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Power Outage Fault Judgment Method Based on Power Outage Big Data

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Abstract

INTRODUCTION: With the deepening of the application of big data technology, the power sector attaches great importance to power outage judgment. However, many factors affect the judgment result of power outage, and the analysis process is very complicated, which can not achieve the corresponding accuracy.
OBJECTIVES: Aiming at the problem that it is impossible to accurately judge the result in judging power failure, a deep mining model of big data is proposed.
METHODS: Firstly, the research data set is established using power outage big data technology to ensure the results meet the requirements. Then, the power failure judgment data are classified using big data theory, and different judgment methods are selected. Using big data theory, the accuracy of power failure judgment is verified.
RESULTS: The deep mining model of big data can improve the accuracy of power failure judgment and shorten the judgment time of power failure under big data, and the overall result is better than the statistical method of power failure.
CONCLUSION: The deep mining model based on power outage big data proposed can accurately judge the power outage fault and shorten the analysis time.

Keywords: Big data theory, Power failure, Judge, Data mining

Received on 21 February 2023, accepted on 14 July 2023, published on 27 July 2023

doi: 10.4108/10.4108/ew.3906

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1. Introduction

With the deepening of the application of big data technology, the power sector attaches great importance to the judgment of power failure. However, many factors influence the results of power failure judgment, and the analysis process is very complex, which can not achieve the corresponding accuracy. The key to power outage fault judgment is to analyze big data and find the primary characteristic data [1]. An extensive power outage data analysis can not only analyze the relationship between characteristic data and power outage fault judgment but also judge its influence degree, which is the main method of power outage fault judgment. Literature research shows that data mining technology can classify the characteristic data of power outage fault judgment, shorten the analysis time, and improve the accuracy of power outage fault judgment. However, external uncertain factors will affect the accuracy and the final result in organizing feature data by data mining technology. Some scholars also proposed a neural network model, which can realize practical power outage fault judgment, but the judgment process is lengthy. In the case of power outage big data, the comprehensive judgment ability of power outage fault judgment decreased significantly [2]. Therefore, some scholars put forward a big data deep mining model to judge power failure and verify the accuracy of the results [3]. The results are shown in Figure 1. Based on this, this paper proposes a deep mining model of big data, analyzes the accuracy of power outage fault judgment results, and verifies the model's effectiveness.

2. Related concepts of power outage big data mining model

2.1 Big Data Theory.

Big data theory refers to the comprehensive analysis of power outage data, realizing sequential analysis of power outage data and improving data analysis efficiency. Data without deep mining can not be analyzed quickly and effectively, and false eigenvalues are easy to appear, reducing the results' accuracy. At the same time, data mining requires high power outage data and has continuous data analysis ability [4] to find eigenvalues from power outage big data. At present, the data weighting methods are mainly local weighting, global weighting, and comprehensive weighting. This paper puts forward the following assumptions to carry out the weighted analysis of power outage fault judgment.

Definition 1: Assume that the outage data set is $s=(s_1,s_2,\cdots s_n)$, the fault judgment index is d_i, and the critical value of fault judgment is q_i a function of outage fault judgment $Y(d_i,q_i,b_i)$. To optimize the power outage fault judgment process, the power outage big data is standardized, and the standardized processing function is $B(d_i,q_i,b_i)$ [5]. The distance between power failure judgment and processed data is S [6], representing the data standardization degree shown in Equation (1).

$$S=a\cdot L(d_i,q_i,b_i)+b\cdot B(d_i,q_i,b_i) \qquad (1)$$

Definition 2: If the mining degree of power outage big data is D_i, a value less than one means that the mining degree of power outage data is low, and a value greater than 1 means that the mining degree is high. The calculation D_i is shown in Equation (2).

$$D_i=\frac{\lambda\cdot Y(d_i,q_i,b_i)}{k^2} \qquad (2)$$

Definition 3: If the relational function is $R(d_i,q_i,b_i)=s\wedge d$, then the calculation $R(d_i,q_i,b_i)$ is shown in Equation (3).

$$R(d_i,q_i,b_i)=\sum o_i\cdot K(d_i,q_i,b_i|\gamma) \qquad (3)$$

Among them o_i reflects the mining degree of outage data.

