

Research Article

Reliability Analysis of Intelligent Electric Energy Meter under Fusion Model Illness Analysis Algorithm

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This work is aimed at solving the morbidity problem of the smart meter fusion model and improve the measurement accuracy and reliability of the smart meter. Starting with the topology of the smart meter, the reason for the serious morbidity of the smart meter model is discussed. First, the basic process of power system state estimation of smart meters is introduced, and the concept of error analysis of smart meters is clarified. Then, the causes and mechanisms of the ill-conditioned problems of the smart meter model are analyzed, and methods to reduce the morbidity of the smart meter calculation model are analyzed. Finally, a data optimization algorithm based on a greedy strategy and an improved Tikhonov regularization method is proposed. The model data is processed and optimized to reduce the morbidity of the smart meter measurement model. The results show that the analysis algorithm for reducing the morbidity error of the smart meter proposed in this study can effectively interfere with the morbidity of the smart meter calculation model. The processing effect shows that it can reduce the measurement error of the smart meter to about 5%, which is an order of magnitude lower than the error before processing, and the processing effect of the least square method is improved by more than 70%. From the perspective of processing speed, when the user number is between 50 and 100, the running time of the algorithm ranges between 1.5 and 3.5 s, which can be fully adapted to the actual situation and has strong practicability. In short, this study is helpful in improving the accuracy and reliability of smart meter calculations and provides a certain reference for related research.

1. Introduction

The smart meter is one of the basic equipment for data collection in the smart grid, and it plays a very important role in the entire smart grid. It is responsible for collecting, measuring, and transmitting raw electric energy data, and for information synthesis, analysis, optimization, and display [1, 2]. In addition to conventional electric meters' basic electric energy measurement functions, smart meters also have two-way multirate metering functions, user-side control functions, and two-way data communication functions [3]. As a powerful sensor terminal, the smart meter plays an essential role in the identification layer of the smart grid. It needs to perform detailed calculations and metering of electric energy for charging. In addition to supplementing

energy billing based on smart meter measurement data, it can also enable and support advanced applications, such as energy consumption behavior analysis, demand response strategy design, and electricity market pricing. The normal operation of the smart grid is guaranteed through the comprehensive operation of these functions [4, 5]. Therefore, whether the smart meter measures electric energy is directly related to the normal operation of the functions as mentioned above. It is also closely related to the vital interests of each user who participates in the use of electricity. Once the smart meter fails, it may affect the transmission and distribution of electric energy, bring troubles to people's lives, and even cause serious losses. Due to the massive and scattered distribution of smart meters, it is very difficult to determine the status of each meter in operation to find and

replace expired or faulty individuals. However, if it is not ruled out and replaced directly in a large area, it will cause a lot of waste of human resources and materials [6, 7].

At present, the common method used to check the status of electric energy meters is sampling verification. The International Organization for Metrology (OIML) established the TC3/SC4 working group to create relevant documents to measure whether private electricity meters can still be used. However, the faults of smart meters are diverse, and it is difficult for sampling verification methods to ensure that all types of faulty meters are tested without omission, which will inevitably cause losses to residents [8, 9]. Some scholars tried to analyze the statistical data of smart meters to find the faults and operating errors of the energy meters. This method of identifying faults in smart meters through data can theoretically realize “full-range state monitoring of energy meters.” However, after it is put into practical application, many errors will be caused due to the influence of the external complex environment and technical means. There are still many technical issues that need to be further studied and resolved. It is mainly reflected in difficulty in obtaining the loss calculation parameters of the station area as well as the poor model conditions, which lead to calculation errors and the inability to form sufficient reference values [10].

Based on the above analysis, the cause and mechanism of the serious morbidity model of the actual smart meter circuit measurement error analysis are analyzed, and methods to weaken the morbidity are discussed. A regularization method based on data preprocessing and improvement is proposed to intervene in the morbidity of the model. In addition, the least square method is introduced as a control group to carry out a simulation experiment to verify the effectiveness of the data preprocessing method, hoping to improve the error calculation accuracy of the electric energy meter.

The remainder of this paper is organized as follows. Section 2 presents some related theories and methods about smart meters. Section 3 considers algorithm verification results and the discussion. Finally, Section 4 provides some concluding.

