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Research Article

Electricity Consumption Prediction for Xinjiang Electric Energy Replacement

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In recent years, the phenomenon of wind and solar energy abandoned in Xinjiang's new energy has become severe, the contradiction between the supply and demand of the power grid is obvious, and the proportion of power in the energy consumption structure is relatively low, thus hindering the development of Xinjiang's green power. In this context, the focus of Xinjiang's power has shifted to promote the development of electric energy replacement. Therefore, using the Xinjiang region as an example, we first select the important indicators such as the terminal energy substitution in Xinjiang, added value of the secondary industry, population, terminal power consumption intensity, and per capita disposable income. Subsequently, eight combined forecasting models based on the grey model (GM), multiple linear regression (MLR), and error back propagation neural network (BP) are constructed to predict and analyse the electricity consumption of the whole society in Xinjiang. The results indicate the optimal weighted combination forecasting model, GM-MLR-BP of the induced ordered weighted harmonic averaging operator (IOWHA operator), exhibits better prediction accuracy, and the effectiveness of the proposed method is proven.

1. Introduction

Xinjiang is located in the northwest of China and contains abundant energy resource. In addition to the three major oil fields, the nine major coal fields, and other fossil resource mining bases, nine wind zones and renewable energy power generation bases such as those for solar energy exist. Among them, the total amount of wind and solar energy of Xinjiang ranks second in China, including wind power of approximately 3 trillion kW·h, and reserve of solar energy of approximately 20 trillion kW·h that provide a solid material foundation for the development of Xinjiang's national economy and electric energy replacement [1, 2]. In addition, a low-level industrial structure, an unbalanced regional economy, highly extensive energy consumption, and increasingly prominent environmental problems exist. Severe air pollution has restricted the economic development of Xinjiang, but the application of electric energy in the terminal consumption is significantly better than that of fossil fuel. With the introduction of energy-saving and emission-reduction policies, the proportion of clean energy generation is increasing. The replacement of energy in the terminal is critical for reducing urban pollutant emissions. According to statistics, as of March this year, Xinjiang Electric Power Company has implemented 6,408 electric energy replacement projects, achieving a total of 8.272 billion kW·h of electricity, thus effectively reducing the consumption of 2.895 million tons of standard coal, reducing carbon dioxide emissions by 7.238 million tons, thus reducing the use of terminal direct-fired coal and direct fuel significantly, and promoting the "electrification" process of various industries [3]. Therefore, it is critical both theoretically and economically to study the power consumption forecasting method under the background of Xinjiang electric energy replacement to maintain the safe, efficient, and stable operation of the power grid system.

Currently, many methods exist for predicting electric load in China. According to the structure of the model, it can be divided into the single prediction method and combined prediction method. Among them, single prediction methods include the time series method [4–6], linear regression method [7–9], grey forecasting method [10, 11], support vector machine [12–14], and BP neural network [15–17]. However, any single prediction method in practical applications, owing to their own defects, causes insufficient prediction accuracy, and it is difficult to accurately predict the future power consumption level of the region. The combined prediction model can comprehensively utilise the information provided by various methods and assign different weights according to the precision of the single prediction method, which is helpful to improve the scientificity and effectiveness of the prediction. The literature [18] analysed the annual peak load changes in Guangzhou and considered the electricity consumption situation in Guangzhou from the perspective of the annual peak load, total output value of the three major industries, population, and the per capita Gross Domestic Product (GDP). Subsequently, the variance-covariance method based on the combined BP neural network, grey prediction model, and multiple linear regression method is proposed to predict the annual maximum load in 2017–2019. The literature [19] selected the total social electricity consumption data of Anhui province from 2000 to 2014 and constructed multiple linear regression based on the economics such as the population, GDP, total energy consumption, household consumption level, and per capita disposable income of urban households. The combined predictive model of the IOWA operator, IOWHA operator, and IOWGA operator based on the multiple linear regression, double exponential smoothing, and polynomial fitting is constructed to predict the total social power consumption in Anhui province for the next five years. However, it is rare to study the long-term load forecasting method under the electric energy replacement in Xinjiang from the perspective of electric energy replacement and electricity intensity. Therefore, we use the IOWHA preferred combination prediction model based on the grey forecasting method, multiple linear regression, and BP neural network (GM-MLR-BP) to analyse the influence of the terminal electric energy replacement amount, terminal electric energy consumption intensity, added value of the second industry, population, and per capita disposable income of residents in the whole district. The experimental results indicate that the prediction method is effective, and a new idea for regional electricity consumption forecasting under electric energy replacement is provided.

