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Research Article

Multisource Data Fusion Analysis of Maintainability for Overlapping Degree High Performance Computing

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With the continuous development of social economy, industry has become the main industry that contributes to the economy. In the process of industrial development, human operation is gradually replaced by machine operation, and the replacement of machines is followed. Over the years, machines have become more and more important in industry. However, although the machine liberates manpower, over time, it has experienced external pressures such as the environment and personnel and is internally affected by the technical level, experience, equipment familiarity, and physical and mental state of the maintenance personnel. Industrial machines tend to cause all sorts of problems when they run for too long. Therefore, it is ensured that the efficient operation and long-term operation of the machine are crucial issues. In view of the current situation and problems, this paper combines different equipment maintenance test data, adopts the method of high-performance computing overlap, establishes corresponding multisource data for data conversion and processing, and then uses the Bayesian method to analyze the multisource data. Parameter fusion and overfitting are performed, and finally the device is tested for prior data fusion using the overlap data model. The simulation results of this paper show that the high-performance overlap calculation method is effective and can effectively support the fusion analysis of maintainable multisource data.

1. Introduction

With the continuous development of social economy and the continuous maturity of industrialization, various machines play a pivotal role in industrial production and assume a very important task in supporting the development of the industry [1, 2]. However, excessive and long-term operation of the machine often brings about various problems and feedback of the machine. Therefore, how to ensure the long-term operation of machinery and equipment and the long-term operation of the factory is extremely important. At the same time, the extensive application of various technologies has promoted the obvious upgrade and complication of equipment, which will increase the corresponding experimental difficulty and increase the corresponding cost, which in turn reduces the effectiveness of the machine [3, 4]. In order to solve this dilemma and difficult problem, experts within the industry try to solve the problem by integrating the maintainability data in various ways [5, 6]. Some scholars have tried to transform and fuse field maintainability data through different experimental environments and different application functions to achieve effective expansion of data samples; in addition, some scholars use D-S theory to perform state comprehensive decision-making data fusion, verifying the effectiveness and experimentation of data fusion technology, and explore the application space and scope of the method. Therefore, in terms of many maintainable data, the fusion method can be used to make full use of the collected data and the data of the previous mobile phone to conduct comprehensive judgment and speculation to expand the capacity of the data, so as to solve the corresponding problems of small amount of maintainable data and low reliability of conclusions in a different form [7–9]. For the maintenance equipment of the machine, its main laboratory equipment is one of the important verification methods. In the design stage of equipment design, due to the small data sample, engineering experiments are conducted usually by using Bayesian correlation methods to verify the experimental data of machine equipment maintainability. The prior distribution calculated according to the experimental data is the basis of maintenance and an important premise to ensure the verification of data results. For machines, it is necessary to continuously improve and perfect using new technologies to achieve comprehensive analysis of maintainability data. Therefore, it is necessary to make full use of the previous information and use appropriate methods for verification. At present, the commonly used fusion methods of multisource maintainability information mainly include weighted data fusion method, maximum likelihood weight fusion method, and typical DS fusion method [3, 10–12]; therefore, a rational choice of experiments needs to be performed according to different methods. The experimental results in different research environments show that the weighted data fusion method is relatively good, but this method leads to the problem that the weighted results are not reasonable enough when the information source distributes the fusion weight, resulting in a situation of large error, which in turn causes a decrease in the reliability of the results of the maintainability of machinery and equipment [4, 13, 14].

In view of these limitations and requirements, this paper introduces a high-performance calculation method of superposition degree. By sorting out the business logic of each stage of machine equipment maintenance, the priori data are analyzed, to realize the superposition and closeness to the field data. At the same time, high-performance computing of decentralized early verification data is carried out, and the superposition degree is used as the corresponding weight for data fusion to realize the verification of maintainability data, aiming to explore the effective fusion analysis of maintainability data.

2. High Performance Calculation of Superposition Degree

High performance calculation of superposition degree is actually a kind of data resampling method, which mainly extracts samples from the database, and performs statistics and analysis on the unknown data of the corresponding samples. Assuming that the sample $X = (x_1, x_2, \ldots, x_n)^T$ is subject to the unknown distribution F, the calculation of the estimated error $T' = kT + \Delta t$ can be as shown in formula as follows:

$$T_n = \widehat{\theta}(F_n) - \theta(F), \tag{1}$$

where θ is the parameter, $\widehat{\theta}$ is the estimation of θ, and F_n represents the distribution obeyed by the used sample for θ.