2.2 Framework of blackout big data mining model

the traditional power outage fault judgment method. Standard power outage fault judgment technology mainly simulates judgment behavior, including crucial power outage fault judgment, in-depth judgment, and deep calculation, to realize power outage fault judgment and analysis. In the decision, the number of power failure judgments and power failure judgments is the same [7]. The characteristic data of different power outage faults are additional. First of all, according to the "Data Management Measures," "Power Outage Fault Judgment Standards," and "Power Outage Fault Judgment System," select power outage fault judgment indicators and judgment schemes, conduct power outage fault judgment analysis, and eliminate redundant data by comparison, about 1/3; Then, it is judged circularly, and the corresponding weight is given according to the degree of conformity [8]; Finally, give up the power outage data that does not meet the judgment standard, and judge the power outage data of other parts.

Assuming A: Power outage fault judgment index, the initial data amount of power outage fault is N, x_i, y_i represents the horizontal and vertical mining depth of power outage fault judgment and z_i represents the mining depth of power outage data under different standards, then the starting set of power outage fault judgment is shown in Equation (4).

$$L_i(d_i,q_i,b_i|3)=\frac{w\cdot z_i\cdot Y(d_i,q_i,b_i)}{Y[(\Delta x_{j\max}-\Delta y_{j\min})k]}\wedge 1 \qquad (4)$$

Among them $x_{j\max}$ are the index's most critical characteristic data and the index's least important characteristic data, and k is the adjustment coefficient of power outage fault judgment.

Hypothesis B: Cross-analysis of different indicators, updating indicators. Under the constraint of fitness, the influence degree of each index on the judgment result is analyzed, as shown in Equation (5).

$$L_i(d_i,q_i,b_i|3)=s\cdot\sum Y(d_i,q_i,b_i) \qquad (5)$$

The power outage fault judgment is based on the historical power outage data p_i, and the power outage fault judgment result is obtained by calculating the historical power outage data[9], and the power outage fault judgment result to judge whether the judgment result meets the threshold shown in Equation (6).

$$p_i=k-\frac{Y(d_i,q_i,b_i)}{1-\sum_{i,j,k}^{n}B(\Delta o_i)} \qquad (6)$$

If the possible power failure judgment standard has not been obtained after passing the preset threshold for the power failure judgment standard, it will be abandoned, and the existing power failure judgment standard will be deeply judged [10]. According to Equation (4), a new power outage fault judgment result is randomly selected for the following judgment. The blackout significant data analysis results of the above Equation are shown in Table 1.

Table 1. Data verification results of power outage fault judgment

Variable	Average	Standard deviation		
Power outage big data	5.2553	20.8469	\	\
Judgment result	5.3858	21.3501	\	\
Correlation coefficient	Power outage big data	Judgment result	p	\
Power outage big data（1）	1	0.9969	0	\
Model subset	x(1)	\	\	\
Single factor	0.9937	\	\	\
Total average	0.9937	\	\	\
Total average	\	\	\	\
Variable	R square containing x	After removing error	Contribution of error	Contribution of x
Power outage big data (1)	0.9937	0	0.9937	100

In the initial stage of power outage fault judgment, the standard review of power outage fault judgment may fall into the wrong decision in the early stage and reduce the accuracy of power outage fault judgment [11]. Therefore, in the power outage fault judgment process, it is necessary to expand the judgment scope as much as possible to improve the accuracy of the result. Some scholars make the adjustment rate of power outage fault judgment v and linear adjustments, but the recognition rate of primary feature data is low. The fault adjustment factor is introduced, and the judgment result is shown in Equation (7).

$$l = v_i \wedge \min v_i \quad (7)$$

Among them v_i is the fitting degree of I times. The cross-value change between critical power outage fault judgment and in-depth judgment is shown in Equation (8).

$$\Delta L\ (x_i, y_i, z_i) = \frac{w}{\lambda} \cdot K(d_i, q_i, b_i) \cdot v_{ijz} \quad (8)$$

the value $F(x_i, y_i, z_i)$ is judgment, which expands the scope of power failure judgment [12] and keeps the comprehensiveness of power failure judgment. The value of $F(x_i, y_i, z_i)$ its relatively large strengthens the search for relevant power outage data, improves the depth of power outage fault research and judgment[13], and enhances the effect of power outage fault research and judgment, as shown in Figure 1