2. Background Theory

2.1. GM (1, 1)

2.1.1. Model Principle. The grey prediction model is a prediction method based on a small amount of incomplete information to establish a mathematical model and predict the future development trend. Through the correlation analysis of system factors, raw data are generated and processed, and the data sequence with strong regularity is generated to obtain the law of system variation to establish the corresponding differential equation model to solve the predicted value. The prediction method is simple to operate and contains a wide range of applications in the field of prediction. Because only a small amount of information is required in the modelling process, high precision requirements can be achieved; therefore, it is also an effective tool for handling small sample prediction problems [20–23].

2.1.2. Modelling Steps. (1) Suppose the raw data sequence of electricity consumption is $\mathrm{X}^{(0)}$,

$$\mathrm{X}^{(0)} = \left[\mathrm{x}^{(0)}(1), \mathrm{x}^{(0)}(2), \ldots, \mathrm{x}^{(0)}(\mathrm{n})\right] \tag{1}$$

$$\mathrm{X}^{(0)}(\mathrm{k}) \geq 0 \quad (\mathrm{k} = 1, 2, \ldots, \mathrm{n}) \tag{2}$$

(2) $\mathrm{X}^{(0)}$ is subjected to an additive preprocessing to generate a new sequence $\mathrm{X}^{(1)}$,

$$\mathrm{X}^{(1)} = \left[\mathrm{x}^{(1)}(1), \mathrm{x}^{(1)}(2), \ldots, \mathrm{x}^{(1)}(\mathrm{n})\right] \tag{3}$$

$$\mathrm{X}^{(1)}(\mathrm{k}) = \sum_{\mathrm{i}=1}^{\mathrm{k}} \mathrm{X}^{(0)}(\mathrm{i}) \quad (\mathrm{k} = 1, 2, \ldots, \mathrm{n}) \tag{4}$$

(3) Establish a corresponding Albino equation:

$$\frac{d\mathrm{X}^{(1)}}{dt} + a\mathrm{X}^{(1)} = u \tag{5}$$

where n is the number of the raw data sequence and a and u are the parameters.

(4) Suppose $A = [\hat{a}, \hat{u}]^{T} = (B^{T}B)^{-1}B^{T}Y_{n}$. Calculate data Array B and data Column Y_n, and solve the parameters $\hat{a}$ and $\hat{u}$,

where A is the pending parameter; $\hat{a}$ and $\hat{u}$ are the predictive values of a and u, respectively; B and Y_n are the known quantities that can be obtained by the following two formulas, respectively:

$$B = \begin{bmatrix} -\frac{1}{2}\left[x^{(1)}(1) + x^{(1)}(2)\right] & 1 \\ -\frac{1}{2}\left[x^{(1)}(2) + x^{(1)}(3)\right] & 1 \\ \vdots & \vdots \\ -\frac{1}{2}\left[x^{(1)}(n-1) + x^{(1)}(n)\right] & 1 \end{bmatrix} \tag{6}$$

$$Y_n = \begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \vdots \\ x^{(0)}(n) \end{bmatrix} \tag{7}$$

(5) Substitute the obtained $\hat{a}$, $\hat{u}$ into formula (5), which can obtain

$$\frac{d\mathrm{X}^{(1)}}{dt} + \hat{a}\mathrm{X}^{(1)} = \hat{u} \tag{8}$$

(6) The generation sequence of GM(1,1) is obtained by the discretisation of equation (9); the grey model is as follows:

$$\hat{X}^{(1)}(k+1) = \left[x^{(0)}(1) - \frac{\hat{u}}{\hat{a}}\right] e^{-ak} + \frac{\hat{u}}{\hat{a}} \tag{9}$$

where $k = 0, 1, 2 \cdots$.

(7) After the subtractive reduction of (5), the grey prediction model is obtained as follows:

$$\begin{aligned} \hat{X}^{(0)}(k+1) &= \hat{X}^{(1)}(k+1) - \hat{X}^{(1)}(k) \\ &= \left(1 - e^{-a}\right)\left[x^{(0)}(1) - \frac{\hat{u}}{\hat{a}}\right] e^{-ak} \end{aligned} \tag{10}$$

where $k = 0, 1, 2 \cdots$.