Assuming $X_i^* = (x_{i1}^*, x_{i2}^*, \ldots, x_{in}^*)^T$, $i = 1, 2, \ldots, m$, according to the extracted sample X, the subsample data set $X^* = (X_1^*, X_2^*, \ldots, X_m^*)$ of m groups can be obtained, which satisfies the empirical distribution function F_n^*, and the estimated value of θ is represented by $\widehat{\theta}(F_n^*)$; then, the calculation of the estimated error of θ corresponding to the obtained subsample is expressed as follows:

$$T_n^* = \widehat{\theta}(F_n^*) - \theta(F_n). \tag{2}$$

T_n^* is used to is express high-performance calculation of estimated error, T_n expresses estimated error for other calculation method, and

$$\begin{aligned} T_n &= \widehat{\theta}(F_n) - \theta(F) \approx \widehat{\theta}(F_n^*) - \widehat{\theta}(F_n) \\ &= T_n^*. \end{aligned} \tag{3}$$

Before the high-performance calculation of superposition degree, according to the obtained k priori data information about the parameter θ, the prior distribution $\pi(\theta)$ can be obtained by the following expression:

$$\pi(\theta) = \sum_{i=1}^{k} w_i \pi_i(\theta), \tag{4}$$

where $\pi_i(\theta)$ represents the i-th information source prior distribution and w_i is its weight. Scientific and reasonable fusion weights can effectively reduce the deviation between the prior distribution and the true distribution [15, 16]. Assume that the field test data is $X_t = (x_{t_1}, x_{t_2}, \ldots, x_{t_n})^T$, and the quality factor λ can be computed by the expression as follows:

$$\begin{cases} \lambda_i = 1 - \dfrac{\left(X^{(i)} - X_t\right)^2}{D^2}, \\ D^2 = \dfrac{S_i^2 + S^2}{n + n_i - 2}, \end{cases} \tag{5}$$

where $X^{(i)}$ represents the i-th group sample and D, S_i, and S are obtained by using the following:

$$\begin{aligned} \overline{X}^{(i)} &= \frac{1}{n_i} \sum_{j=1}^{n_i} x_j^{(i)}, \\ \overline{X}_t &= \frac{\sum_{h=1}^{n} x_h + \sum_{i=1}^{k} \sum_{j=1}^{n_i} x_j^{(i)}}{n + \sum_{i=1}^{k} n_i}, \\ S_i^2 &= \sum_{j=1}^{n_i} \left(x_j^{(i)} - \overline{X}_t\right)^2, S^2 = \sum_{i=1}^{n} \left(x_i - \overline{X}_t\right)^2. \end{aligned} \tag{6}$$

Then, the calculation of the weight is shown in the following formula:

$$w_i = \frac{\lambda_i}{\sum_{i=1}^{k} \lambda_i}. \tag{7}$$

The calculation of the mean credibility weight factor μ_1 is defined as the following formula:

$$\mu_1^{(i)} = \frac{1/\left|\overline{X}^{(i)} - \overline{X}_t\right|}{\sum_{i=1}^{k}\left(1/\left|\overline{X}^{(i)} - \overline{X}_t\right|\right)}, i = 1, 2, \ldots, k. \tag{8}$$

Therefore, define the sample size credibility weight factor μ_2, as shown in the following formula:

$$\mu_2^{(i)} = \frac{n_i}{\sum_{i=1}^{k} n_i}. \tag{9}$$

Integrating μ_1 and μ_2, the quality factor λ_i is defined, as shown in the following formula:

$$\lambda_i = \mu_1^{(i)} \mu_2^{(i)}. \tag{10}$$

Among them, λ_i is the quality factor of the i-th pre-test data information.

The maintainability multisource data fusion process is mainly used to solve the weight value problem of different types of data fusion [17]. The accuracy of the data fusion weights is directly related to the data fusion accuracy. Therefore, this paper uses the collected prior data to superimpose the corresponding high-performance calculation of superposition degree and experimental data to form the corresponding superimposed area between the two curves. The area occupied by low-probability data is removed to improve the accuracy of data fusion analysis.

The high-performance calculation method of superposition degree is used to carry out information prior distribution, which is represented by $\pi_1(\theta), \pi_2(\theta), \ldots, \pi_n(\theta)$. By taking the extracted data as a comparative sample, a standard prior distribution $\pi_s(\theta)$ is obtained.