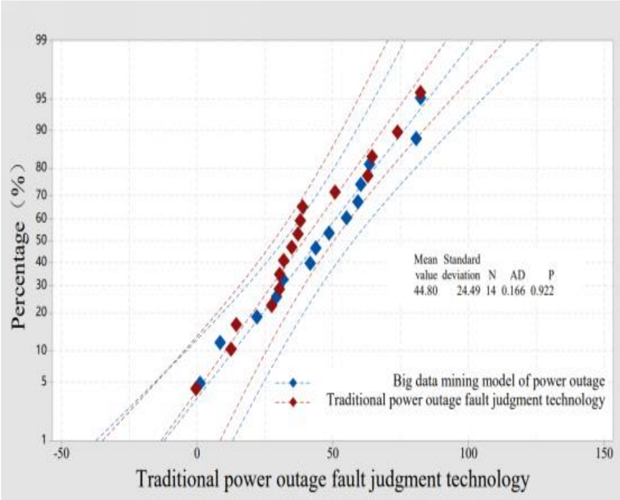

Figure 1. Adjustment effect of power failure judgment standard

Adjusting the power outage fault judgment standard can improve the accuracy of power outage fault judgment. As can be seen from Figure 1, the distance between the power outage data adjustment and the actual bar is close[14]. Therefore, adjusting the power failure judgment standard meets the requirements of power failure judgment.

The Fault Regulation Factor. Due to the poor anti-disturbance ability of power outage fault judgment results, the error rate will increase in the power outage fault judgment process. The fault adjustment factor is introduced in this paper, and the uncertainty of power failure judgment is reduced by historical judgment function, and the influence rate of error is reduced. The calculation is shown in Equation (9).

$$L(x_i, y_i, z_i) = \pi \sum_{i,t,k=1}^{+\infty} \frac{|K(\Delta o)|}{\sum t \cdot} \quad (9)$$

Because of the slow, gradual change speed on both sides $L(x_i, y_i, z_i)$, the analysis process is longer, which increases the uncertainty of power outage fault judgment results. Moreover, the peak value $L(x_i, y_i, z_i)$ is less than 1, which weakens. the fault adjustment factor can be transformed into Equation (10)

$$\Delta L_i = \frac{K(d_i, q_i, b_i)}{\sum K(\Delta d_{ik}, q_{ik}, \Delta b_{ik})} \quad (10)$$

2.3 Analysis of the Power Failure Judgment Scheme

The Selection of Power Failure Judgment Scheme. The rationality of the scheme selection of power outage fault judgment is the main content to measure the power outage fault judgment. Analyzing critical judgment data, in-depth judgment data, and deep calculation [15] can measure the relationship between power outage fault judgment and power outage fault judgment and improve the accuracy of judgment results. It can be seen from Equation (8) that characteristic data judgment, the analysis of comprehensive factors, and in the later stage of distinct data judgment, attention is paid to judgment standards. At the same time, according to different power failure judgment standards, various power failure judgment schemes are selected. At present, besides the power outage big data mining model, there are other improved judgment schemes.

1) The power failure judgment scheme of a single line, as shown in Equation (11)

$$alone(x_i, y_i, z_i) = \frac{p_i \cdot \sum_{t,i=1} \Delta L_{i-1}}{k} \qquad (11)$$

2) The judgment scheme of the whole power grid, as shown in Equation (12)

$$coxp(x_i, y_i, z_i) = \frac{g \cdot \max[\sum_{t} \Delta L_{i-1}(o)]}{\Delta L_{i-1}(o)} \qquad (12)$$

3) Judge the adjustment scheme, as shown in Equation (13)

$$adjust(x_i, y_i, z_i) = \frac{\omega \cdot \sum_{adjust=1}^{n/2} \Delta L_{i-1}(x_i, y_i, z_i)}{\Delta L_{i-1}(o)} \qquad (13)$$

4) Multi-line judgment scheme, as shown in Equation (14)

$$mutip(x_i, y_i, z_i) = \frac{A \cdot \sum_{t} \Delta L_{i-1}(o_{i-1})}{K(\Delta o_{i-1k})} \wedge p_i \qquad (14)$$

Among them, t is the time to judge the power outage fault. The power outage big data mining model proposed in this paper has two advantages: on the one hand, when judging any power outage fault, setting the mapping threshold λ [16]. At the same time, the power outage big data mining model is randomly selected from five judgment schemes, and the judgment work is completed. The individual power failure judgment is balanced, and the iterative factor v_i and standard fitness function $F(x_i, y_i, z_i)$ are integrated to judge power failure more accurately.