2. Related Theories and Methods for the Study of Morbidity Models of Smart Meters

2.1. Analysis of Topological Structure Model of Electric Energy Error. The origin of power system state estimation research is traced back to 1970. With the maturity of electronic technology and the development of computer communication technology, power system measurement technology has also been further developed and improved. The related research and application of state estimation have become common, which has become an indispensable part of the power system [11]. It is responsible for helping transmission network operators to obtain real-time status information of the power system, while providing corresponding services for power users. At this stage, estimating the state of the power system is also one of the research hotspots of power energy management systems. It involves functions such as state estimation, data error management, and information prediction. The specific process is illustrated in Figure 1 [12, 13]. In addition, the state

estimation of the power system also includes a reliability analysis and static safety analysis. Today, with the rapid development of network communication technology, the Internet of Everything has become a normal state. Moreover, data has also become a silent language. In 2019, Shen et al. [14] conducted bilingual text mining and analyzed the trend of *Online to Offline* business from the perspective of social media. The results of bilingual text mining were compared according to company, region, service app, and operating mode. The research provides important insights from crowd intelligence and reveals an analysis of recent trends in the development of *Online to Offline* in different language regions. Many needed information can be obtained through data analysis and mining. Therefore, the security control of network power data and the network has become more important. The general electrical topology is illustrated in Figure 1.

With the rapid development of computer technology and communication technology, the concepts of “smart city” and “smart transportation” have emerged one after another. In addition, in terms of power detection and management, new concepts such as smart meters and smart management systems have also emerged [15]. Remote online verification of smart meters in low-voltage stations is essential for maintaining the power grid. It can ensure the stable operation of users’ rights and interests and reduce operating costs and power consumption [16, 17]. However, due to the serious morbidity of the fusion model, the calculation result of the smart meter has a large error, and there are still many uncertain data. The existence of these problems greatly reduces the accuracy of smart meters [18]. The focus of this research is on the serious ill-posed problems of the error analysis model of smart meters. Therefore, the causes and mechanisms of error in mathematical models and ill-conditioned models are analyzed to explore a method to reduce the ill conditions of computational models. The research mainly focuses on smart meters, and the electrical topology of smart meters is illustrated in Figure 2.

In Figure 2, the high-precision energy metering smart meter is used as a total meter to accurately measure the entire system’s electrical energy and power consumption. Smart meters are installed on the user side of each residence [19, 20]. In the actual energy consumption information collection system, the measured value of the total table is defined as the energy consumption of the total station, which is because the accuracy of the total meter in the station area is higher than the accuracy of the counter-supported meter. It is assumed that there is no measurement error in the entire meter, and it is also assumed that the weighted average of the relative errors remains stable within several consecutive measurement periods [21, 22]. In addition, determining the correct relationship between household changes is a basic requirement for theoretical calculations. Suppose the collected power data is insufficient and the optimal amount of data is greater than the number of a single meter. In that case, this problem can be solved by deleting all meter data in the period.

2.2. Error Analysis of Smart Meter. In the topology diagram of the smart meter layout illustrated in Figure 2, it is

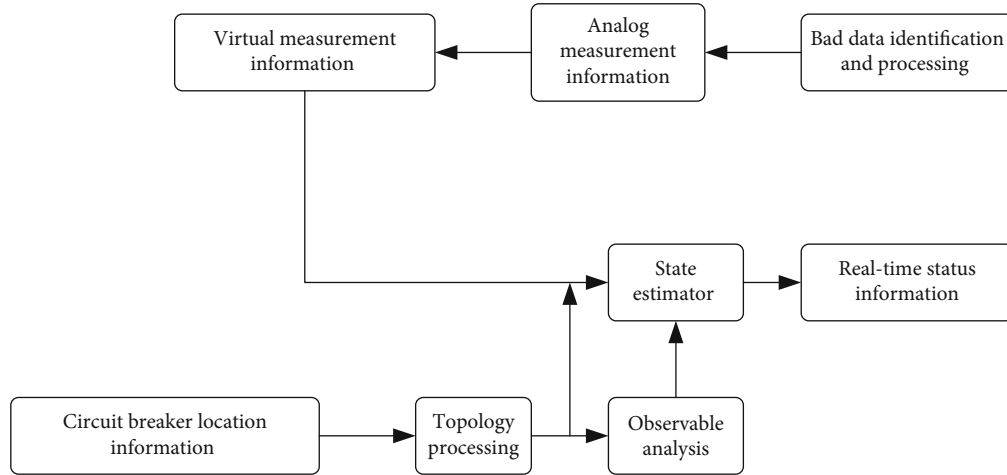


FIGURE 1: Basic process of power system state estimation.