According to the superposition degree of the obtained multisource prior distribution $\pi_i(\theta), i = 1, 2, \ldots, n$ and the benchmark prior distribution $\pi_s(\theta)$, the superposition degree of each source prior data can be obtained by the following expression:

$$A_i = \int_{\Omega} \min\left(\pi_i(\theta), \pi_s(\theta)\right) d\theta. \tag{11}$$

The proportion of the total superposition degree occupied by the superposition degree of each source prior data is calculated using the following expression:

$$\omega_i = \frac{A_i}{\sum_{i=1}^{n} A_i}. \tag{12}$$

The smaller the contrast weight difference, the greater the weight. Finally, the comprehensive prior distribution $\pi_p(\theta)$ is determined, using the following expression:

$$\pi_p(\theta) = \sum_{i=1}^{n} \omega_i \pi_i(\theta), \sum_{i=1}^{n} \omega_i = 1. \tag{13}$$

3. Multisource Data Fusion Analysis of Maintainability

If θ is used to represent the time parameter of the multisource data to be predicted for maintainability, the sub-distribution values of the multisource data corresponding to the k parameters θ can be obtained. Then, the sub-distribution of the i-th multisource data is represented as $\pi_i(\theta)$, and the corresponding weights are represented by ω_i. Through high performance calculation of superposition degree of multisource fusion data, the distribution of θ can be calculated, which is expressed as

$$\pi_p(\theta) = \sum_{i=1}^{k} \omega_i \pi_i(\theta), \sum_{i=1}^{k} \omega_i = 1. \tag{14}$$

The fusion process is mainly as follows. According to the distribution weight value of multisource data, high reliability can be obtained according to the actual data information [18, 19]. Therefore, the field data are used as the basis, and the information error value between multisource data weight distribution and actual data can be used to construct a multisource data weight model. If the value of the maintainability parameter of the equipment is represented by the formula $g(\eta)$, then the calculation steps of the obtained weight are as follows:

Step 1. According to the collected multisource data, an appropriate method is selected to convert it into different types of multisource data distribution, which is represented by $\pi_1(\eta), \pi_2(\eta), \ldots, \pi_k(\eta)$.

Step 2. According to the actual test data, the maintainability parameter η can be calculated, which is represented by $\pi_s(\eta)$, and at the same time, it can be used for the reference of multisource data distribution according to the distribution situation.

Step 3. According to the distribution of multisource data, the expected value $E[g(\eta)]$ of $g(\eta)$ can be solved in turn, and $E_s[g(\eta)]$ is used as the reference standard to calculate the "distance" l_i:

$$l_i = \left| E_s[g(\eta)] - E_i[g(\eta)] \right|. \tag{15}$$

Step 4. l_i is used to calculate the weight value of different multisource data. In general, it can be efficiently calculated using $E[g(\eta)]$; assuming that the complex function $g(\eta)$ of the distribution can be calculated, then $E[g(\eta)]$ can be obtained by using numerical integration. If the value of l_i becomes smaller, it can indicate that the error value between the multisource data distribution $\pi_i(\eta)$ and the multisource data distribution $E_s[g(\eta)]$ will become smaller, and the multisource data are consistent with the experimental information; then, the weight of $\pi_i(\eta)$ will get larger.

Then, the following expression can be used:

$$l_i' = \frac{1}{l_i}, \omega_i = \frac{l_i'}{\sum_{i=1}^{k} l_i'}. \tag{16}$$

Then, $\omega = (\omega_1, \omega_2, \ldots, \omega_k)$ can get the distribution weight value of multisource data. If $l_i = 0$, then $\omega_i = 1$ can be obtained, and other multisource data distribution weights are 0. The weighted fusion of multisource information can be accomplished using (16). The calculation process can be analyzed according to the weight vector. The method used in this paper does not contain subjective data information, so it can vividly reflect the distribution of different types of multisource data.

If the maintenance time conforms to $N(\theta, \sigma^2)$, then it has a decisive role in the index of maintenance time. The most important thing is the mean value of multivariate data, but it is not very important for the variance value [20, 21]. The larger the variance value, the greater the range of maintenance time expands, so the expression $g(\eta) = \theta^2$ is used.

If the key information set of equipment maintenance time is represented by T, and $T = (t_1, t_2, \ldots, t_m)^T$, and t_i $(i = 1, 2, \ldots, m)$ represent the detection time, decomposition time, replacement time, reorganization time, and adjustment time of the equipment in turn, then the maintenance time M of the equipment is expressed as

$$M = \sum_{i=1}^{m} t_i. \tag{17}$$

If $K = (k_1, k_2, \ldots, k_m)$ represents the set of conversion factors, expression (17) represents the time to remove a certain fault in the early test stage, and M' represents the maintenance time under the corresponding conversion conditions; then, it can be obtained:

$$M' = K \times (T + \Delta T). \tag{18}$$

Among them, $\Delta T = (\Delta t_1, \Delta t_2, \ldots, \Delta t_m)^T$ indicates the troubleshooting time performed. Compared with the previous test result, the test result constitutes the database. Because of the multisource data fusion degree of equipment maintenance, if the failure cannot be eliminated, the time will be shortened, so $\Delta t_i \leq 0\,(i = 1, 2, \ldots, m)$ is usually used. $k_i\,(i = 1, 2, \ldots, m)$ represents the troubleshooting mainly ratio of the maintenance time. Maintenance time between the maintenance personnel and the technical personnel of the contractor shall be ensured under the condition that the quantity and technical level meet the actual demand in the actual testing stage.

