data layer of the filtered data is output; and the basic data are processed. The final characteristics of the basic data are divided according to the degree of fusion. The feature layer extracts the feature data and transfers them to the decision layer, and then the final decision is made [20]. The fusion of the data layer is the simplest and most fundamental. Usually, it is carried out directly by extracting the feature from all the data sources of the detection object to calculate the required feature. In this layer, all the types of data can be processed, and the requirements are low. The fusion of the feature layer is at the middle, and it is conducted by extracting the feature vector from all the original data sources and then fusing with the feature vector extracted by the primary fusion at the previous level. The fusion of the decision layer is at the highest level, and it is carried out by using the decision vector to combine with the relevant algorithm for making decisions [21].

*2.3.1. Information Fusion Model of Power Enterprises.* At present, there are three requirements for the power system, namely, information sharing, interaction, and high efficiency. According to the three requirements and the three-layer structure of data fusion, the three layers structure of data can correspond to the principle of the three-layer structure of the power system and then be combined with the power system to build a general framework for data fusion. The data layer corresponds to the sensing measurement layer, the feature layer to the power data management layer, and the decision-making layer to the application layer. The sensing measurement layer collects data, and the data can be applied specifically in the application layer. The goal is to make the power system an intelligent, information sharing, and fault self-healing system and ensure the stable and reliable operation of the system. According to the management demand of power enterprises, a management information fusion model of power enterprises is implemented according to the three levels of information fusion, that is, the data layer should

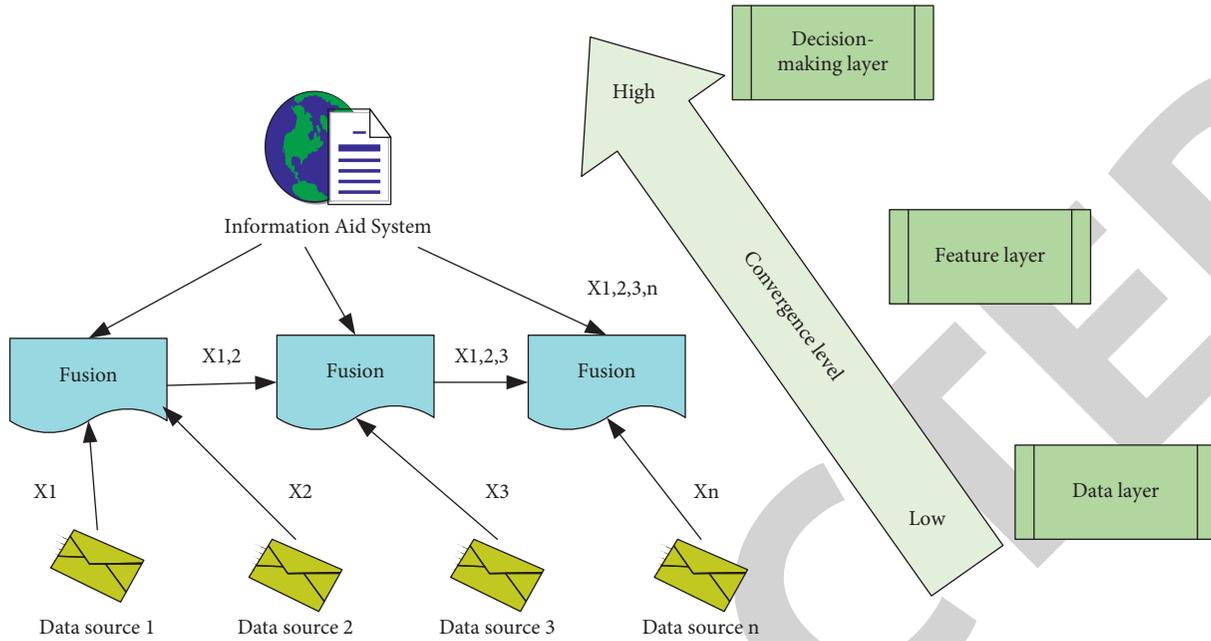


FIGURE 4: Structure of the information fusion model.

correspond to the sensing measurement layer, the feature layer to the data management layer, and the decision layer to the application layer [22]. The specific model structure is shown in Figure 5.