2.2. Multiple Linear Regression (MLR)

2.2.1. Model Principle. MLR is based on the optimal combination of multiple independent variables to predict or estimate the dependent variable and subsequently establish a statistical method for the quantitative relationship of linear mathematical models of multiple variables. It reflects the relationship between a phenomenon and a variety of influencing factors. Therefore, it is used widely in all aspects of society [24–26].

Suppose $x_1, x_2, \ldots, x_i$ $(i \geq 2)$, where i are independent variables without collinearity, Y is a dependent variable; therefore, the MLR model is expressed as follows:

$$Y = \alpha_0 + \alpha_1 x_1 + \alpha_2 x_2 + \cdots + \alpha_i x_i + \varepsilon \tag{11}$$

$$\varepsilon \sim N\left(0, \sigma^2\right) \tag{12}$$

where $\alpha_0, \alpha_1, \alpha_2 \cdots \alpha_i$ are the unknown parameters; α_0 is a constant;

$\alpha_1, \alpha_2, \cdots, \alpha_i$ are the regression coefficients of the multiple linear equation;

$\varepsilon \sim N(0, \sigma^2)$ is a random error.

2.2.2. Modelling Steps

(1) Filter the problem's independent variables x_1, $x_2 \cdots x_p$ $(p \geq 2)$ and dependent variable Y. Perform the correlation analysis and collinearity diagnostics of the data using SPSS software to test the model fitness and collinearity between independent variables.

(2) Perform the holistic test to test the significance of the overall regression relationship.

(3) Test the regression coefficient to discover the significance of each regression coefficient.

(4) Define the final independent variables $x_1, x_2 \cdots x_i$ and the corresponding parameters $\alpha_0, \alpha_1, \alpha_2, \cdots, \alpha_i$, and establish a multiple linear regression equation.

2.3. Error Back Propagation Neural Network (BP)

2.3.1. Model Principle. BP is an intelligent learning machine trained by an error inverse propagation algorithm. It consists of an input layer, hidden layer, and output layer. One or more nodes exist between each layer, and each node represents a specific one. The excitation function that is the connection between the node and the next node represents a weighting value for the signal passing through the connection, thus reflecting the strength of the connection between the units. The BP neural network has the characteristics of learning and storing a large number of input–output mode mapping relationships. It is suitable for solving any complex nonlinear problems and exhibits good approximation and generalisation ability. It has been used widely in pattern recognition, function approximation, data compression, etc. [27–30].

2.3.2. Modelling Steps. (1) Establish a sample data classification that is used as the training set, test set, and prediction set.

(2) Normalise the data.

(3) Establish a neural network to determine the number of layers in the input layer, hidden layer, output layer, number of nodes between each layer, transfer functions, etc.

(4) Set the network training parameters, including the training times, training accuracy, learning rate, and training network.

(5) Test the model using the test suite.

(6) The prediction results are antinormalized.

(7) Analyse and evaluate the prediction results.

3. Induced Ordered Weighted Harmonic Averaging Operator

3.1. Simple Average Combination [31, 32]. Suppose that the predicted variable Y has m prediction results $Y_1, Y_2, \cdots, Y_m$, and each prediction result is given a weight; subsequently, the predicted simple average combined value is 1/m. The predicted simple average combined forecast value is as follows:

$$Y = Y_1 \frac{1}{m} + Y_2 \frac{1}{m} + \cdots + Y_m \frac{1}{m} \tag{13}$$

3.2. Induced Ordered Weighted Harmonic Averaging Operator (IOWHA). The traditional prediction method only assigns the weights of different prediction indicators, ignoring the influence of the time point on the prediction accuracy, which leads to the accuracy of one time point prediction in the prediction; however, the prediction error is large. At this time, the combined prediction model IOWHA that overcomes the defect of the traditional combined prediction model's weight is constructed by the minimum squared error sum of the inverse of the predicted value [33–35].