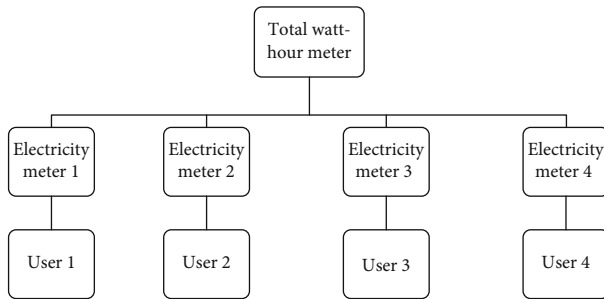


FIGURE 2: Smart meter electrical topology.

assumed that the measurement period of the total meter is a , and c_a is the power consumption of the period a . The number of users in this area is n , the actual power consumption of a user is m , the actual measured power of the smart meter is $a_{x,y}$, and the actual power consumption during the power consumption process is z [23, 24]. Then, in the case that there is no error in the measured value of the total meter, the relationship between the actual power consumption of the user during a certain period of time and the actual power loss during the power process is shown as follows:

$$c_a = z_a = \sum m_{x,y}. \quad (1)$$

It is assumed that the relative error of the electric energy meter is ξ , and the relative error calculation equation is shown as follows:

$$\xi = \frac{a_{x,y} - m_{x,y}}{m_{x,y}} \times 100\%. \quad (2)$$

The real power consumption at this time is expressed as follows:

$$m_{x,y} = \frac{1}{1 + \xi} c_{x,y}. \quad (3)$$

The operation error of the smart meter is obtained by transforming and solving the above equations simultaneously. On this basis, the measurement error involved in the study is not the measurement error at a certain instant, but the overall error level analyzed by the instrument over a period of time.

2.3. Model Ill-Condition Analysis. The measurement error analysis model of the smart meter is represented by a linear equation set, which is shown as follows:

$$Fx = y - m = n. \quad (4)$$

In equation (4), F is the coefficient matrix, x is the measurement error analysis solution vector, y is the total power list of the smart meter, m is the power loss vector of the user's power consumption area, and n is the constant vector measured by the smart meter [25, 26]. In equation (4), the constant vector on the right side of the equal sign of the equation system contains two elements, including the total power of the meter and the power consumption of the user. In general, when the measurement error of a smart meter is calculated theoretically under ideal conditions, the total meter error and the loss in the electricity use process can be ignored. In practical applications, however, many issues need to be considered [27, 28]. The total counter is generally a high-precision counter, and the measurement accuracy is higher than that of the submeter, but there is still no guarantee that there will be no measurement errors. Moreover, the energy loss in the actual electricity use process cannot be completely accurately calculated. The occurrence of these errors and uncertain factors will cause the constant vector value on the right side of the model to be disturbed and become inaccurate. The perturbation of the constant vector-matrix n is amplified in the calculation and solution process of equation (4), which greatly influences the solution of the equation. The specific expression is shown as follows:

$$\frac{\|\omega x\|}{\|x\|} \leq \|F\| \|F^{-1}\| \frac{\|\omega n\|}{\|n\|} = \text{cond}(F) \frac{\|\omega n\|}{\|n\|}. \quad (5)$$

In equation (5), the notation $\|\bullet\|$ denotes the norm. ωx is the perturbation of the vector x , and $\text{cond}(F)$ represents the condition number of the vector matrix. From the above mathematical relationship, the perturbation of the equation system to the vector-matrix will be magnified $\text{cond}(F)$ times, and when it is solved, it will affect the stability of the solution process. The fluctuation of stability is one of the important indicators for judging the morbidity of the model. Generally speaking, when the value of $\text{cond}(F)$ is greater than 103, it will be regarded as a pathological model [29, 30]. If $\text{cond}(F)$ exceeds the rated value, then it indicates that the model is very ill conditioned. The solution (counter error) obtained by the error analysis model of the smart meter is very sensitive to input interference. Even if the solution is completed, the real error value of each subcounter obtained is very large, causing the smart meter to have small fluctuations or large loss errors. Therefore, to calculate the smart meter's operating error, it is necessary to study the ill-conditioned problem of the model and propose a solution algorithm. In addition, it is necessary to reduce the influence of pathological conditions on measurement errors and improve the measurement accuracy of smart meters.

2.4. Discussion on Methods of Reducing Illness of Smart Meter. When the smart meter shows the ill condition of the error calculation model, the two algorithms can eliminate the difficulty in solving the model caused by the poor model condition. These two algorithms are the preprocessing of the measurement data and the regularization of the measurement data.

The preprocessing methods of the measurement data includes two parts of the data optimization algorithm based on the greedy strategy and the row-by-row difference method.

A greedy algorithm means that when a problem is being solved, it always makes the best choice in the current view. Without considering the overall optimality, the algorithm obtains a locally optimal solution in a sense. In this research, the greedy algorithm is applied to intervene in the morbid problems of the smart meter system. The energy consumption information collection system of smart meters can provide measurement data that exceeds the requirements of typical modeling. Choosing different data from these measurement data to build different models will change the morbidity of building models. Therefore, the optimization technique is applied to select the best performing data set from the data pool to make the smart meter error model ill conditioned. The linear equation is solved, and the result shows that when the number of users in the power consumption area is n , n periods of data are needed to represent it. It is assumed that the measurement system provides the measurement data of the m period. There are C_m^n ways to select the data [31]. In this case, a strictly exhaustive method is adopted to calculate the number of conditions in each data set, one at a time, and the amount of calculation and load will become quite large. Based on the above analysis, a data optimization algorithm based on a greedy strategy is proposed to quickly select the most useful data set to solve the model. The solution process is illustrated in Figure 3.