Assuming that maintenance time for the failure of similar equipment is represented by M' in the evaluation of equipment troubleshooting, then

$$M' = kM + \Delta t. \tag{19}$$

Among them, k represents the conversion coefficient value, but from the overall analysis, if there is an error in the maintainability of the equipment to be evaluated and its similar equipment, then the two types of equipment used have the same maintenance process for the failure. However, similar parts of the two equipment differ in weight and volume. If there is no difference, then $k = 1$; Δt means that the difference in maintenance time of the two types of equipment is considered from individual maintenance operations, so that there is a certain difference in the structure of the equipment, so the maintenance process is not exactly the same.

4. Analysis of Experiment and Results

This paper starts the research directly from the establishment of the superposition model.

(1) By taking similar models of equipment as an example, perform high performance calculation of superposition degree.

Because the maintenance time needs to conform to the logarithmic state distribution, it is necessary to take the logarithm of the superimposed data to calculate the following:

The maintainability data of the equipment in the design stage can be calculated by superimposing as follows:

$$T_1 = (3.226, 3.124, 3.433, 2.978, 3.431, 3.433, 3.124). \tag{20}$$

By superimposing the experimental maintainability data of the virtual prototype of the equipment, it can be calculated as follows:

$$T_2 = (3.056, 3.744, 2.967, 3.066, 3.577, 3.978, 3.591, 3.388, 3.777). \tag{21}$$

By superimposing the maintainability data of the equipment in the design stage, it can be calculated as follows:

$$T_3 = (3.355, 3.155, 3.456, 3.066, 3.278, 3.578, 3.587, 2.977, 3.187). \tag{22}$$

Then, after taking the logarithm of the number of trials, it can be obtained through calculation as follows:

$$T_s = (3.173, 3.341, 3.564, 2.992, 3.422, 3.091, 3.343, 3.262). \tag{23}$$

The corresponding confidence level is set, using the corresponding test method to test the consistency of the data before and after the superposition, and the specific probability is analyzed at the same time, as shown in Figure 1. Through the actual comparison results, it can be found that in this paper, the superimposed model effectively realizes the high-performance calculation of superposition degree of the collected maintainability data and the field data.

(2) Using the corresponding differential value method, high performance calculation of superposition degree of parameter on the collected prior data is performed, repeating the simulation multiple times at the same time, and the existing test results and methods are used to adjust and test the high-performance calculation of superposition degree of the parameter, until the normality is satisfied, and finally the corresponding data specific distribution function is obtained.

Adjust and experiment until normality is satisfied, and finally get the specific distribution function of the corresponding data:

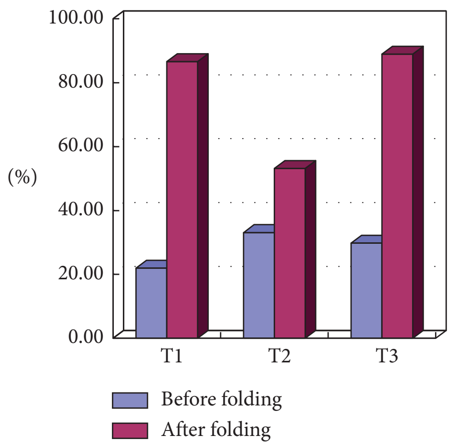

Figure 1: Comparison of equal probability of prior data and field data before and after superimposition.

$$\begin{aligned}\pi_1(\theta) &= N(3.232, 0.145),\\ \pi_2(\theta) &= N(3.362, 0.255),\\ \pi_3(\theta) &= N(3.293, 0.204),\\ \pi_s(\theta) &= N(3.271, 0.184).\end{aligned} \tag{24}$$

(3) Calculate the fusion weight of each source prior data through the superposition degree:

$$\begin{aligned}\omega_1 &= 0.2945,\\ \omega_2 &= 0.3224,\\ \omega_3 &= 0.3867.\end{aligned} \tag{25}$$

Calculate the weight coefficients, and use the corresponding software to perform the high-performance calculation of superposition degree after data fusion [22]. The result of the high-performance calculation of superposition degree is shown in Figure 2.

