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Smart meter failure prediction based on weakened grey Markov model with IOWA operator

Ziqi Li[1, 2, 3], Jingqi Xu[1, 4]

[1]West Campus, Wuhan University of Technology, 122 Luoshi Road, Hongshan District, Wuhan, Hubei Province, China
[2]Corresponding author

[3]derekli147@zohomail.com
[4]xujingqibest@163.com

Abstract. Scientifically predicting the annual failure quantity of smart meters is of significant importance for enhancing the economic benefits of smart meters and promoting the stable operation of smart grids. In this paper, traditional Grey Markov prediction models and Grey Markov models with weakened buffering operators are employed to predict smart meter failure data. To improve prediction accuracy, an Induced Ordered Weighted Averaging (IOWA) operator is introduced to construct a combination prediction model. Based on this approach, we predict the annual failure quantity of smart meters for a certain company in Wuhan, China, from 2020 to 2022 using data from 2012 to 2019. Accuracy indicators, such as correlation degree (G) and average relative error (P), have improved from level three to level two, indicating that the combination prediction model based on the IOWA operator effectively enhances prediction accuracy. This method demonstrates the feasibility and effectiveness of predicting smart meter failures.

Keywords: Smart meter, combination prediction, Grey prediction, IOWA operator

1. Introduction

As global attention to energy conservation, emissions reduction, and sustainable development increases, carbon reduction policies have become important objectives in many countries and regions. The electricity industry, as a significant contributor to carbon emissions, faces pressure to reduce emissions. Maintenance and failure prediction of smart meters can help identify and repair faulty meters in a timely manner, reducing energy waste and electricity loss. Faulty meters during operation can lead to energy wastage of over 10%. Precise prediction and repair of these meters can reduce energy consumption and carbon emissions. Additionally, real-time monitoring and prediction of faulty meters enable electricity providers to take preemptive measures, reducing downtime and enhancing power supply reliability.

Scholars both domestically and internationally have conducted research related to the evaluation and lifespan prediction of smart meters. Reference [1] addresses the issue of reliability prediction for smart meters and proposes a Time Delayed Bayesian Network (TDBN) model, which updates conditional probability tables by adding cross-correlation coefficients and time shifts to improve prediction accuracy. Reference [2] builds a degradation model for meters based on failure data from accelerated lifespan tests and estimates the parameters of the Wiener model using the Maximum Likelihood method, thereby

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introducing a smart meter reliability and lifespan prediction model that accounts for nonlinear effects. Reference [3] uses polynomial regression to establish the relationship between the physical properties and lifespan of smart meters based on daily operational data of smart meters and regional transformers, thus creating a lifespan prediction model. Reference [4] employs the random forest algorithm to build a smart meter lifespan prediction model by mining and analyzing accumulated data from numerous smart meters. Reference [5] develops a method for smart meter fault recognition based on the Apriori and C5.0 algorithms, obtaining initial prediction rules through data mining and association rule mining. Reference [6] addresses the characteristics of smart meter fault data and employs normal distribution complementation and box plot methods for data preprocessing, eliminating irrelevant features and resolving issues related to imbalanced fault data. Reference [7] combines time information with spatiotemporal convolutional neural networks to construct a smart meter fault prediction model and optimizes its parameters using the Adam algorithm. Reference [8] designs a deep neural network structure capable of extracting deep attributes of faulty data, using a cost-sensitive multiclass XGBoost model to address the issue of imbalanced multi-class smart meter fault prediction. Reference [9] constructs a smart meter fault identification model based on metering data and various factors influencing smart meter faults to predict whether smart meters will experience metering or non-metering faults. Reference [10] designs a vertical analysis model for running smart meter fault data to evaluate the quality of a batch of meters through fault data analysis.

The aforementioned references [1-4] mainly focus on predicting the remaining lifespan of smart meters, while references [5-9] pertain to the prediction of smart meter fault types, involving various stress models that require substantial computational resources and are challenging to apply in industrial practice. Reference [10] addresses the prediction of smart meter fault data. Furthermore, the models constructed in the above references mostly rely on single models for prediction and demand extensive sample data and substantial computations to achieve accurate predictions. For small-sample and information-scarce smart meter lifespan or fault data, these models face difficulty in making accurate judgments. To address this issue, this paper utilizes Grey Markov models, which exhibit good performance in predicting small-sample data, to predict smart meter failures. In response to the limitation of traditional single prediction models that provide limited information from a single perspective, this paper proposes a combination optimization prediction method. It first uses Grey Markov models and Grey Markov models with weakened buffering operators to make individual predictions. Subsequently, it employs the IOWA operator to calculate the optimal weight coefficients for the two individual prediction models, resulting in a combination prediction model for predicting the annual failure quantity of smart meters. Practical cases demonstrate that this combination prediction method can achieve accurate predictions with only a small amount of smart meter failure data, providing an effective solution for smart meter maintenance and management.