The model is defined as follows:

Suppose n two-dimensional combinations (v_1, u_1) $(v_2, u_2) \cdots (v_n, u_n)$ exist and the n-dimensional induced ordered weighted harmonic mean operator f_w is expressed as

$$f_w\left[(v_1,u_1),(v_2,u_2),\cdots(v_n,u_n)\right] = \frac{1}{\sum_{i=1}^{n}\left(\omega_i/u_{\nu-\mathrm{index}(i)}\right)} \tag{14}$$

where the function f_w is generated based on the sequence $v_1, v_2, \cdots, v_n$, the induction value of u_i is v_i, and $u_{\nu-\mathrm{index}(i)}$ is the ith data after $v_1, v_2, \cdots, v_n$ are arranged by size. The weight vector of the function is $W = (\omega_1, \omega_2, \cdots \omega_n)^T$ that corresponds to $\sum_{i=1}^{n}\omega_i = 1$, $\omega_i \geq 0$, $i = 1, 2, \cdots n$. Obviously, the formula indicates that the IOWHA operator is an ordered weighted harmonic average of the data in the corresponding $u_1, u_2, \cdots u_n$ after sorting the $v_1, v_2, \cdots, v_n$. The weight vectors ω_i have no concern with position and size of u_i but are related to the position and size of the induced value v_i. Suppose that v_{it} represents the prediction accuracy of the **i**th prediction method at the **t**th time; subsequently, n prediction methods form n two-dimensional arrays at time t, and v_{it}, x_t, and $\hat{x}_{it}$ represent the prediction accuracy, actual observations, and predicted values, respectively. The formula is as follows:

$$v_{it} = \begin{cases} 1 - \left|\dfrac{(x_t - x_{it})}{x_t}\right|, & \left|\dfrac{(x_t - x_{it})}{x_t}\right| < 1 \\ 0 & \left|\dfrac{(x_t - x_{it})}{x_t}\right| \geq 1 \end{cases} \tag{15}$$

where $i = 1, 2, \cdots m$, $t = 1, 2, \cdots N$.

Suppose $W = (\omega_1, \omega_2, \cdots \omega_m)^T$ is used as the weighting variable of the prediction model, and the predicted value at time t can be calculated by equation (14):

$$\mathrm{IOWHA}\left[(v_{1t},x_{1t}),(v_{2t},x_{2t}),\cdots(v_{nt},x_{nt})\right] = \frac{1}{\sum_{i=1}^{n}\left(\omega_i/u_{\nu-\mathrm{index}(i)}\right)} \tag{16}$$

where $i = 1, 2, \cdots n$, $t = 1, 2, \cdots M$

The M phase based on the squared sum of the predicted reciprocal errors of the optimal combination prediction model of IOWHA is s^2, which is as follows:

$$\begin{aligned} s^2 &= \sum_{t=1}^{M}\left(\frac{1}{x_i} - \frac{1}{\hat{x}_i}\right)^2 \\ &= \sum_{t=1}^{M}\left(\sum_{i=1}^{m}\omega_i\left(\frac{1}{x_i} - \frac{1}{x_{\nu-\mathrm{index}(it)}}\right)\right)^2 \\ &= \sum_{i=1}^{n}\sum_{j=1}^{n}\omega_i\omega_j\left(e_{\nu-\mathrm{index}(it)}e_{\nu-\mathrm{index}(jt)}\right) \end{aligned} \tag{17}$$

$$e_{\nu-\mathrm{index}(it)} = \frac{1}{x_i} - \frac{1}{x_{\nu-\mathrm{index}(it)}} \tag{18}$$

Subsequently, the combined prediction model based on the minimum squared error sum of the inverse of the predicted value is as follows:

$$\text{s.t.}\begin{cases}\sum_{i=1}^{n}\omega_i = 1 \\ \omega_i \geq 0,\ i = 1, 2, \ldots, n\end{cases} \tag{19}$$

The algorithm steps of the IOWHA optimal weighted prediction model GM-MLR-BP are shown in Figure 1.

4. Results and Discussion

4.1. Data Processing

4.1.1. Definition of Terminal Energy Replacement. To analyse the impact of electric energy substitution policy on Xinjiang's electric load, this paper quantifies the potential of electric energy replacement and uses terminal electric energy replacement as an influencing factor of the whole society's electricity consumption under the replacement of Xinjiang electric energy. Suppose the total annual energy consumption is Y_B in the base year, electrical energy consumption is Y_{Be} in the base year, actual energy consumption is Y_t in the **t**th year, and $Y_{e.t}$ is the electrical energy consumption in the **t**th year. Subsequently, the terminal electric energy replacement amount in the **t**th year is expressed as follows [36]:

$$D_{e.t} = Y_{e.t} - Y_t\frac{Y_{Be}}{Y_B} \tag{20}$$

4.1.2. Model Application Indicators. In this study, we used four indicators to compare the statistical characteristics between a single prediction model and a combined prediction model.