Due to the variety of power grid data and less correlation between the information, the initial data are redundant and noisy, and they need to be preprocessed and classified. The three steps for data preprocessing are: (1) cleaning data, which means removing invalid and missing data from all collected data; (2) data unification; and (3) data compression. If the validity and integrity of the sample data are ensured, the data compression can greatly save the limited storage space and improve the computational efficiency in the fusion.

**2.3.2. Data-Level Fusion.** Most of the data in data-level fusion in power systems come from the data collected by various sensors. These data are divided into three types: electrical quantity, process quantity, and state quantity [23]. In the data-level fusion stage, two-dimensional correlation analysis is first carried out, mainly for the same type of data after they are preprocessed, and then the cross-category two-dimensional correlation is carried out. This step is mainly based on physical models and intelligent algorithms. The accuracy of the results can be guaranteed by data-level fusion. The specific process of data-level fusion is shown in Figure 6.

The original data of data-level fusion of the power system are obtained by the advanced and reliable sensor technology in the power grid and the aggregation with the goal of information fusion [11]. With the rapid development of monitoring technology, it is easier to master the operation rules of equipment, and the fusion of the level becomes more accurate and comprehensive. The primary data fusion has two main characteristics. First, the physical model is taken as an important basis. As in Figure 6, homogeneous and cross-

class two-dimensional relationships are the data that can be observed or monitored. In Figure 6,  $I$  is the current of the grid system per unit;  $U$  is the voltage value of the grid system; and  $P$  and  $Q$  are the total power and the total energy of the grid system, respectively.  $X$  is the reactance of the grid system, and  $R$  is the resistance of the grid system. Second, the requirements for information level fusion are taken as the goal of data transformation. According to the needs of the information level, the data in the data-level fusion should be collated as follows: (1) data are preprocessed and (2) the data are reordered and sorted according to different application objectives and attributes and sorted and screened to prepare for the subsequent decision-making.

**2.3.3. Model-Level Fusion and Decision-Level Fusion.** Model-level fusion is at the intermediate level of three fusions, which is more intelligent. The advantage of it is that the original data are extracted and processed for fusion, which can reduce the number of data and the complexity in the calculation. The disadvantage is that the information may be lost, making the data have low accuracy. The decision-level fusion is the highest level of multisource information fusion. It is based on model fusion and makes comprehensive decisions on the final processing results. The advantage is that different types of data can be fused with a small amount of calculation, strong fault tolerance, and anti-interference, but the shortcomings are also obvious, and the loss of information will lead to low accuracy [24].

**2.4. Enterprise Performance Evaluation Methods Based on Multisource Information Fusion.** Under the multisource information fusion, enterprise performance is evaluated based on big data, and the dimensions of the evaluation index are shown in Figure 7.