2. Grey Model

2.1. Grey System Theory

Grey system theory is a mathematical approach for dealing with systems that possess incomplete information and uncertainty. It describes the dynamic behavior of a system by establishing grey differential equations and utilizes grey correlation to analyze the development trends and patterns of the system. Grey prediction, established by the renowned scholar Ju-Long Deng in the 1980s, revolves around the core idea of reducing the randomness of disordered sequences through accumulation or attenuation, resulting in structured data sequences that can be analyzed [11]. This method is highly effective for predicting future values of systems characterized by “small samples” and “scarce information.”

2.2. Application of Grey Theory in Predicting Smart Meter Failure Data

Smart meter failures originate from complex sources, and the changes in smart meter failure data constitute a complex dynamic process with random fluctuations. It is challenging to acquire a substantial amount of accurate and comprehensive statistical data on associated factors. The Grey GM(1,1) Markov model is particularly suited for the analysis and prediction of problems with limited, unprototypic, complex, and uncertain data. It serves to attenuate the random factors within irregular initial data sequences, thereby enhancing and revealing the inherent patterns within the data sequences.

2.3. Construction of Grey Prediction Models (GM Models)

Construction Steps:

(1) $x^{(0)}(k)$ represents the original failure data column. To ensure the feasibility of the GM(1,1) modeling method, necessary verification and processing of the known data are required.

$$\lambda(k)=\frac{x^{(0)}(k-1)}{x^{(0)}(k)},k=2,3,.....,n \tag{1}$$

If all the ratios fall within the allowable coverage interval X, a grey model can be established.

$$X=(\mathrm{e}^{\frac{-2}{n+1}},\mathrm{e}^{\frac{2}{n+1}}) \tag{2}$$

Otherwise, appropriate data transformations are applied, such as translation:

$$y^{(0)}(k)=x(0)(k)+c,k=1,2,.....,n \tag{3}$$

Where c is chosen to ensure that all level ratios of the data column fall within the allowable coverage.

(2) Establishment of the grey differential equation for the model:

$$x^{(0)}(k)+\alpha z^{(1)}(k)=q \tag{4}$$

Where α and q represent the development coefficient and grey action quantity, and $z^{(1)}(k)$ denotes the adjacent values and sequences of $x^{(0)}(k)$.

(3) Determination of equation parameters through the least squares method: *a*=(*α*,*q*)*T*=(*BTB*)−1*BTY,* where

$$Y=\begin{pmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ ..... \\ x^{(0)}(n) \end{pmatrix},B=\begin{pmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(3) & 1 \\ ..... & ..... \\ -z^{(1)}(n) & 1 \end{pmatrix} \tag{5}$$

(4) Establishment of the whitening differential equation:

$$\frac{dx^{(1)}}{dt}+ax^{(1)}=q \tag{6}$$

(5) Construction of the time response function:

$$\hat{x}^{(1)}(t+1)=(1-e^{a})(x^{(0)}(1)-\frac{q}{a})e^{-at},t=1,2,.....n \tag{7}$$

(6) Original numerical prediction:

$$\hat{x}^{(0)}(t+1)=\hat{x}^{(1)}(t+1)-\hat{x}^{(1)}(t) \tag{8}$$

Where $x^{(0)}$ is the original sequence, and $x^{(1)}$ is the cumulative sequence.

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3. Grey Model with Weakened Buffer Operator

3.1. Theoretical Basis of the Weakened Buffer Operator

Compared to traditional grey models, the weakened buffer operator can enhance the weight of new information while attenuating the influence of earlier variations. Therefore, when the growth (decay) rate of the first half of the original data sequence is faster, and the growth (decay) rate of the second half is slower, applying the constructed weakened buffer operator to the original data sequence results in a smoother sequence. Additionally, it adheres to the principle of prioritizing new information, meaning that the most recent information remains unchanged under the buffer operator's influence. Consequently, it significantly improves the modeling accuracy of prediction models. The weakened buffer operator effectively eliminates disturbances caused by abrupt changes in the system data sequence during the modeling and prediction process [12, 13].