As illustrated in the flow chart of Figure 3, data is deleted from the selected data set in sequence, and the condition number of the matrix obtained after deletion of the corresponding data is saved. The data that meets the minimum number of conditions is found and deleted from the candidate data set, which means that the data is successfully deleted from the candidate data set. The above steps are repeated. Data is deleted until the amount of data in the data set drops to the specified value, then the data set is the output. After the best data set is obtained, the linear equation is optimized by providing a row-by-row finite difference method, which further reduces the number of conditions in the equation coefficient matrix and reduces the ill condition of the solution model. First, the column with the highest cumulative total is found in the coefficient matrix. All rows are sorted in descending order in this column. Then, the two adjacent equations are subtracted one by one to obtain the processed linear equation. Regularization is a concept in linear algebra, which refers to how a complex ill-posed problem is usually defined as a set of linear algebraic equations in linear algebra theory. This set of equations is usually derived from an inverse problem corresponding to an ill-posed problem condition. The use of massive conditions means that rounding errors and other errors will seriously affect the outcome of the problem. The regularization matrix is a diagonal matrix, and the diagonal elements can apply different resistance stresses according to different solutions. Given that different smart meters have different levels of measurement accuracy, the accuracy level of the energy meter is set as the constraint parameter of the corresponding solution.

The regularization method of measurement data is as follows. In this research, an improved Tikhonov regularization method is adopted to further reduce the mathematical model's morbidity. Data preprocessing is carried out to reduce the incidence of the model. The classic Tikhonov regularization method is used to solve the ill-conditioned problem of unfavorable conditions. Due to the prior information of the solution based on two least-squares residual norm constraints, new constraints are added to improve the stability of the solution. A suitable solution is found, such that $Mx = N$ holds for the linear model, and the regularization parameter equation is shown as follows:

$$\underset{x}{\text{Min}}\varphi(x) = \|Mx - N\|_2^2 + \alpha\|P_a x\|_2^2. \quad (6)$$

In equation (6), the value of α is positive, which represents the regularization parameter. P_a represents a normalized matrix, $\|P_a x\|_2^2$ is a norm, and the norm vector is two. x indicates the solution corresponding to the minimum objective function $\varphi(x)$. Although Tikhonov's classic regularization method can eliminate the variability in the solution, it does not provide the option of specifying a range before the resolution. It cannot be directly applied to the solution of the problem in this research. Therefore, the corresponding improvement is needed, and the improved regularization parameter equation is shown as follows:

$$\underset{x}{\text{Min}}\varphi(x) = \|Mx - N\|_2^2 + \alpha\|P_a(x - L)\|_2^2. \quad (7)$$

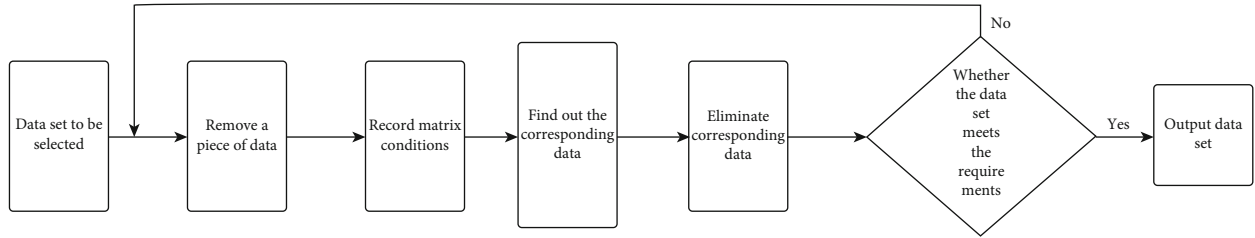


FIGURE 3: Data optimization algorithm flow based on the greedy strategy.