Collaborative analysis is the primary way to realize the judgment of different power outage faults. Based on the data on power outage faults, this paper constructs a collective power outage fault judgment scheme [17]. Different standards adopt power failure judgment schemes, complex indicators, and judgment processes. It will be randomly divided into five projects, each representing a sub-range. In each iteration process, different collaborative analysis standards will be randomly selected. After each power failure data is comprehensively analyzed, compare the matching degree of additional data and the depth of power failure judgment, and record the best judgment results.

2.4 Steps of power outage fault judgment based on big data

The basic idea of the power outage big data mining model is to optimize the results of complex power outage faults by using various schemes [18] to improve the results. The specific implementation process is shown in Figure 2.

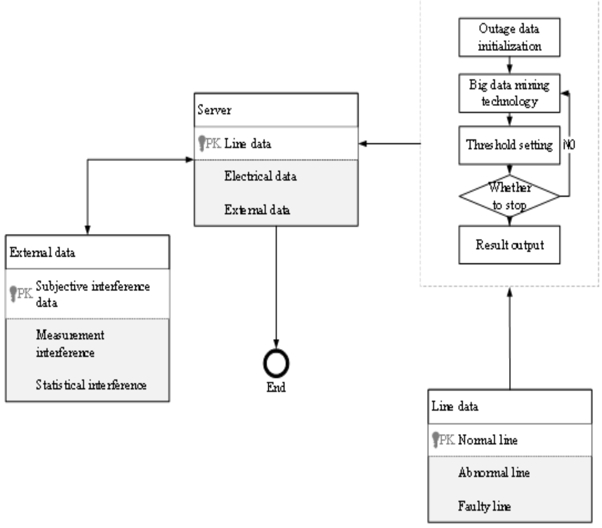

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Figure 2. Implementation flow of power failure judgment

Step 1: Initialize the power outage fault judgment model. According to the power outage data, the power outage fault is judged. The number of power failure judgments is n=30, and the judgment criteria are consistent with the number of judgment results.

Step 2: The big data theory is used to analyze the power outage fault data, and it is mapped to the two-dimensional range. Optimize the judgment results of power outage faults and judge the matching degree between the judgment results of each power outage fault and the actual results.

Step 3: Adjust the judgment standard of power failure and the best judgment scheme of power failure judgment results. Randomly select the power outage fault judgment scheme, obtain the fitness, and compare the analysis results of the projects.

Step 4: Judge the scheme and update the iteration of deep computing. According to the change of power failure judgment standard, the fault adjustment factor is adjusted.

Step 5: Realize collaborative analysis among power outage fault judgment results. Other standards judge the power outage data, and the final judgment results are obtained.

Step 6: Judge whether the power failure judgment result reaches.

3. Empirical analysis of power failure judgment

3.1 Analysis of judgment results

The results of the power outage big data mining model, four test functions of judgment results are selected: judgment time, judgment quantity, judgment accuracy, and judgment comprehensiveness.

(1) The time function is judged, and the result is shown in Equation (15).

$$Tim(x)=\frac{\sum_{t=1} x_i^{\,2}}{x_{s\tan d}} \qquad (15)$$

(2) Judge the quantity function, and the result is shown in Equation (16)

$$vol(x)=\lambda\cdot\sum_{totle=1} x_i \qquad (16)$$

(3) Judge the accuracy is shown in Equation (17)

$$cour(x)=\frac{x_i}{n\cdot\max(x_i)}\times 100\% \qquad (17)$$

(4) Judge the comprehensive function as shown in Equation (18)

$$coxp(x)=\sum_{i=1}\frac{x_i^{\,2}}{n-\max(x_i)} \qquad (18)$$

The value range x_i is (0, 1). In this paper, the index of the simulation experiment is set: the number of power failure judgments and analyses is 100, and the single judgment is four times. The calculation results in judgment are shown in Table 2.