3.2. Construction of the Grey Model with Weakened Buffer Operator

(1) Construct a new sequence:

$$
\begin{aligned}
y^{(0)}(t) &= \frac{1}{n-t+1}(x^{(0)}(t)+x^{(0)}(t+1)+.....+x^{(0)}(n)) \\
&= \frac{1}{n-t+1}\sum_{j=t}^{n} x^{(0)}(j), t=1,2,.....,n
\end{aligned} \tag{9}
$$

In the construction of the buffer operator described above, each time the transformation occurs, the weights for n-t+1 data points are identical, all being 1/(n-t+1). This implies that these n-t+1 data points contribute equally to the predicted value, which clearly does not align with the "closeness principle." To better consider the impact of new information, a weighted operation is performed on the data.

(2) Weighted operation:

$$
\begin{aligned}
y^{(0)}(t) &= 2\frac{tx^{(0)}(t)+(t+1)x^{(0)}(t+1)+.....+nx^{(0)}(n)}{(n-t+1)(n+t)} \\
&= 2\frac{1}{(n-t+1)(n+t)}\sum_{i=t}^{n} ix^{(0)}(i), t=1,2,.....,n
\end{aligned} \tag{10}
$$

In this operation, the sum of angular codes of the data sequence is used as the denominator for the weights, while the angular code position of each data point in the summed data serves as the numerator for the weights. This approach better reflects the importance of new data, thus increasing the contribution of new data to the prediction value. It adheres to the "closeness principle," and the predicted values obtained in this manner are theoretically more accurate, restoring them closer to the initial values.

4. Markov Chain Correction

4.1. The Theoretical Basis of Markov Chain Correction

Markov chains primarily study the probabilistic relationships between states that may exhibit mobility. The probability of transitioning to a particular state depends solely on the current state and is independent of other states. Due to the inherent fluctuation and randomness in the original sequence, the GM(1,1) prediction model can have some errors in practical applications. This paper extensively overcomes the limitations of the original model's data fluctuations by using first-order Markov chains for residual correction [14]. One of the main characteristics of Markov chains is their lack of memory, that is:

$$
P(X_{t+1}=j \mid X_t=i)=P(X_{t+1}=j \mid X_t=i_t, X_{t-1}=i_{t-1},...,X_0=i_0) \tag{11}
$$

Where $X_n \in E_j$, for any $t \in E$, $i \in E$.

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4.2. Correction Process:

(1) Establishment of the State Transition Matrix:

The relative residuals ε of the grey model and the grey model with the weakened buffer operator are used to divide the correction state intervals based on their magnitudes. Each interval is equally divided with the same spacing, and equal subintervals Ei=[Li, Ui] are established. Finally, a first-order state transition matrix Pij is constructed. This matrix reflects the likelihood of transitions between various residual state intervals, that is, the probability of moving from the current state to the next state:

$$p = (p_{ij}) = \begin{pmatrix} p_{11} & p_{12} & \cdots & p_{1n} & \cdots \\ p_{21} & p_{22} & & p_{2n} & \cdots \\ \cdots & \cdots & & \cdots & \cdots \end{pmatrix} \tag{12}$$

Where $P_{ij} \in [0,1]; \sum_{j=1}^{n} P_{ij}; i, j = 1, 2, ..., n$

P_{ij} represents the probability of transitioning from state i to state j, and the transition matrix for moving n steps can be derived as:

$$P_{(n)} = [P_{(1)}]^n \tag{13}$$

(2) Corrected Prediction:

Specific intervals Ei are determined through the transition matrix. The corrected values for the Grey Markov model and the Grey Model with Weakened Buffer Operator are calculated as:

$$y = \frac{\hat{x}^{(0)}(k)}{1 \pm 0.5 \times (L_i + U_i)} \tag{14}$$

5. Traditional Grey Markov Model for Failure Prediction

Based on the methods mentioned above, which involve the Grey Model and Markov correction chain, we conducted traditional Grey Markov prediction on the maintenance data of smart meters for a certain company in Wuhan, as shown in Table 1, covering the years 2012 to 2019. By fitting the data from the first 8 years, we constructed a traditional Grey Markov model and applied it to predict the data for the years 2020 to 2022 to assess its predictive accuracy. The total number of smart meters in this batch was 27,000.