(4) Determine fusion distribution parameters and fusion distribution types. According to the calculation results, the specific judgment of the normal distribution can be roughly carried out. If the distribution after data fusion is a normal distribution, that is, the function is a probability function, the data processing and calculation of the corresponding peak value and abscissa may be required. The probability of normal distribution can be obtained by the corresponding formula. When the sample size of the experimental data is small, the small sample data can be used for testing to obtain the final data sample distribution (Figure 3).

Before performing multisource maintainability data fusion, it is first necessary to carry out a consistent data test to determine whether all the collected data obey the corresponding distribution type [23]. The specific distribution is shown in Figure 4.

According to the results in Figure 4, it can be judged that the collected data obey the normal distribution, and the corresponding inspection method can be used to conduct a reasonable inspection. Specifically, it can be verified whether the collected maintainability data obey the logarithmic normal distribution. Similarly, it can be used to verify whether the corresponding equipment sample data and the data collected on-site obey the normal distribution.

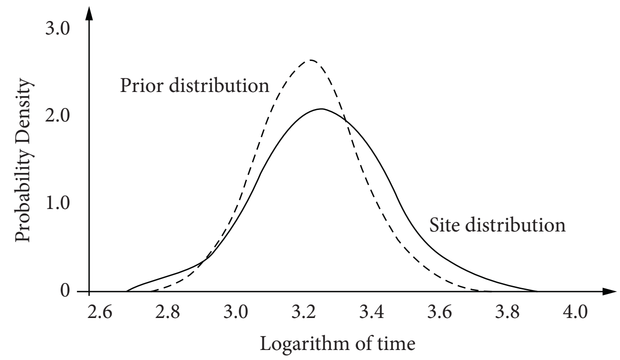

Figure 2: Schematic diagram of superposition degree.

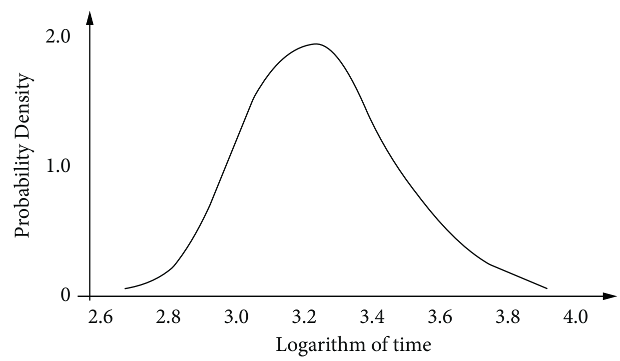

Figure 3: Distribution curve after fusion.

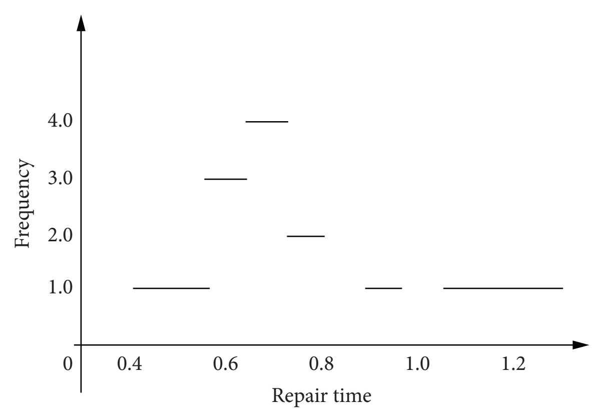

Figure 4: MTTR distribution histogram.

The collected maintenance multisource data and on-site data are tested with corresponding detection methods, so as to judge whether the two groups of data come from the same population.

Taking historical test data and field test data as examples, both logarithms are taken and recorded as X and X_1. It is known that the sample sizes of the two groups of data are

$n = 15$ and $n_1 = 10$, and the mean and variance are $\overline{X} = 0.3152$, $S^2 = 0.1043$, $\overline{X}_1 = 0.3126$, and $S_1^2 = 0.0704$, and the significance level is $\alpha = 0.1$.

Test mean is as follows:

$$\begin{aligned} t &= \frac{\overline{X} - \overline{X}_1}{\sqrt{nS^2 + n_1 S_1^2 / n + n_1 - 2}\sqrt{1/n + 1/n_1}} \\ &= 0.0203, t_{0.95}(23) \\ &= 1.7139. \end{aligned} \tag{26}$$

Therefore, $|t| < t_{0.95}(23)$; that is, there is no difference in the mean.