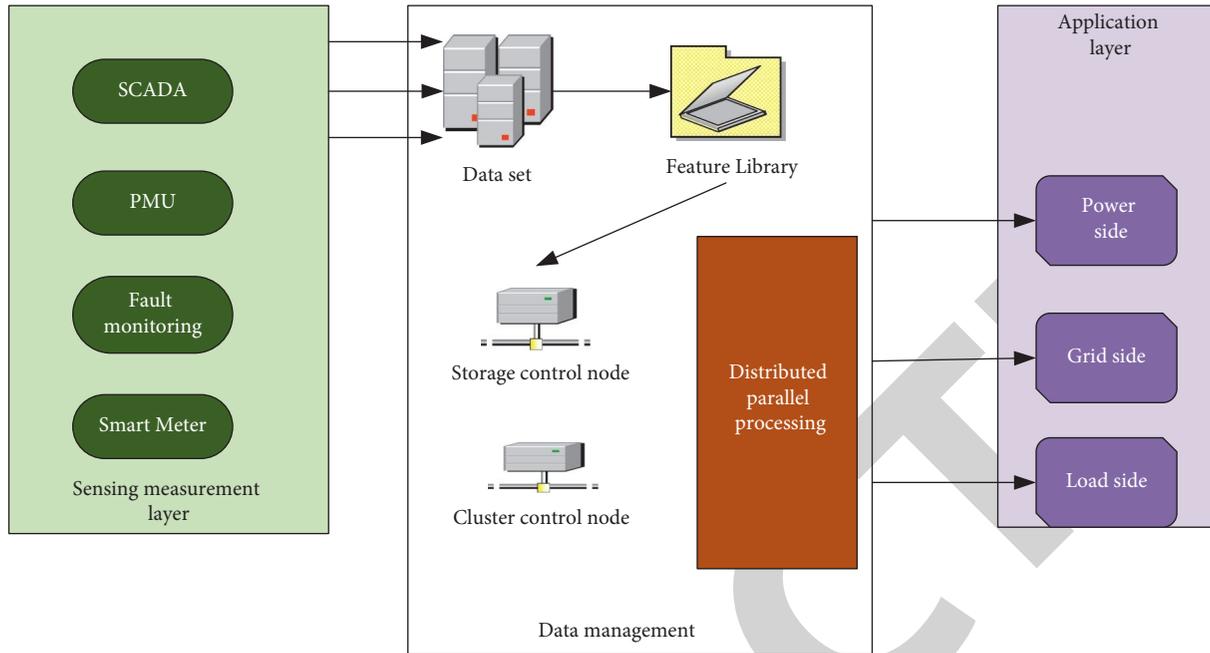


FIGURE 5: Information fusion model for power enterprise.

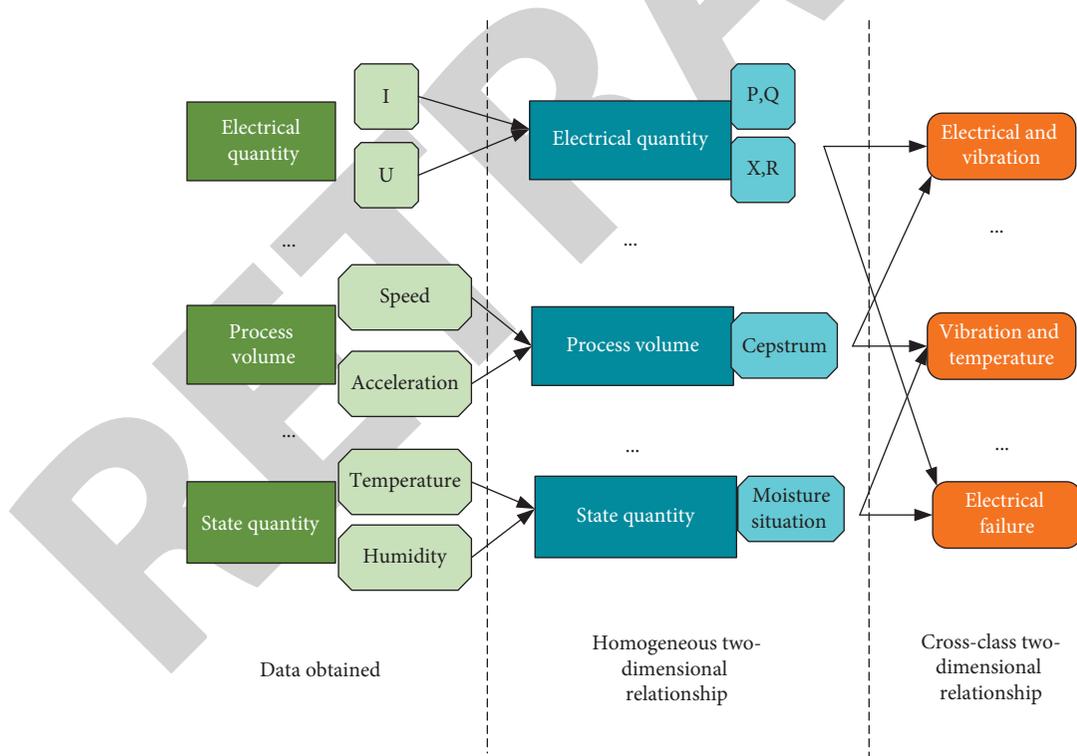


FIGURE 6: Process of data-level fusion.