Table 1. Maintenance Data for Smart Meters in a Wuhan Company

Year	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Failure Count	100	131	173	231	348	435	605	782	903	1060	1302

Using the Grey Model:

$x_{(1)}^{(0)} = 100$, $x_{(2)}^{(0)} = 131$, $x_{(3)}^{(0)} = 173$, $x_{(4)}^{(0)} = 231$, $x_{(5)}^{(0)} = 348$, $x_{(6)}^{(0)} = 435$, $x_{(7)}^{(0)} = 605$, $x_{(8)}^{(0)} = 782$

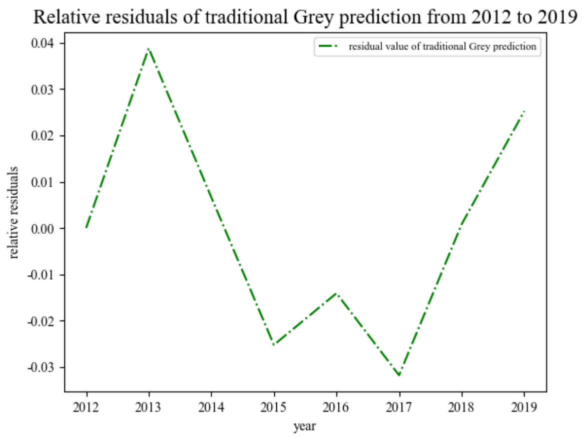

Figure 1. Relative Residual Values Predicted by the Traditional Grey Model

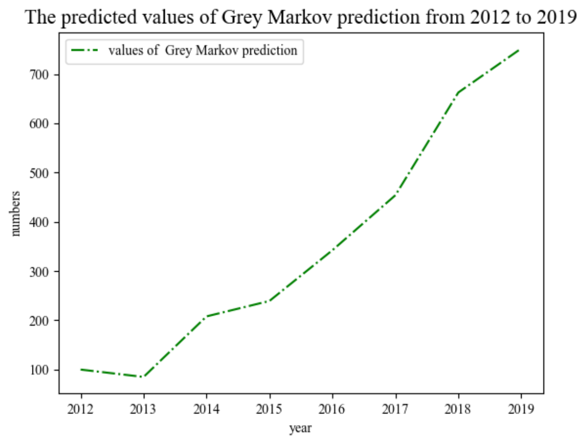

Figure 2. Predicted Values after Markov Chain Correction

Based on the establishment of the traditional Grey prediction model as described in section 2.2, relative residuals $\varepsilon_{(k)}$ were obtained, as shown in Figure 1. These residuals were divided into three corresponding state intervals: [-0.031, -0.0075], [-0.0075, 0.016], and [0.016, 0.0395], following the Markov chain correction method outlined in section 3.2. This yielded the predicted values of the Grey Markov model, which are presented in Table 2.

Table 2. Predicted Values by the Traditional Grey Markov Model

Year	2012	2013	2014	2015	2016	2017	2018	2019
Failure Count	100	85.018	207.956	239.321	342.345	453.934	662.544	751.943

6. Fault Prediction with Grey Markov Model and Weakened Buffer Operator

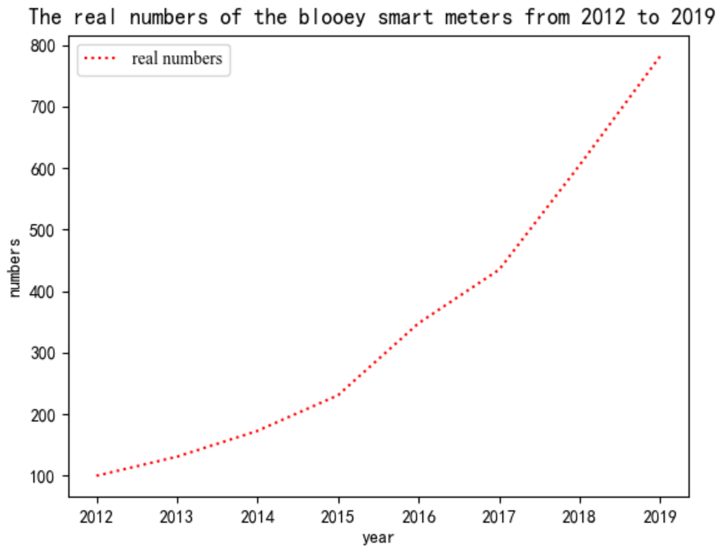

Figure 3. Actual Fault Data for Smart Meters from 2012 to 2019

Analyzing the data in Figure 3, it is evident that there was a relatively smooth increase in faults from 2012 to 2015, followed by an upward trend from 2015 to 2019. To achieve precise prediction for fault data from 2020 to 2022, it is essential to weaken the influence of earlier variations and enhance the

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contribution of new information. The introduction of the weakened buffer operator effectively achieves this and reduces prediction errors.