(1) The RMSE error is expressed as follows:

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(x_t - \hat{x}_t\right)^2} \tag{21}$$

(2) The MAPE is expressed as follows:

$$\mathrm{MAPE} = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{x_t - \hat{x}_t}{x_t}\right| \tag{22}$$

(3) The MSPE is expressed as follows:

$$\mathrm{MSPE} = \frac{1}{N}\sqrt{\sum_{i=1}^{N}\left[\frac{x_t - \hat{x}_t}{x_t}\right]^2} \times 100\% \tag{23}$$

4.2. Data Source. Through the correlation analysis of SPSS, the correlation coefficient between the added value of Xinjiang's secondary industry, per capita disposable income of the whole district, population, terminal energy replacement, power consumption intensity, actual GDP and per capita disposable income of residents in the whole district are both

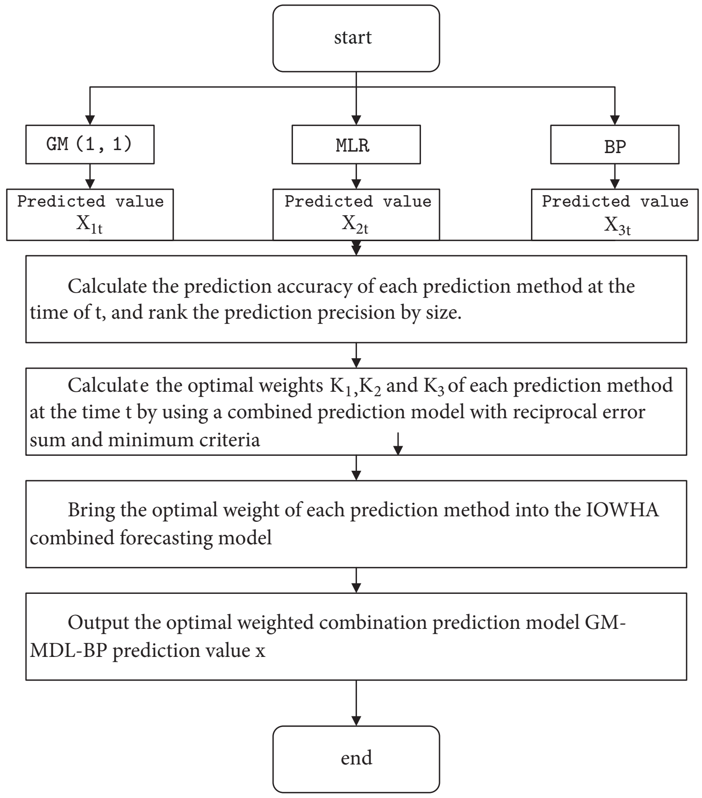

Figure 1: Algorithm flow chart of IOWHA optimal weighted prediction model GM-MLR-BP.

above 0.8, and the P values are less than 0.05. These indicate that the differences between the samples are significant. Therefore, we selected the added value of Xinjiang's secondary industry, per capita disposable income, population, terminal energy replacement, electricity consumption intensity, and actual GDP from 2000 to 2017 as the influencing factors of the whole society's electricity consumption in Xinjiang (see Table 1).

The total social power consumption in Xinjiang from 2000–2017 was selected as the research object. The data from 2000 to 2012 was used as the training sample, and the data from the previous five years (2013–2017) were used as the test sample to test the effectiveness of the prediction model. (See Figure 2).

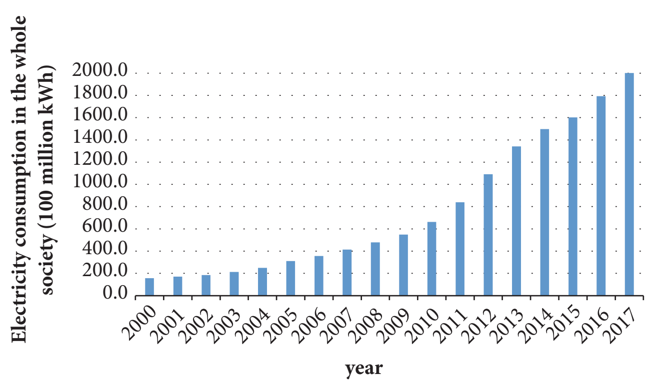

Figure 2: Electricity consumption in the whole society in Xinjiang from 2000 to 2017.