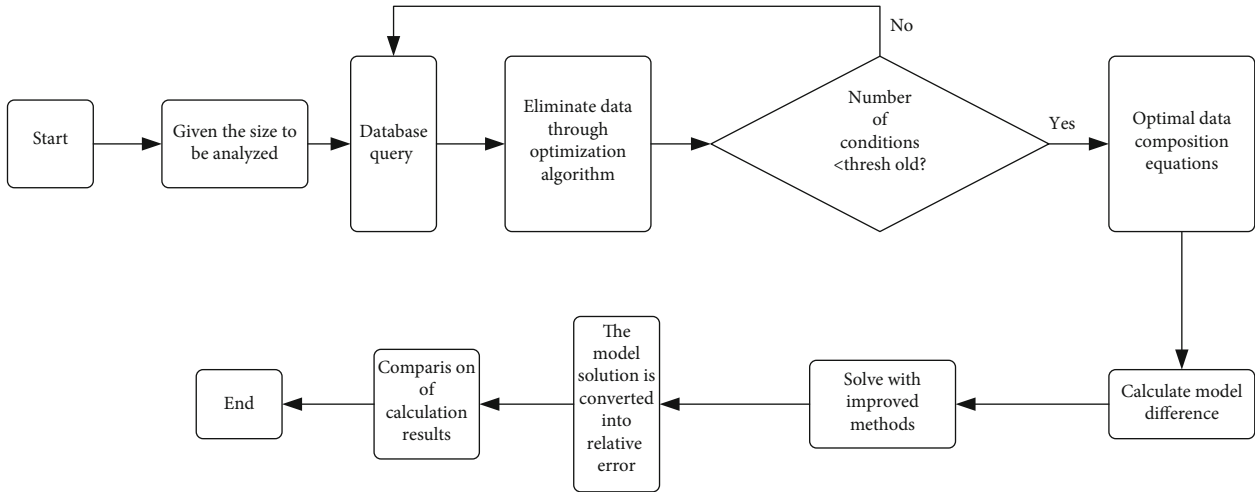


FIGURE 4: Analysis algorithm flow of smart meter to reduce ill-conditioned error.

In equation (7), column vector L is introduced to make the model distributed near the column vector. The value of α is positive, which indicates the regularization parameter. P_a represents a normalized matrix, and x represents the solution corresponding to the minimum objective function $\varphi(x)$. Equation (7) is solved to obtain the following:

$$x = (MM^T + \alpha P_a)^{-1} (M^T N + \alpha P_a L). \quad (8)$$

In equation (8). The value of α is positive, which indicates the regularization parameter. P_a represents a normalized matrix, and x represents the solution of equation (7). In summary, the analysis algorithm flow of the smart meter to reduce ill-conditioned errors is illustrated in Figure 4.

2.5. Performance Evaluation of Smart Meter Operation Error Analysis Algorithm. In this subsection, the effectiveness of the algorithm is verified by experiments. The data used come from the electric energy metering data of a low-voltage station in a city grid, and the universality of the experimental data is considered. The high-rise residential, isolated small residential, old residential, rural radio stations, and laboratory analog radio stations are selected and numbered as 1-5. Each type has data for 365 days a year from 10 such stations. First, all types of station data undergo preprocessing and line-by-line differential data selection. Then, the data

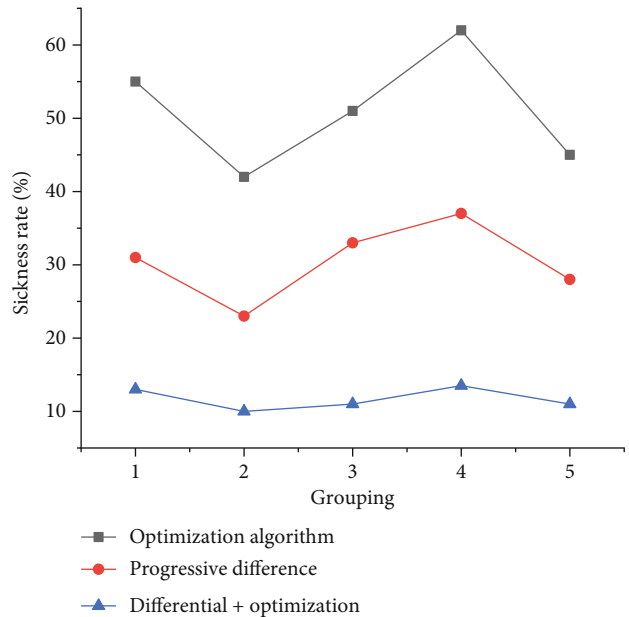


FIGURE 5: The effect of reducing morbidity rate of different treatment methods.

preprocessing strategy is combined with Tikhonov's improvement. The regularization method is adopted to find the measurement error and calculate it by the least square

TABLE 1: The relationship between user scale and running time.

User scale/user number	10	20	30	40	50	60	70	80	90	100
Running time (s)	0.45	0.63	0.92	1.27	1.59	2.01	2.43	2.87	3.35	3.86

method. The actual error of the meter is compared to determine the power of different algorithms to verify the accuracy of the meter error. The test index equation for the effect of pathological reduction is shown as follows:

$$r = \frac{a_o}{a_u} \times 100\%. \quad (9)$$

In equation (9), a_o/a_u is the ratio of the condition number of the original data to the condition number of the processed data.

3. Algorithm Verification Results and Discussion

3.1. Data Preprocessing to Test the Effect of Morbidity Reduction. To test the morbidity reduction effect of the data preprocessing method, three preprocessing methods of row-by-row difference, data optimization, and data optimization after row-by-row difference are applied to test the morbidity reduction effect of different data. The results are illustrated in Figure 5.