Utilizing the weakened buffer operator and the Markov correction chain methods described earlier, we conducted fault prediction with the Grey Markov model while applying the weakened buffer operator to the data in Table 1. We constructed a sequence after processing with the weakened buffer operator.

$$y_{(1)}^{(0)}=180.5,\ y_{(2)}^{(0)}=256.2,\ y_{(3)}^{(0)}=341.9,\ y_{(4)}^{(0)}=465.2,\ y_{(5)}^{(0)}=616.1$$

The aforementioned sequence was subjected to level ratio testing, and it was found that it did not fall within the allowable coverage interval X. To address this, a translation process was applied, resulting in the sequence:

$$y_{(1)}^{(0)}=1180.5,\ y_{(2)}^{(0)}=1256.2,\ y_{(3)}^{(0)}=1341.9,\ y_{(4)}^{(0)}=1465.2,\ y_{(5)}^{(0)}=1616.1$$

Using the least squares method, we obtained a = -0.085 and b = 1089.4. The GM(1,1) grey differential equation was transformed into the corresponding white differential equation:

$$\hat{y}^{(1)}(t+1)=(y^{(0)}(1)-\frac{1089.4}{-0.085})e^{0.085t}-\frac{1089.4}{0.085},t=1,2,.....n \tag{15}$$

This allowed us to calculate:

$$\hat{y}^{(0)}(t+1)=\hat{y}^{(1)}(t+1)-\hat{y}^{(1)}(t) \tag{16}$$

Through a reverse transformation of the buffer operator sequence, the corresponding predicted values were deduced:

$$\hat{x}_{(5)}^{(0)}=1313.8,\ \hat{x}_{(6)}^{(0)}=1489.08,\ \hat{x}_{(7)}^{(0)}=1603.28,\ \hat{x}_{(8)}^{(0)}=1737.73$$

By substituting the relative residual values $\varepsilon_{(k)}$ into the Markov chain and applying the necessary residual correction, we obtained the corrected predicted values. Finally, subtracting the translation factor c = 1000 yielded the ultimate practical predicted values in Table 3.

Table 3. Predicted Values with Weakened Buffer Operator Grey Markov Model

Year	2012	2013	2014	2015	2016	2017	2018	2019
Predicted Fault Count	100	124.087	165.830	223.476	279.024	479.977	593.480	727.108

The predicted values were subjected to error testing, and the accuracy levels are presented in Table 4. The original sequence's variance was s_1^2, and the average relative error was p=0.0647, falling within the third level of accuracy. The correlation coefficient λ was calculated as the discrimination coefficient, taken as 0.5. Thus:

$$g(k)=\frac{\varepsilon_{\min}+\lambda\varepsilon_{\max}}{\left|\varepsilon^{(0)}(k)\right|+\lambda\varepsilon_{\max}} \tag{17}$$

Where ε_{min} and ε_{max} represent the minimum and maximum residual values of the prediction results, respectively:

$$G=\frac{1}{n-1}\sum_{k=1}^{n}g(k)=0.767 \tag{18}$$

G falls within the third level of accuracy:

$$\rho=\rho(\left|\Delta^{(0)}(k)-\bar{\Delta}^{(0)}(k)\right|<0.6745s1)=1 \tag{19}$$

Where $\Delta_{(0)}(k)$ represents the residual of the prediction results, and s_1^2 is the variance of the original sequence.