According to the collected data information, the BP neural network structure was constructed, including an input layer with 6 nodes, an intermediate layer with 10 nodes, and an output layer for 1 node. Subsequently, correlation analysis, collinearity diagnostics, and the test of regression coefficient were performed for multiple linear regression equations. Finally, the five indicators of power consumption intensity, such as the added value of Xinjiang's secondary industry, per capita disposable income of the whole district, population, and terminal energy replacement from 2000 to 2017, were used as independent variables [37].

4.3. Comparison of Prediction Accuracy. Based on the principle of the simple average combined model and the IWOHA operator optimal weighted combination model, the simple average combined weights of GM-MLR, GM-BP, and MLR-BP are $k_1 = k_2 = 0.5$, The weight of GM-MLR-BP is $k_1 = k_2 = k_3 = 1/3$. The comparison results of the actual social electricity consumption value and the simple average combined forecast value in Xinjiang in 2013–2017 are shown in Figure 3. The IWOHA optimal weighted combination weight is obtained by Matlab, and the weights of GM-MLR are $k_1 = 0.9239$, $k_2 = 0.0761$. The weights of GM-BP are $k_1 = 0.7656$, $k_2 = 0.2344$; the weights of MLR-BP are $k_1 = 0.9714$, $k_2 = 0.0286$; the weights of GM-MLR-BP are $k_1 = 0.7908$, $k_2 = 0.1194$, $k_3 = 0.0898$. The comparison between

Table 1: Correlation analysis between the factors affecting the electricity consumption of the whole society in Xinjiang and the electricity consumption of the whole society.

		Electricity consumption	Added value of secondary industry	Per capita disposable income of residents in the whole district	Population	Terminal electricity replacement	Terminal power consumption intensity	Actual GDP
Electricity consumption	Pearson correlation	1	0.919	0.873	0.976	0.972	0.980	0.977
	Significant (two-sided)		.000	.000	.000	.000	.000	.000

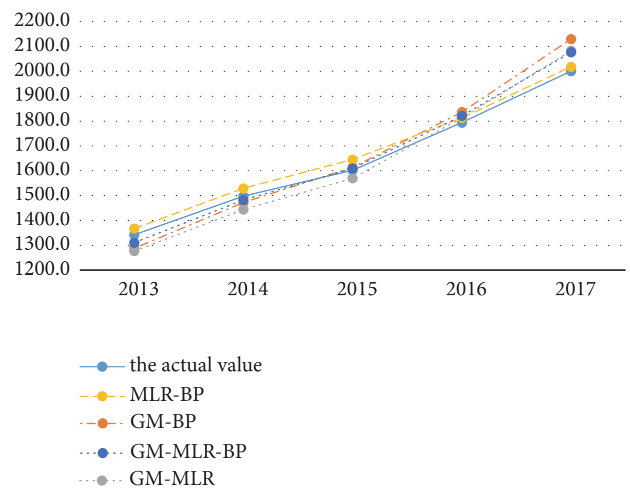

Figure 3: Simple combined forecasting results of the whole society's electricity consumption in Xinjiang.

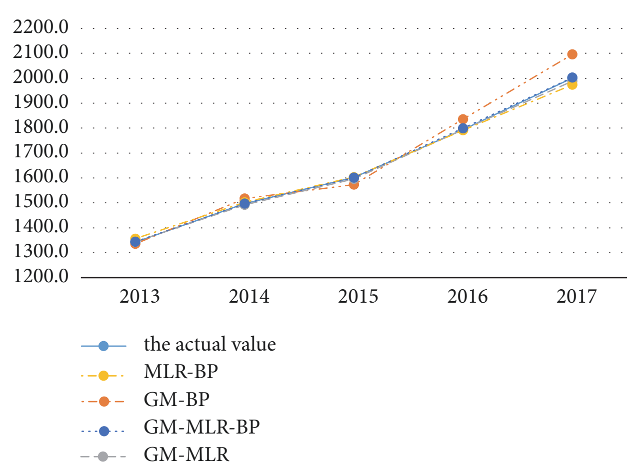

Figure 4: IOWHA optimal weighted combination forecasting result of the total social power consumption in Xinjiang.

the actual value of the total social electricity consumption in Xinjiang and the optimal weighted combination forecast of the IWOHA operator from 2013 to 2017 is shown in Figure 4.