Table 2. Results of different test functions

Indicators	Results				
Big data mining model of power outage	625975.9648	\	\	\	\
Traditional power outage fault judgment technology	25039.3152	\	\	\	\
Cross results of different methods	-1693.8483	\	\	\	\
Correlation coefficient	-0.0135	\	\	\	\
Non-zero correlation CMH Chi-Square	1.5312	df=1	p=0.21593	\	\
\	\	\	\	\	\
\	Linear Trend Test with two-way ordered contingency table	\	\	\	\
Source	Sum of square	df	Mean Square	F-value	p-value
Linear regression component	4.5834	1	4.5834	1.5313	0.2160
Departure component of Linear-regression	25034.7318	8364	2.9932	\	\
Total	25039.3152	8365	2.9933	\	\
	\	\	\	\	\
Regression coefficients	-0.0027	se(b)=0.002187	\	\	\
Chi-squared for Regression =1.5313	\	df=1	p=0.21592		

It can be seen from Table 2 that the power outage big data mining model is superior to the traditional power outage fault judgment technology; power outage big data mining models are smaller than those of conventional power outage fault judgment technology. The following analysis graphs are given to verify the power outage big data mining model more intuitively and compare different judgment schemes, as shown in Figure 3.

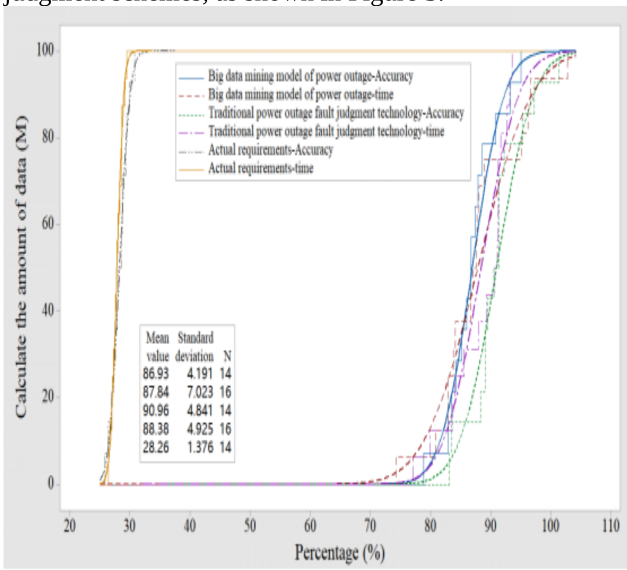

Figure 3. Results of power failure judgment by different methods

The analysis speed of the power outage big data mining model is superior to the traditional power outage fault judgment technology. Therefore, the power outage big data mining model performs better regarding judgment accuracy, and the judgment process is relatively stable.

3.2 Judgment results of different indicator

According to the requirements of State Grid for blackout fault judgment, the indexes of blackout fault judgment are classified into four categories: single index, comprehensive index, local index, and global index. This paper is based on theoretical review, practical verification, and the accuracy of judgment results. To avoid redundant data, call the fillmissing function for repeated analysis, and the results are shown in Table 3.

Table 3. Judgment results of different indicators

Judgment and classification of power outage faults	Accuracy rate of power failure judgment (%)	Judgment time (minutes)
Single indicator	87.42	5.78
Comprehensive index	89.56	4.97
Local index	67.42	3.79
Global index	79.59	3.94
Each sample of the two treatments is paired, and its mean difference test	t=1.7209	df=29
	p=0.0959	

3.3 Final experimental results

According to the above experimental conditions, the power failure data structure is 1-2-1, and the standardized processing degree is 95%. Under this standard, the result is shown in Figure 4 to verify the distribution of data.