Table 4. Accuracy Levels

Accuracy Level	Average Relative Error	Variance Ratio	Small Error Probability	Correlation
Level 1	$\bar{p}$<0.01	0.35>C	0.95<ρ	G>0.9
Level 2	0.01<= $\bar{p}$<0.05	0.35<=C<0.50	0.85<ρ<=0.95	0.8<G<=0.9
Level 3	0.05<= $\bar{p}$ <0.1	0.50<=C<0.65	0.70<ρ<=0.85	0.7<G<=0.8
Level 4	$\bar{p}$>=0.1	C<=0.65	ρ<=0.70	0.6<G<=0.7

7. Establishment of Combination Models Based on the IOWA Operator and Fault Prediction

By comparing the correlation coefficient G and average relative error p, it is apparent that the Grey Markov model with the weakened buffer operator, as discussed previously, falls into the third level of accuracy and is not ideal for predictions. To further enhance the model's predictive accuracy, this paper adopts the Induced Ordered Weighted Averaging (IOWA) operator's combination forecasting method. This method assigns weights in order of the predictive accuracy of each individual forecasting method for sample points. The combination prediction is based on the criterion of minimizing the sum of squared errors [15, 16].

7.1. Establishment of the Combination Model Based on the IOWA Operator

The actual data sequence is denoted as x, and its value at time t is x_t. We consider m possible individual forecasting methods for x, and let x_{it} represent the predicted value for the i-th forecasting method at time t. Furthermore, a_{it} represents the prediction accuracy of the i-th forecasting method at time t. We define:

$$a_{it} = \begin{cases} 0,\ when\ \left|\frac{x_t - x_{it}}{x_t}\right| > 1 \\ 1 - \left|\frac{x_t - x_{it}}{x_t}\right|,\ when\ \left|\frac{x_t - x_{it}}{x_t}\right| \le 1 \end{cases} (i = 1,2, \ldots m, t = 1,2, \ldots ., N) \quad (20)$$

W=(w1, w2, …, n) as an ordered weighted average vector for various forecasting methods in the combination prediction. We arrange the forecasting methods based on their prediction accuracy, and $x_{a\text{-}index(it)}$ represents the predicted value corresponding to the i-th prediction accuracy for time t. Therefore, the predicted value based on the IOWA operator at time t is given by:

$$\hat{x}_t = IOWA(\langle a_1(t), x_{1t}\rangle, \langle a_2(t), x_{2t}\rangle, \ldots.., \langle a_m(t), x_{mt}\rangle = \sum_{i=1}^{m} w_i x_{a-index(it)} \quad (21)$$

Here, $e_{a\text{-}Index(it)}=x_t-x_{a\text{-}Index(it)}$ and the total sum of squares can be calculated as:

$$S = \sum_{t=1}^{N}(x_t - \hat{x}_t)^2 = \sum_{t=1}^{N}(x_t - \sum_{i=1}^{m} w_i x_{a-index(it)})^2 = \sum_{i=1}^{m} \sum_{j=1}^{m} w_i w_j (\sum_{t=1}^{N} e_{a-index(it)} e_{a-index(jt)}) \quad (22)$$

Let $E_{ij} = \sum_{t=1}^{N} e_{a-index(it)} e_{a-index(jt)} (i = 1,2,\ldots..,m, j = 1,2,\ldots..,m)$, $E = (E_{ij})_{m\times m}$ be the induced ordered weighted average combination prediction error information matrix. Therefore, the induced ordered weighted average combination prediction model can be expressed as follows:

$$\min S(W) = \sum_{i=1}^{m} \sum_{j=1}^{m} w_i w_j (\sum_{t=1}^{N} e_{a-index(it)} e_{a-index(jt)}) = WEW^T, s.t. \begin{cases} \sum_{i=1}^{m} w_i = 1 \\ w_i \ge 0 \end{cases} \quad (23)$$

This allows us to calculate the optimal weight coefficients and obtain the unique solution for the model.

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7.2. Fault Prediction with the Combination Model Based on the IOWA Operator

Following the establishment process of the combination model based on the IOWA operator as described above, we can substitute the weakened buffer operator Grey Markov model and the Grey Markov model into the error information matrix [17, 18]:

$$E = \begin{pmatrix} 1582.409226971804 & 2233.2462595233874 \\ 2233.2462595233874 & 16510.51865019062 \end{pmatrix} \tag{24}$$

As a result, the combination prediction model is given by:

$$\min S = 1582.409226971804\, w_1^2 + 16510.51865019062 w_2^2 + 4466.492519046775 w_1 w_2, s.t. \begin{cases} w_1 + w_2 = 1 \\ w_1, w_2 \geq 0 \end{cases} \tag{25}$$

We get $w_1 = 0.99, w_2 = 0.01$. This model provides the corresponding predicted value $\hat{x}_t - x_{a-index(it)}$, as presented in Table 5, and the error values are presented in Table 6. Visualization of the results can be seen in Figure 4.