Test variance is as follows:

$$\begin{aligned} F &= \frac{n(n_1 - 1)S^2}{n_1(n-1)S_1^2} \\ &= 1.4286, F_{0.05}(9, 14) \\ &= 0.3305, \ F_{0.95}(9, 14) \\ &= 2.6458. \end{aligned} \tag{27}$$

Therefore, $F_{0.05}(9, 14) < F < F_{0.95}(9, 14)$; that is, there is no difference in variance.

The historical data are resampled by the test method, and the calculated mean value is simulated and analyzed by the corresponding software. The simulation results are shown in Figures 5–7. It can be seen from the simulation results that the simulation curves are all approximately obeying the normal distribution.

From the parameter estimation results of the historical data mean in Table 1, it can be seen that the prior distribution determined by the improved high-performance computing method of superposition degree in this paper is the closest to the real distribution and has the smallest error.

According to the previous formula, the mean confidence weight factors $\mu_1^{(1)}$ and $\mu_1^{(2)}$ can be calculated:

$$\begin{aligned} \mu_1^{(1)} &= 0.6083, \\ \mu_1^{(2)} &= 0.3917. \end{aligned} \tag{28}$$

According to the formula above, calculate the sample size credibility weight factors $\mu_2^{(1)}$ and $\mu_2^{(2)}$:

$$\begin{aligned} \mu_2^{(1)} &= 0.6000, \\ \mu_2^{(2)} &= 0.4000. \end{aligned} \tag{29}$$

According to the previous formula, calculate the quality factors λ_1 and λ_2:

$$\begin{aligned} \lambda_1 &= 0.3655, \\ \lambda_2 &= 0.1564. \end{aligned} \tag{30}$$

According to the formula in the previous article, calculate the fusion weights ω_1 and ω_2:

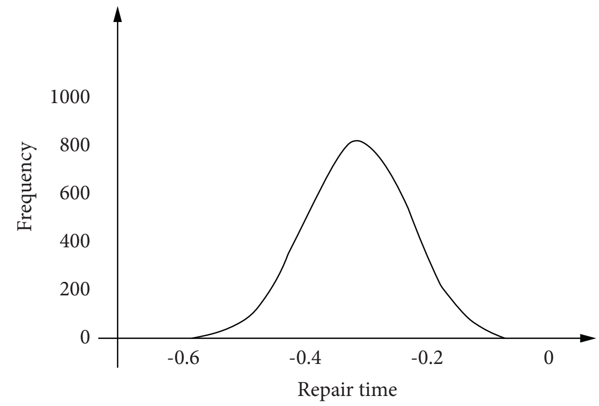

Figure 5: The chart for pre-test distribution simulation of the high-performance calculation of superposition degree with high performance calculation of the superposition degree method.

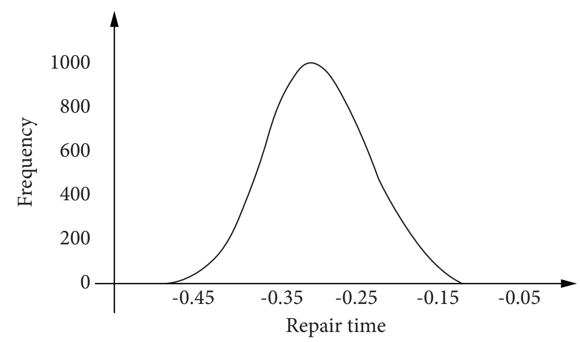

Figure 6: The chart for pre-test distribution simulation of the high-performance calculation of superposition degree with the random weighting method.

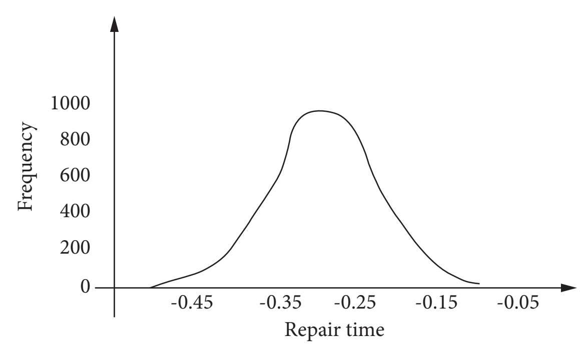

Figure 7: The chart for pre-test distribution simulation of the high-performance calculation of superposition degree with the improved high-performance computing method of the superposition degree method.

$$\begin{aligned} \omega_1 &= 0.6993, \\ \omega_2 &= 0.3002. \end{aligned} \tag{31}$$

Comparing the weight determination methods based on bias and quality factor, the results are shown in Table 2.