Based on the above five dimensions of the evaluation index, the analytic hierarchy process based on fuzzy language is used to evaluate the performance of enterprises [25]. The fuzzy analytic hierarchy process is a combination of the analytic hierarchy process and the

fuzzy evaluation method. When the fuzzy comprehensive evaluation is conducted, the analytic hierarchy process is used to assign weights to various factors. The analysis process is as follows: (1) the hierarchical structure is built; (2) the judgment matrix is constructed; (3) the

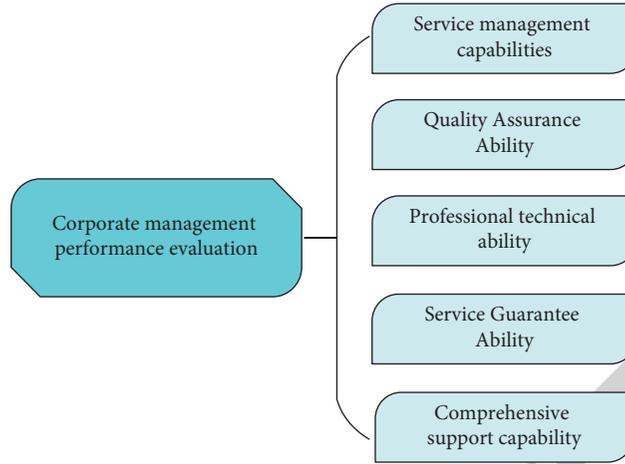


FIGURE 7: Dimensions of the enterprise evaluation index.

hierarchical single ranking of judgment matrix is calculated by

$$CW = \lambda W, \quad (10)$$

where  $\lambda = (\lambda_1, \lambda_2, \dots, \lambda_n)^T$  is the eigenvalue of judgment matrix  $C$  and  $W = (w_1, w_2, \dots, w_n)^T$  is the weight of the eigenvector of matrix  $C$ ; and (4) the consistency of the judgment matrix is tested.

### 3. Results

**3.1. Experimental Simulation of the Fusion Algorithm.** The monitoring data in September 2020 of a wind field in Xi'an are selected to conduct experiments. The total amount of data is 5GB. After that, the number of data needs to be verified to explore the prediction effect, and the data in October and November can be filled in to expand the size of data in the experiment. The MATLAB R2015b software is used to process the data in the simulation experiment. The configuration is Intel (R) i5-7500 with 3.40 GHz and 8 GB RAM and a computer loaded with Windows 7 operating system for experimental analysis and research. Table 1 shows the data types used.

Some of the monitoring data are shown in Figure 8:

Figure 8 shows that the monitoring data of wind speed, reactive power, cabin temperature, and outdoor temperature are listed. In this experiment, the calculation effect of the proposed algorithm MP – Hermite and the specific effect of the BPNN algorithm are compared, and the previous state of the fusion algorithm of input data is changed into the MP – Hermite algorithm. The collected parameters, such as  $v$ ,  $Q$ ,  $T1$ , and  $T2$ , are used as input attributes to fuse different types of data and predict the power in the wind field. Finally, the accuracy of the power prediction in the wind field in the simulation experiment is analyzed. Figure 9 shows the prediction power of the BPNN algorithm and the actual power.

Figure 9 shows that the power predicted by the proposed algorithm in practical application is closer to the actual

value, that is, the accuracy of the proposed algorithm is relatively high, and the prediction results are closer to the actual value of 0.35. The acceleration ratio is taken as a measurement of the standard to verify the timeliness of the algorithm in processing big data by expanding the capacity of the data set so that the experiments are carried out under different dataset capacities. Generally speaking, speedup means the ratio of the time  $T1$  spent on single machine processing to time  $TP$  spent on cluster processing in completing the same task, namely,  $Sp = T1/TP$ . The specific performance and efficiency of the model MapREDuce are measured by the acceleration ratio. In the experiment, the acceleration ratios of the traditional single-processing system and the parallel system are calculated when big data are processed. Then, the differences between the acceleration ratios are compared and analyzed. The comparison of the acceleration ratios of each group of data is shown in Figure 10.

Figure 10 shows that the more the number of cluster points is, the greater the value of the speedup is. The calculation rate of the algorithm increases with the increase of nodes under the same data sample. Under the same number of nodes, the greater the capacity of the data sample is, the greater the value of the speedup is. The maximum value of the speedup can reach 7. This shows that the structure is suitable for processing big data and can be applied to enterprise performance management based on big data.

**3.2. Analysis of Enterprise Performance Evaluation Results under Multisource Information Fusion.** According to the above division of indexes and dimensions of enterprise performance evaluation, the calculation results of the weight of secondary indexes in each dimension of enterprise performance evaluation are shown in Table 2.

Table 2 shows that the weight of the “product reliability ratio” in the dimension of “professional technical ability” is greater than or equal to “equally significant” compared with “significant impact on the engineering change rate,” the weight of “product reliability ratio” is between “obviously

TABLE 1: Data types.