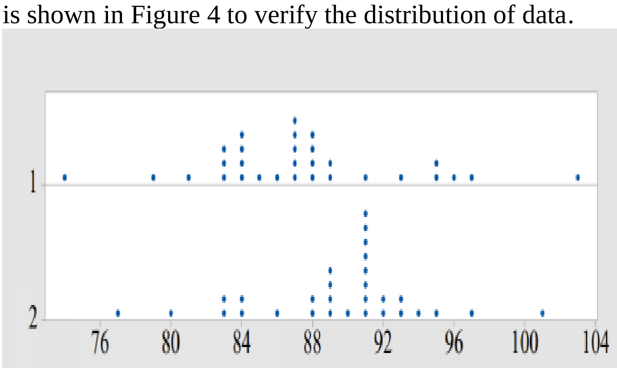

Figure 4. Classification results of power outage data by different methods (Note: 1 is Big data mining model of power outage； 2 is Traditional power outage fault judgment technology）

Through comparative analysis, it can be seen that the outage data processed by the outage big data mining model is discrete, while the traditional outage fault judgment technology is concentrated in processing outage fault data, which cannot meet the needs. In addition, the data processed by the power outage big data mining model is not affected by external factors, while the data processed by the traditional power outage fault judgment technology is influenced by uncertainty and is more concentrated. The reason is that the power outage big data mining model incorporates adjustment factors, maps power outage fault data to a two-dimensional range, and realizes standardized index power outage data processing.

Compared with different methods, the final results of power outage fault judgment are mainly traditional power outage fault judgment technology and power outage big data mining model, and the results are shown in Figure 5.

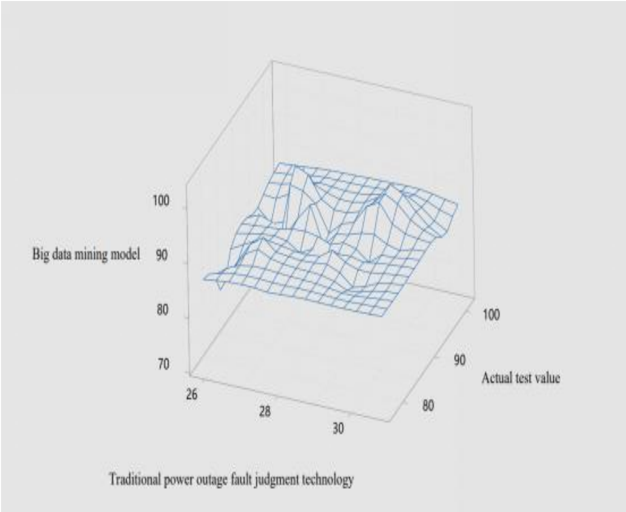

Figure 5. Comparison of the matching degree of different methods

the matching degree of power outage in the big data mining model is the highest, reaching the limit at the earliest. The power outage big data mining model has higher stability, followed by the traditional power outage fault judgment technology. The reason is that the power outage big data mining model constantly adjusts the judgment standards. At the same time, the power outage big data mining model provides different power outage fault judgment schemes, which improves the accuracy of power outage fault judgment results and is consistent with relevant research [19]. The characteristic data of different models should be analyzed, and the results are shown in Table 4.

Table 4. Accuracy of power failure judgment by different methods

Judgment and classification of power outage faults	Big data mining model of power outage		Traditional power outage fault judgment technology	
	Partial judgment	Global judgment	Partial judgment	Global judgment
Single indicator	99.34	98.33	97.32	96.31
Comprehensive index	99.37	98.32	98.37	98.30
Local index	99.31	95.34	95.33	92.31
Local index	99.34	97.32	94.33	95.36
The logarithm of observed values = 30	Mean =-2.1701		Standard deviation = 6.9068	
95% confidence interval-4.7491 ~ 0.4089		Standard error = 1.26101		

It can be seen from Table 4 that the accuracy of the power outage big data mining model is high, the change of power outage fault judgment standard. The fault adjustment factor adjusts the power outage data standard [20], reduces the occurrence rate of redundant data[21], and can make the power outage fault judgment more flexible. Therefore, the power outage big data mining model can reduce the influence of uncertainty on the accuracy of results and improve the accuracy of power outage fault judgment.

4. Conclusion

A judgment method based on power outage big data theory is proposed, and the comprehensive judgment of power outage fault is realized by setting threshold, weight, collaborative process, and power outage fault judgment scheme. The results show that: 1) the Big data mining model can reasonably classify outage data and improve the processing effect of initial data; 2) The big data mining model has high judgment accuracy and standards on judgment results; 3) the Big data mining model can reduce the rate of redundant data and shorten the time of judgment. However, there are still some shortcomings in judging different power outages, mainly reflected in the relationship between judgment indicators and the influence of standardized processing methods on judgment results.

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