As shown in Figure 3, the GM-MLR-BP model exhibits a better fitting effect in the results of the simple combined prediction model.

As shown in Figure 4, the GM-MLR-BP model exhibits a better fitting effect in the IOWHA optimal weighted combination forecasting model.

The comparison between the actual value of total electricity consumption in Xinjiang and the single and combined forecasting model is shown in Table 2. The data indicates that the maximum errors of GM, MLR, and BP are 10.75%, 1.46%, and 4.86%, respectively, and the errors of MLR and BP are relatively small. The error of GM is relatively large, but less than 10%; the maximum phase difference errors of the simple average combination models GM-MLR, GM-BP, MLR-BP, and GM-MLR-BP are 4.86%, 6.44%, 2.68%, and 3.81%, respectively. The maximum phase difference errors of the four IWOHA operator optimal weighted combination prediction models are 0.62%, 4.74%, 1.33%, and 0.33%, respectively. As shown, the IWOHA operator optimal weighted combination prediction model reduces the single prediction. The stability is relatively strong and the prediction accuracy is high.

The comparison of the prediction accuracy of the single evaluation method and the combined prediction method by the application evaluation indexes RMSE, MAPE, and MSPE is shown in Table 3. The study found that the RMSE, MAPE, and MSPE of the single prediction method MLR model demonstrate the lowest index values, indicating that the model is more reasonable for power load forecasting. The prediction accuracy of the simple combination prediction model is smaller than that of the MLR model. The prediction accuracy of the IOWHA optimal weighted combination prediction model is better than that of the corresponding simple combination prediction model and single prediction model. Meanwhile, the RMSE, MAPE, and MSPE values of the GM-MLR-BP model are significantly smaller than those of the MLR model, and the prediction accuracy is higher.

4.4. Analysis of Xinjiang Power Load Forecasting. The GM-MLR-BP model of the optimal weighted combination of IOWHA is used to predict the power load in Xinjiang in the next 10 years, as shown in Table 4.

As shown in Figure 5, the total electricity consumption in Xinjiang is from 15.75 billion kWh in 2000 to 563.791 billion kWh in 2027; the overall trend is increasing, and the upward trend is gradually increasing. In general, it is primarily due to the continuous improvement in relevant plans for electric energy substitution in Xinjiang and the rapid development of the following aspects.

Table 2: Comparison of actual social electricity consumption values and single and combined forecasting models in Xinjiang.

Year	electricity consumption (twh)	Relative error %										
		Single prediction method			Simple combination forecasting method				IOWHA optimal weighted combination forecasting method			
		GM	MLR	BP	GM MLR	GM BP	MLR BP	GM MLR BP	GM MLR	GM BP	MLR BP	GM MLR BP
2013	1342.3	-10.75	1.03	2.70	-4.86	-4.03	1.86	-2.34	0.13	-0.45	1.07	0.17
2014	1497.5	-7.32	0.24	3.99	-3.54	-1.66	2.12	-1.03	-0.33	1.34	0.35	0.01
2015	1602.3	-4.01	-0.07	5.42	-2.04	0.71	2.68	0.45	-0.37	-1.80	0.09	-0.05
2016	1793.8	2.36	-0.20	2.35	1.08	2.35	1.07	1.50	-0.01	2.35	-0.13	0.33
2017	2000.9	9.65	-1.46	3.23	4.09	6.44	0.88	3.81	-0.62	4.74	-1.33	0.09

Table 3: Comparison of prediction accuracy between single forecasting model and combined forecasting model for power load forecasting.

Index	Single prediction method			Simple combination forecasting method				IOWHA optimal weighted combination forecasting method			
	GM	MLR	BP	GM MLR	GM BP	MLR BP	GM MLR BP	GM MLR	GM BP	MLR BP	GM MLR BP
RMSE	123.32	14.67	60.66	55.17	66.43	28.82	39.51	6.58	49.06	13.79	3.00
MAPE (%)	6.82	0.60	3.54	3.12	3.04	1.72	1.83	0.29	2.14	0.59	0.13
MSPE (%)	3.37	0.36	1.66	1.53	1.63	0.83	0.97	0.16	1.15	0.35	0.08

Table 4: GM-MLR-BP prediction results of the optimal combination model of IOWHA under electric energy substitution in Xinjiang in 2018–2027.