Types of data	Wind speed	Reactive power	Cabin temperature	Outdoor temperature
Unit	m/s	kW	°C	°C
State parameter	$v$	$Q$	$T2$	$T1$

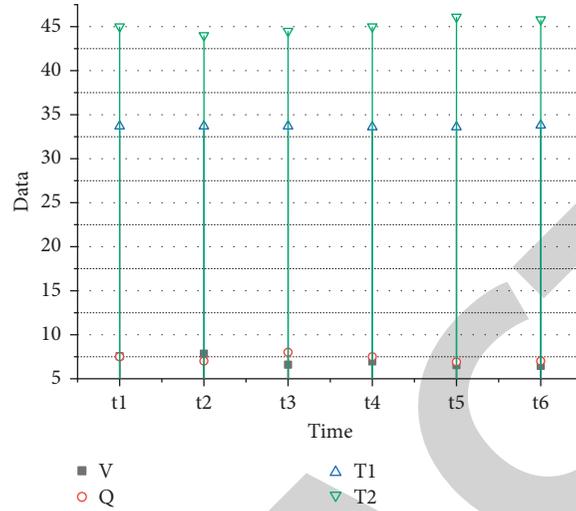


FIGURE 8: Some monitoring data in the wind field.

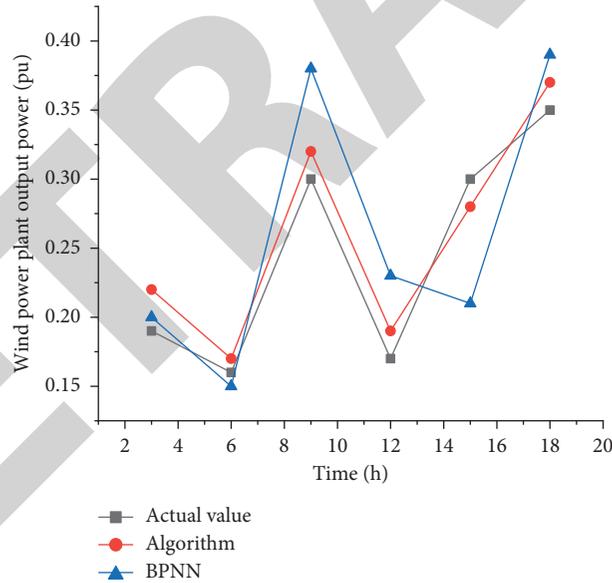


FIGURE 9: Power comparison of different fusion algorithms.

significant” and “very significant” compared with “technical problem-solving rate,” and the weight of “product reliability ratio” is greater than “slightly significant” compared with “technical feedback rate.” The “significant impact engineering change rate” is greater than or equal to “equally significant” compared with the “technical problem-solving rate,” and the “significant impact engineering change rate” is less than “slightly insignificant” compared with the “technical feedback rate.” Table 2 shows the judgment matrix of indexes in this dimension.

$$C1 - c1n = \begin{bmatrix} 1 & 4.436 & 6.5 & 6.225 \\ \frac{1}{4.436} & 1 & 4.436 & 1.791 \\ \frac{1}{6.5} & \frac{1}{4.436} & 1 & 0.904 \\ \frac{1}{6.225} & \frac{1}{1.791} & \frac{1}{0.904} & 1 \end{bmatrix}. \quad (11)$$

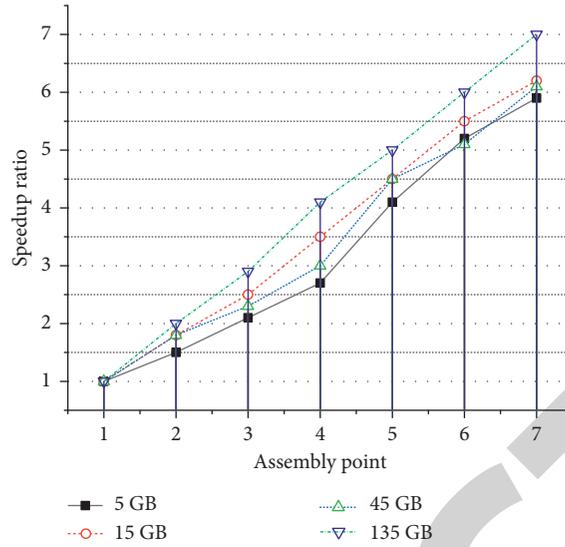


FIGURE 10: Acceleration ratios of different data.