Figure 5 shows the effect of the coefficient matrix of the optimization algorithm, the row-by-row difference algorithm, and the combination of the two on the treatment strategy of the ill-conditioned rate. According to the comparison results of three sets of different strategies, the number of conditions in the coefficient matrix after data optimization is reduced to 42%-60% of the number of initial conditions. After the row-by-row differential data processing, the matrix condition number is reduced to 22%-35% of the original condition number. The two methods are combined, and differencing is performed after data optimization. It is found that the morbidity rate drops to about 9%-14%, which is an order of magnitude lower than the original morbidity rate. In summary, all the proposed data preprocessing strategies can effectively reduce the number of conditions in the coefficient matrix for different types of low-voltage substations, thereby reducing the morbidity rate of the model.

After previous discussions, it is found that the user size can also affect the performance of the algorithm. The larger the number of users around the site, the more data is needed, and the demand for data provided by the optimization algorithm will increase, leading to an increase in time-consuming algorithm manipulation. Therefore, it is necessary to calculate the time-consuming algorithm under different user scales, and the calculation results are shown in Table 1.

Table 1 shows the relationship between the user scale and the time required for the algorithm to run, and the selected user scale range is 10-100 households. As the scale

of user usage increases, the data optimization differential algorithm's running time gradually increases and maintains a linear trend. In practical applications, however, the number of users served in a complete low-voltage zone system is roughly in the range of 50-100. When the user number is between 50 and 100, the running time range of the algorithm is between 1.5 and 3.5 s. Due to the linear growth relationship between the two, even if the number of users in the station area increases to about 110, the algorithm's running time will remain below 4 s. In summary, the data preprocessing algorithm proposed in this research can be put into practical application.

3.2. Smart Meter Error and Accuracy Calculation Results. To study the interference effect of the method proposed in this research on the measurement error and accuracy of the smart meter, the error of the smart meter of the users in the low-voltage station area is calculated, and the least square method is introduced as the control group to verify the effectiveness of the algorithm. The comparison result is illustrated in Figure 6.

Figure 6 shows the comparison of the interference error of the least square method and the method proposed on the smart meter. To further reflect the interference effect of data preprocessing on the error of the smart meter, the experimental results of data preprocessing combined with the least square method are also added as a comparison. If the least-squares method is used directly, the ill conditioning of the model will have a great impact on the measurement results of the smart meter, and the error in some nodes may even reach more than 80%, which results in a huge error. If the data is preprocessed first, and then the least square method is applied, it is clear that the relative error of the smart meter is reduced by as much as 60% and maintained at about 20%. From the comparison between the error of the algorithm processing result and the actual error, the data is optimized first, and the relative error value of the result obtained after processing by the difference method is very small, which is close to the true value of the error. Therefore, the data preprocessing method proposed has a significant effect on the morbidity reduction of the model, which can greatly reduce the relative error of the smart meter.

Further analysis of the deviation results of the three different processing methods is performed, and the deviation distribution of the three other methods is obtained. Finally, the specific results are illustrated in Figure 7.

In Figure 7, the deviation results of the three different processing methods are further statistically analyzed. The deviation results of the large and small extremes and the quartile points are selected for display to discuss the interference effect of the method in this paper proposed on the error

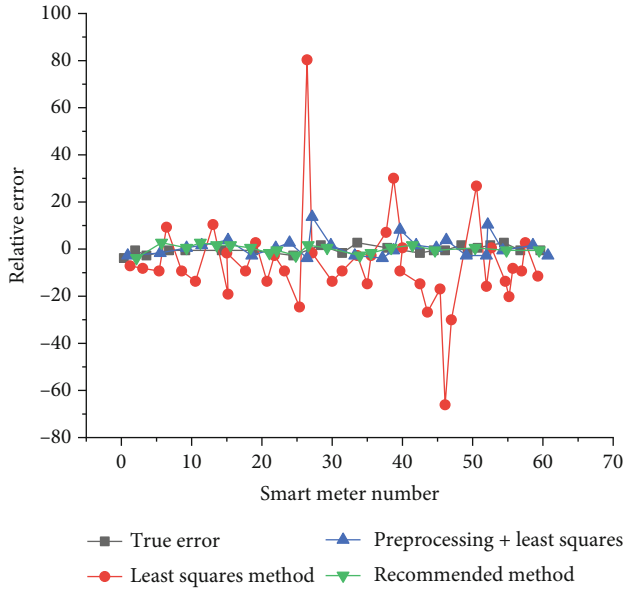


FIGURE 6: Error comparison of different calculation methods.