According to the analysis of experimental test comparison results, it can be seen that the weight of historical

Table 1: Comparison of mean estimation results.

Method	M estimated value	M confidence interval	μ interval length	Σ estimated value	σ confidence interval	σ interval length
Classical statistics	−0.3152	[−0.4621, −0.1680]	0.2941	0.3229	[0.2483, 0.4713]	0.2230
High-performance computing method of superposition degree	−0.3166	[−0.3182, −0.3149]	0.0033	0.0984	[0.0972, 0.0995]	0.0023
Random weighting method	−0.3064	[−0.3049, −0.3079]	0.0030	0.0834	[0.0824, 0.0845]	0.0021
Improved high-performance computing method of superposition degree	−0.3023	[−0.3036, −0.3010]	0.0026	0.0783	[0.0774, 0.0792]	0.0018

Table 2: Results comparison of different weight determination methods based on credibility weighting.

Method	The prior distribution weight w_1 of historical information	Predistribution weight w_2 of similar equipment information
Based on deviation	0.4966	0.5054
Based on quality factor	0.5066	0.5044
High performance calculation of superposition degree	0.6956	0.3046

data information and similar equipment data can be calculated by using the high-performance calculation of the superposition degree method. According to the experimental results, it can be concluded that there are certain differences. The error of the weight value of the prior distribution of historical data information is relatively large, but compared with the calculation results obtained by the other two methods, the error is relatively small. The average value of the prior distribution of historical data information is similar to the information of similar equipment and is almost the same as the actual test data. Therefore, the weight of the prior distribution of historical information of the equipment accounts for a large proportion, indicating that the test results using the high-performance calculation of superposition degree are more accurate and reasonable, in line with the actual needs of the project.

5. Conclusions

With the continuous development of social economy, the scale of industrialization is also growing, and in the meantime, it has brought a lot of machinery and equipment. When many economic benefits are produced, how to use these devices efficiently and maximally to bring considerable economic benefits is worthy of the attention of the industry and researchers. This paper collects, processes, and distributes the equipment maintainability test data by introducing the high-performance calculation method of superposition degree and proposes the abnormal data that exist with a small probability. According to the collected prior data and on-site collected data, the superposition degree analysis is carried out, which improves the rationality of the weight distribution, performs the corresponding multisource data fusion and processing, and uses the Bayesian method to perform data fusion and high-performance calculation of superposition degree of parameter. The results of the simulation experiments show that the high-performance calculation method of superposition degree is effective, which can effectively support the fusion analysis of multisource data of maintainability, and has certain practical value.

Data Availability

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

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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References

[1] A. Porwal and E. J. M. Carranza, "Introduction to the Special Issue: GIS-based mineral potential modelling and geological data analyses for mineral exploration," *Ore Geology Reviews*, vol. 71, no. 3, pp. 477–483, 2015.

[2] M. Cristina, M. I. López, R. Itziar, and M. P. Callao, "FT-Raman and NIR spectroscopy data fusion strategy for multivariate qualitative analysis of food fraud," *Talanta*, vol. 161, no. 4, pp. 80–86, 2016.

[3] Q. Wu, J. V. Li, F. Seyfried, and C. W. H. T. W. A. J. K. E. N. J le Roux, "Metabolic phenotype-microRNA data fusion analysis of the systemic consequences

of Roux-en-Y gastric bypass surgery," *International Journal of Obesity*, vol. 39, no. 7, pp. 1126–1134, 2015.

[4] F. Comino, M. Ayora-Cañada, V. Aranda, A. Díaz, and A. Domínguez-Vidal, "Near-infrared spectroscopy and X-ray fluorescence data fusion for olive leaf analysis and crop nutritional status determination," *Talanta*, vol. 188, no. 3, pp. 676–684, 2018.

[5] Y. Yu, X. Tang, J. Wu, B. G. Kim, T. Song, and Z. Han, "Multi-leader-follower game for MEC-assisted fusion-based vehicle on-road analysis," *IEEE Transactions on Vehicular Technology*, vol. 2, no. 99, pp. 1–10, 2019.

[6] H. Wu, Y. Han, J. Jin, and G. Zhiqiang, "Novel deep learning based on data fusion integrating correlation analysis for soft sensor modeling," *Industrial & Engineering Chemistry Research*, vol. 60, no. 27, pp. 56–63, 2021.

[7] K. A. Semmens, M. C. Anderson, W. P. Kustas, F. J. G. L. J. H. C. R. C. Y. T. L. M. Gao, and M. Vélez, "Monitoring daily evapotranspiration over two California vineyards using Landsat 8 in a multi-sensor data fusion approach," *Remote Sensing of Environment*, vol. 185, no. 185, pp. 155–170, 2016.