TABLE 2: Calculation results of the index weight of each dimension of enterprise performance evaluation.

Professional technical ability	Product reliability ratio	Significant impact engineering change rate	Technical problem-solving rate	Technical feedback rate
Product reliability ratio	S4	≥S4	S6–S7	>S5
Significant impact engineering change rate	—	S4	≥S4	<S3
Technical problem-solving rate	—	—	S4	—
Technical feedback rate	—	—	—	S4

Note. S0 denotes “extremely insignificant”; S1 denotes “very insignificant”; S2 denotes “obviously insignificant”; S3 denotes “slightly insignificant”; S4 denotes “equally significant”; S5 denotes “slightly significant”; S6 denotes “obviously significant”; and S7 denotes “extremely significant.”

TABLE 3: Error comparison of two algorithms.

Algorithm types	BP neural network algorithms	MH-Hermite algorithms
RMSE	1.255	2.584

TABLE 4: Weights of each index in performance evaluation.

Indexes	Professional technical ability	Quality assurance ability	Schedule management ability	Service guarantee ability	Comprehensive support capability
Weights	0.353	0.414	0.120	0.066	0.047

When  $CR = CI/RI = 0.073/0.89 = 0.082 < 0.1$ , the matrix satisfies the conditions of the consistency test, and  $\lambda_{max} = 4.219$  is obtained. Similarly, the indexes of the other four judgment matrices also meet the conditions of the consistency test. The standard error comparison of the two algorithms is shown in Table 3, and the weight of each index in performance evaluation is shown in Table 4.

Tables 3 and 4 show the standard error and the average absolute percentage error of the proposed algorithm and the traditional algorithm. The error rate of this algorithm proposed is much lower than the traditional, and its fluctuation of the average absolute percentage error is smaller, indicating that the algorithm prediction model is closer to the real value. According to the weights of the five indexes, it can be concluded that the enterprise attaches the most importance to the quality assurance ability in the

formulation of performance evaluation indexes. Its weight reaches 0.414, which is much higher than others. Compared with the professional technical ability of the enterprise, its schedule management ability is more prominent, and the weight gap between the indexes is relatively large. The secondary indexes of enterprise management performance have a high impact on enterprise performance evaluation, and the weight gap between the indexes is large. This weight analysis can help enterprises save the cost of performance evaluation and improve their R & D ability.

#### 4. Conclusion

At present, information fusion and big data are widely used in industries, transportation, environmental monitoring, finance, meteorology, and other fields. The application of big

data to enterprise management can assist the enterprise in decision-making, judging the developing trend, and increasing the scientificity of decision-making. Therefore, the performance management of power enterprises based on big data technology is studied under multisource information fusion. It is found that the multisource information fusion algorithm proposed has high power, and its prediction ability is closer to the actual value than other algorithms in practical application. The maximum value of the acceleration ratio reaches 7, indicating that the algorithm is suitable for processing big data. In the performance evaluation of enterprises, it is found that enterprises attach the most importance to quality assurance ability with the weight reaching 0.414, and the weight of each index varies greatly. The study provides a reference for fusing big data and enterprise performance management. Also, it promotes the reform of enterprise performance management mode and improves the management efficiency of enterprises. However, there is a shortcoming in the performance evaluation of enterprises, that is, the indexes are not refined enough, and the information of enterprise performance evaluation is just partially reflected. This will be improved in the subsequent research.

### Data Availability

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

### Conflicts of Interest

The authors declare that there are no conflicts of interest.

### Acknowledgments

This work was supported by phase results of 2021 Guangxi Education Science Planning Funding Key Project (2021A038); stage results of 2019 Guangxi Higher Education Undergraduate Teaching Reform Project Key Topic (2019JGZ145); 2018 National Social Science Foundation of China (18BJY015); 2018 Academic Research Project of Master of Taxation (SWX20180010); Phase Results of the Integration Innovation Project (2020JGA166) of Guangxi University for Nationalities in 2020; and 2015 China-ASEAN Economic and Trade Development and South China Sea Strategic Collaborative Innovation Center Project (15&YBB06).

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