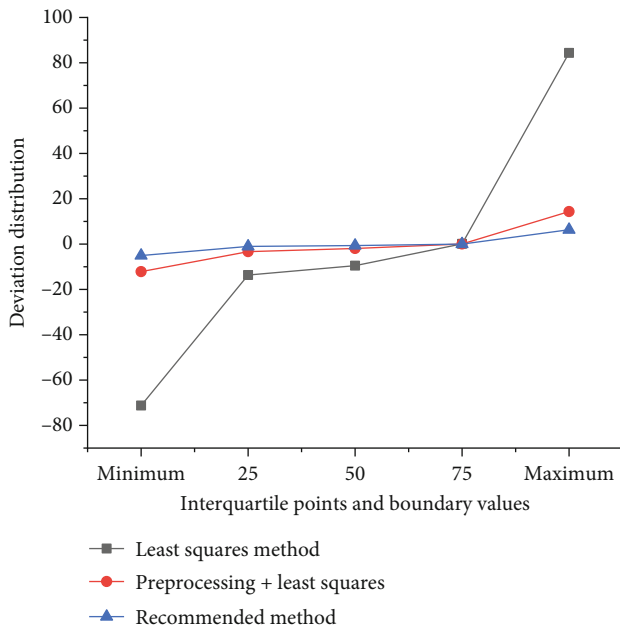


FIGURE 7: Deviation distribution of different calculation results.

of the smart meter. When only the least-squares method is used for processing, the maximum deviation of the smart meter calculation results is 84.53%, and the minimum deviation is -72.14%. After data preprocessing, the least-squares method is used. It turns out that the maximum deviation of the calculation result of the smart meter is 14.43%, and the minimum variation is -12.21%. Then, the proposed method is adopted, and the optimal selection of data is performed first. It is found that the maximum deviation of the calculation result obtained after the regu-

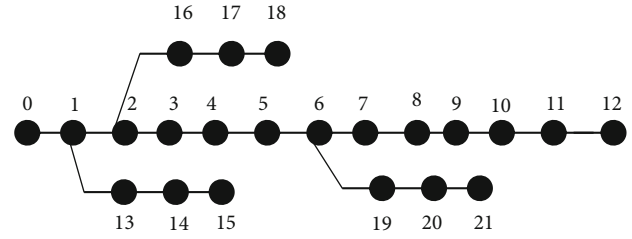


FIGURE 8: Experimental single-line node system.

larization processing is 6.26%, and the minimum deviation is -5.03%. Through the comparison of the above results, the calculation results of the algorithm proposed in this article have smaller errors and more accurate results. Compared with no ill-conditioned treatment method, the algorithm proposed can improve the calculation accuracy of smart meters.

The above results show the overall interference effect of the method proposed on the error of the smart meter. To further explore the effect of the algorithm in this research on each node, seven nodes are randomly selected from the node system illustrated in Figure 8, and the voltage and current at different nodes are measured. The resulting error and phase distribution are illustrated in Figure 9.

In Figure 9, the average voltage amplitude error of the node voltage phase error is 0.0468 V, and the node voltage phase error is 0.000215 rad before the ill-conditioned treatment method is applied. The error of the nodal branch current is 14.49%, and the phase error of the branch current is 0.1328 rad. After the ill-conditioned treatment, the average amplitude error of the node voltage is 0.0015 V, and the error of the node phase voltage is 0.000067 rad. The error of the branch current of the node is 0.2613%, and the phase error of the branch current is 0.004 rad. Thus, after the ill-conditioned processing method is applied, the calculation error of each node is greatly reduced, especially in the current error.

In summary, the analysis algorithm for reducing the ill-conditioned errors of smart meters proposed in this study can effectively interfere with the ill condition of the smart meter calculation model. The processing effect shows that it can reduce the measurement error of the smart meter to about 5%, which is an order of magnitude lower than the error before processing, and the processing effect of the least square method is improved by more than 70%. From the perspective of processing speed, when the user range is between 50 and 100, the algorithm's running time ranges between 1.5 and 3.5 s, which can be fully adapted to the actual situation and has strong practicability. In addition, the data measurement of each node also plays a role in reducing errors. The proposed smart meter reduces the ill-conditioned error analysis algorithm, which can reduce the interference of the morbidity of the fusion model on the measurement accuracy of the smart meter, and the smart meter can accurately reflect the true error level of the electric energy meter.