Table 5. Predicted Values for Various Models

Year	Actual Value	Predicted Value for Grey Markov Model with Weakened Buffer Operator	Predicted Value for Grey Markov Model	Combined Model Predicted Value
2012	100	100.000	100.000	100.000
2013	131	124.087	85.018	123.696
2014	173	165.830	207.956	166.251
2015	231	223.476	239.321	223.634
2016	348	279.024	342.345	341.712
2017	435	479.977	453.934	454.194
2018	605	593.480	662.544	594.170
2019	782	727.108	751.943	751.695

Table 6. Error Values for Various Models

Year	Error Value for Grey Markov Model with Weakened Buffer Operator	Error Value for Grey Markov Model	Combined Model Error Value
2012	0.000	0.000	0.000
2013	0.052	0.351	0.055
2014	0.041	-0.202	0.039
2015	0.033	-0.036	0.032
2016	0.198	0.016	0.018
2017	-0.103	-0.043	0.044
2018	0.019	-0.095	0.018
2019	0.070	0.038	0.039

The combined prediction model underwent post-analysis, yielding P=0.0306, which is in the second accuracy level, and G=0.821, also in the second accuracy level. Thus, the combined prediction model elevates the accuracy levels of P and G by one level.

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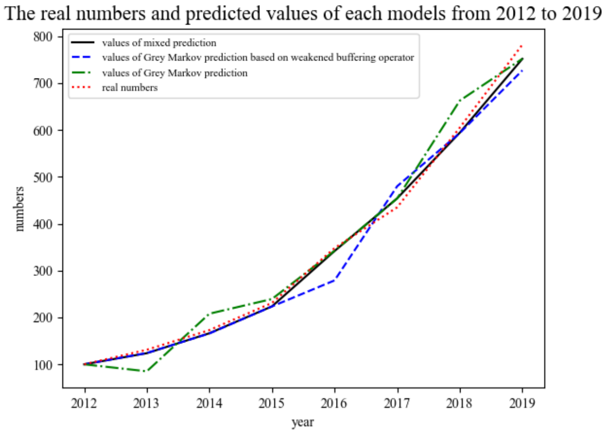

Figure 4. Predicted Values and Actual Values for Various Models

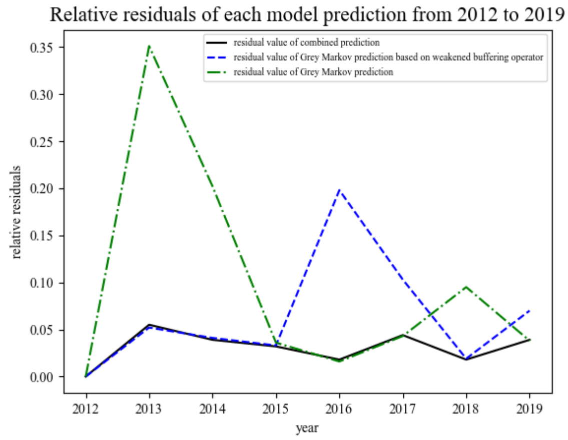

Figure 5. Relative Residual Values for Various Models

From the prediction chart, it can be deduced that the Grey Markov model with the weakened buffer operator exhibits high accuracy in the early stages but has some fluctuations in the middle and later stages. In contrast, the Grey Markov model displays higher fluctuations in the early stages but better fits the data in the middle and later stages. However, the combined model leverages the strengths of both models, making better use of existing data resources. Through training, it can provide more accurate predictions for smart meter fault data. Therefore, this combined model is chosen to predict the fault counts for smart meters in 2020 to 2022, as shown in Table 7.

Table 7. Predicted Smart Meter Fault Counts for 2020-2022 by Various Models

Year	Predicted Value for Grey Markov Model with Weakened Buffer Operator	Predicted Value for Grey Markov Model	Combined Model Predicted Value
2020	923.115	886.689	921.560
2021	1040.897	1104.553	1043.923
2022	1264.631	1250.650	1263.391
Average Relative Error p	0.02275	0.03293	0.02141

Analysis of the average relative error p indicates that the combination prediction outperforms the individual models' predictions.

In summary, the process for predicting smart meter fault counts is illustrated in Figure 6.