Year	Predictive value (twh)	Year	Predictive value (twh)
2018	2375.36	2023	3949.69
2019	2683.86	2024	4272.20
2020	3059.51	2025	4567.83
2021	3338.47	2026	4969.39
2022	3567.10	2027	5367.91

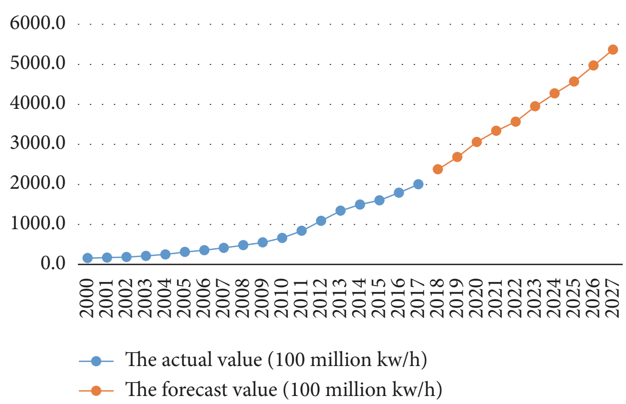

Figure 5: Schematic diagram of fitted values and predicted values of total social electricity consumption in Xinjiang.

In terms of technology, the Xinjiang region has continuously improved the charging service price mechanism, accelerated the construction of new energy vehicles and charging piles, and promoted the development of transportation electrification. Simultaneously, it has promoted the construction of wind energy storage projects and increased the research and development of energy storage core technologies. The ability is expanded to dissipate the electricity locally.

In terms of policies, the Xinjiang Electric Power Company has continuously accelerated the research and implementation of electric heating price policy to promote the construction of heating facilities such as electric heating and electric boilers. In addition, to fully utilise other provinces' policy of power transmission and deeply study the scale and development speed of the power market from other provinces, it vigorously promoted the power poverty alleviation policy in southern Xinjiang and established free electricity use files for poor households to improve the rural electrification level. Meanwhile, to accelerate the expansion of Xinjiang's layout of power silk, it also established long-term cooperative relations with other provinces to improve the power consumption capacity in Xinjiang.

In terms of management, the Xinjiang government guided by market demand has continuously deepened the reform of power supply measurement and scientifically controlled the development pace of new energy projects and the construction scale. Moreover, it continuously improved the market-based economic compensation mechanism to promote the construction of the electricity market, expanded the direct transaction scale of new energy enterprises, and increased the proportion of new energy in peaking alternative trading.

5. Conclusions

In this study, we combined the characteristics of Xinjiang's current development policy and selected some indicators such as terminal electric energy substitution, power consumption intensity, added value of secondary industry, per capita disposable income of the whole district, and population as the influencing factors of Xinjiang's electric load. Simultaneously, to fully utilise the useful information of the model and improve the limitations of the single model load forecasting, the optimal weighted combination model of IOWHA was proposed. By comparing the prediction results of the single prediction model and simple combination prediction model, the RMSE, MAPE, and MSPE of the IOWHA optimal weighted combination model GM-MLR-BP were small. Therefore, we effectively verified that the prediction accuracy of the IOWHA optimal weighted combination model GM-MLR-BP was higher than that of the corresponding single model prediction and simple combination prediction model and that it exhibited good practicability for predicting the electricity consumption in the background of electric energy substitution in Xinjiang.

Data Availability

The relevant data involved in this paper are provided by State Grid Xinjiang in China. According to the confidentiality agreement of State Grid Power Company, the relevant data cannot be released completely. However, some data can be found at http://www.xjtj.gov.cn/ from the Bureau of Statistics of Xinjiang, and the data presented herein are summarised in Table 5.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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Table 5

Data type	Data scope
Electricity consumption in the whole society of Xinjiang (100 million kW/h)	300–2100
Xinjiang's terminal electricity replacement (10,000 tons of standard coal)	5–1000
Added value of secondary industry (ten million Yuan)	1000–4500
The population (ten thousand people)	2000–2500
Terminal power consumption intensity (kW·h /billion Yuan)	0.1–0.2
Per capita disposable income of residents in the whole district (Yuan)	7000–20000
Actual GDP (ten million Yuan)	2000–11000

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