[8] M. O. Williams, C. W. Rowley, I. Mezić, and I. G. Kevrekidis, "Data fusion via intrinsic dynamic variables: an application of data-driven Koopman spectral analysis," *EPL (Europhysics Letters)*, vol. 109, no. 4, Article ID 40007, 2015.

[9] A. Majumder, L. Behera, and V. K. Subramanian, "Automatic facial expression recognition system using deep network-based data fusion," *IEEE Transactions on Cybernetics*, vol. 48, no. 1, pp. 103–114, 2018.

[10] Z. Marinka and Z. Blaz, "Jumping across biomedical contexts using compressive data fusion," *Bioinformatics*, vol. 32, no. 12, pp. 90–100, 2016.

[11] G. Yao, Y. M. Yin, Y. Li, and Y. Haonan, "High-precision and wide-wavelength range FBG demodulation method based on spectrum correction and data fusion," *Optics Express*, vol. 5, no. 4, pp. 1–8, 2021.

[12] C. Song and K. Liu, "Statistical degradation modeling and prognostics of multiple sensor signals via data fusion: a composite health index approach," *IISE Transactions*, vol. 50, no. 10, pp. 853–867, 2018.

[13] J.-H. Cheng and D.-W. Sun, "Data fusion and hyperspectral imaging in tandem with least squares-support vector machine for prediction of sensory quality index scores of fish fillet," *Lebensmittel-Wissenschaft und -Technologie- Food Science and Technology*, vol. 63, no. 2, pp. 892–898, 2015.

[14] Q. Chen, C. Sun, Q. Ouyang, and Y. A. H. J. Wang, "Classification of different varieties of Oolong tea using novel artificial sensing tools and data fusion," *Lebensmittel-Wissenschaft und -Technologie- Food Science and Technology*, vol. 60, no. 2, pp. 781–787, 2015.

[15] D. Zhou, K. Zhang, A. Ravey, and F. A. Gao, "Online estimation of lithium polymer batteries state-of-charge using particle filter-based data fusion with m approach," *IEEE Transactions on Industry Applications*, vol. 52, no. 3, pp. 2582–2595, 2016.

[16] A. Cherchar, M. Thameri, and A. Belouchrani, "Performance improvement of direction finding algorithms in non-homogeneous environment through data fusion," *Digital Signal Processing*, vol. 41, no. 4, pp. 41–47, 2015.

[17] J. Tan, R. Li, and Z.-T. Jiang, "Chemometric classification of Chinese lager beers according to manufacturer based on data fusion of fluorescence, UV and visible spectroscopies," *Food Chemistry*, vol. 184, no. 1, pp. 30–36, 2015.

[18] W. Hao, Y. Pei, L. Bo, K. Zongzhan, L. Xiaoxin, and L. Hao, "Item recommendation in collaborative tagging systems via heuristic data fusion," *Knowledge-Based Systems*, vol. 75, no. 2, pp. 124–140, 2015.

[19] L. F. Ramos, T. Miranda, M. Mishra, and F. M. E. Fernandes, "A Bayesian approach for NDT data fusion: the Saint Torcato church case study," *Engineering Structures*, vol. 84, no. 1, pp. 120–129, 2015.

[20] K. A. Obisesan, A. M. Jiménez-Carvelo, L. Cuadros-Rodriguez, and I. M. P. Ruisánchez, "HPLC-UV and HPLC-CAD chromatographic data fusion for the authentication of the geographical origin of palm oil," *Talanta*, vol. 170, no. 5, pp. 413–418, 2017.

[21] D. Ning, S. Sun, L. Wei, and B. H. W. Zhang, "Vibration reduction of seat suspension using observer based terminal sliding mode control with acceleration data fusion," *Mechatronics*, vol. 44, no. 4, pp. 71–83, 2017.

[22] X. Bai, Z. Wang, L. Sheng, and W. Zhen, "Reliable data fusion of hierarchical wireless sensor networks with asynchronous measurement for greenhouse monitoring," *IEEE Transactions on Control Systems Technology*, vol. 5, no. 5, pp. 1–11, 2018.

[23] A.-R. Mohammadi-Nejad, G.-A. Hossein-Zadeh, and H. Soltanian-Zadeh, "Structured and sparse canonical correlation analysis as a brain-wide multi-modal data fusion approach," *IEEE Transactions on Medical Imaging*, vol. 36, no. 7, pp. 1438–1448, 2017.