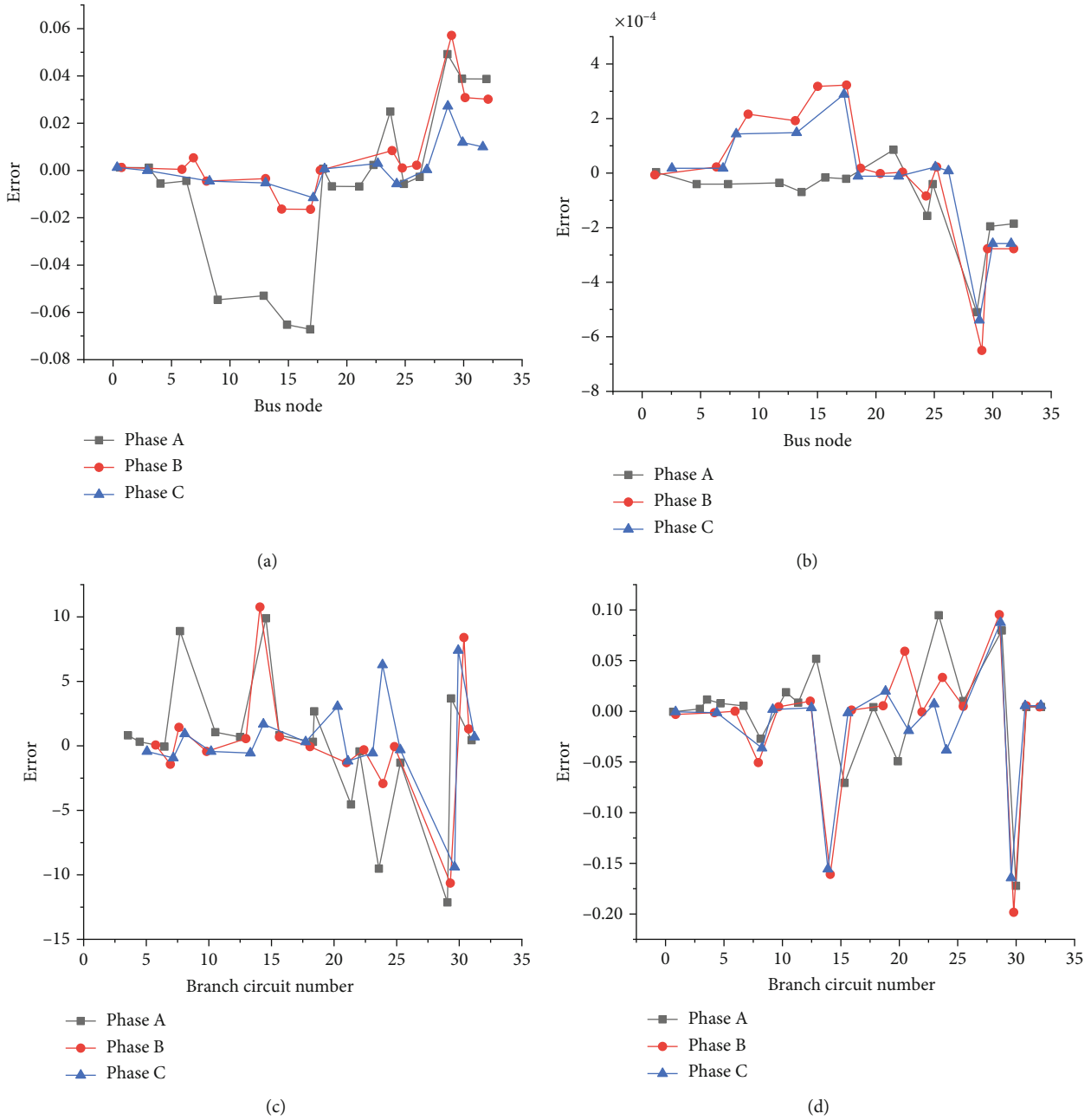


FIGURE 9: Node error and phase distribution of each branch ((a) represents the node voltage amplitude error, (b) represents the node voltage phase error, (c) represents the branch power amplitude error, (d) represents the branch current phase error).

4. Conclusion

To effectively solve the problem of serious morbidity in the smart meter fusion model, data preprocessing and regularization algorithms are used to solve the bad model of the smart meter running error-checking algorithm and improve the actual situation of low calculation accuracy of the smart meter. The results show that the proposed method can effectively solve the difficult problems caused by the ill-conditioned model and remove the verification errors and calculation failures caused by the ill-conditioned model itself due to its nature. For serious problems, it can be used to ver-

ify power measurement and provide operations and deployment operations, providing certain reliable data protection. Although certain research results are harvested in this work, there are still many deficiencies in the research process due to the limitations of the research methods and some objective conditions, which are summarized as follows. First, the ill-conditioned interference method for the smart meter fusion model is only demonstrated in the ideal state, which needs further adjustment and improvement if it is to be put into practical application. Second, the impact of objective problems on the precision of smart meters caused by the environment and service life of smart meters and various

components of the circuit is not taken into account. Third, few control groups are selected in the experiment; therefore, there is no improvement in the method proposed in the research. In future studies, the above three points will be improved, more comprehensive factors will be taken into account, and more control algorithms and experiments will be set up to make the research results more convincing.

Data Availability

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

Conflicts of Interest

The authors declare no competing interests.

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