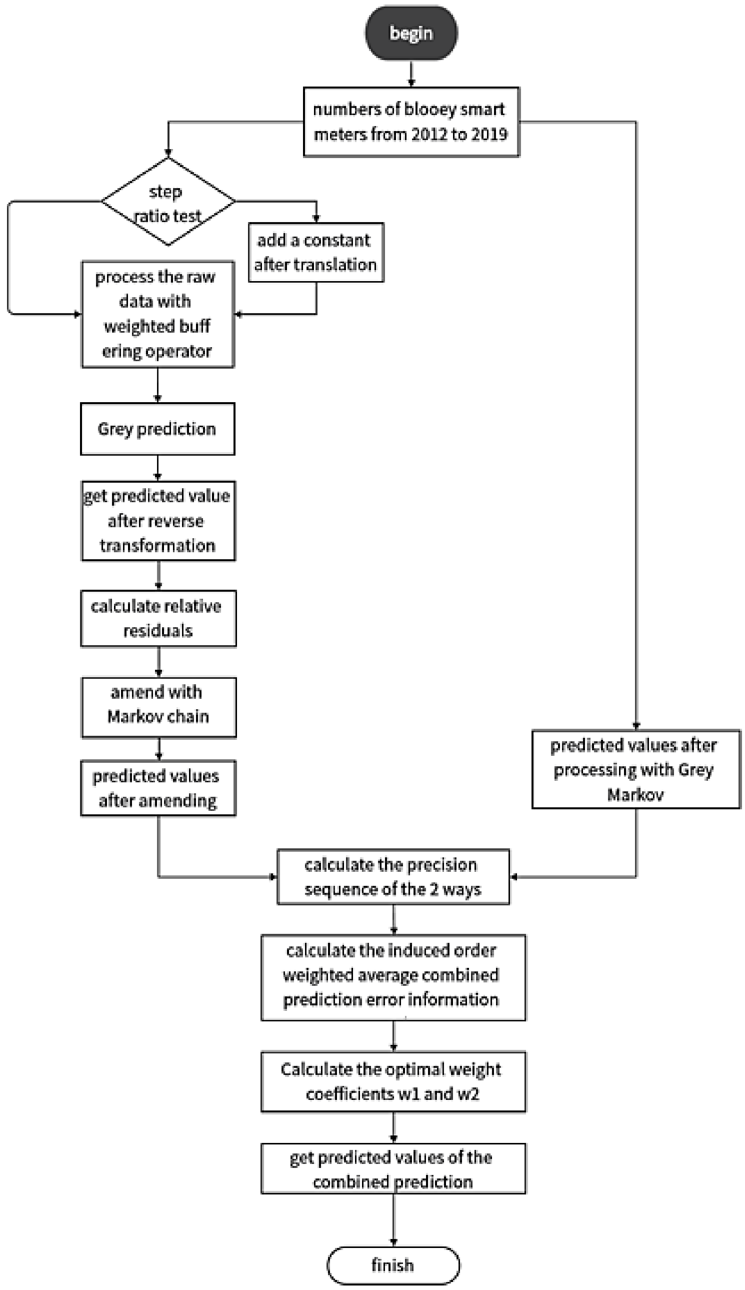

Figure 6. Flowchart of Smart Meter Fault Count Prediction Process

8. Conclusion

In summary, for the fault prediction of smart meters with limited information, a comprehensive comparison of posterior error p, C, and correlation coefficient G indicates that the combination model has distinct advantages. Therefore, the combined Grey Weakened Buffer Markov model based on the IOWA operator, compared to the methods in the literature [19-20], significantly improves prediction accuracy, enabling more precise medium- to long-term fault predictions. Through an overall prediction of the number of faults, this method can reveal potential issues and fault trends for smart meters. For instance, the growth trend in fault data can be used to assess whether the batch of meters meets quality standards. Predictive data for the coming year can be used to estimate the power supply instability and economic losses resulting from meter faults and maintenance, thereby providing data support for decisions on whether to replace this batch of meters or implement comprehensive meter maintenance. For example, by accurately predicting the number of faults, a company can make informed decisions on the allocation of maintenance personnel and fault handling resources, formulate relevant maintenance plans and strategies, proactively procure necessary spare parts and equipment, reduce prolonged power outages and energy losses due to faults, and subsequently improve the reliability and stability of the power grid. This approach plays a crucial role in guiding the maintenance of smart meters.

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