

Research Article

Short-Term City Electric Load Forecasting with Considering Temperature Effects: An Improved ARIMAX Model

Herui Cui and Xu Peng

School of Economics and Management, North China Electric Power University, Baoding 071003, China

Correspondence should be addressed to Xu Peng; donaldpengxu@163.com

Received 13 April 2015; Revised 9 June 2015; Accepted 21 June 2015

Academic Editor: Marco Mussetta

Copyright © 2015 H. Cui and X. Peng. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

Short-term electric load is significantly affected by weather, especially the temperature effects in summer. External factors can result in mutation structures in load data. Under the influence of the external temperature factors, city electric load cannot be easily forecasted as usual. This research analyzes the relationship between electricity load and daily temperature in city. An improved ARIMAX model is proposed in this paper to deal with the mutation data structures. It is found that information amount of the improved ARIMAX model is smaller than that of the classic method and its relative error is less than AR, ARMA and Sigmoid-Function ANN models. The forecasting results are more accurately fitted. This improved model is highly valuable when dealing with mutation data structure in the field of load forecasting. And it is also an effective technique in forecasting electric load with temperature effects.

1. Introduction

Short-term load forecasting (STLF) is mainly used to forecast the power load for the next few days or week [1–3]. It plays an important role in the modern electricity Demand Side Management (DSM), as its accuracy directly affects the economic cost of operators in the electricity market. Accurate load forecasting is helpful for security, stability, and economic operation in power grid. It is also advantageous in making reasonable arrangements for maintenance plan. Meanwhile, power load forecasting can optimize power system dispatch and reduce production cost.

Short-term daily peak power load in summer fluctuates regularly, showing an obvious periodical characteristic. It is greatly affected by temperature, wind, precipitation, and other meteorological factors. There are significant mutation structures in load data [4–6]. There are traditional methods in power load forecasting, such as regression model, gray model, support vector machines, neural networks, and time series. Ramón Cancelo et al. [7] used Red Eléctrica de España (REE) to forecast the electricity load from a day to a week ahead. Hipperta et al. [8] adapted large neural networks in electricity load forecasting to handle nonlinear time series data. Felipe Amarala and Castro Souza [9] used

smooth transition periodic autoregressive (STPAR) models for short-term load forecasting. Amjady and Keynia [10] proposed a new neural network learning algorithm based on a new modified harmony search technique. This learning algorithm is widely used to search the solution space in various directions, by which overfitting problem and trapping in local minima and dead bands can be avoided. Wangdi et al. [11] adapted ARIMAX model to determine predictors of malaria for the subsequent month. And the test showed that prediction accuracy has been greatly improved. Chadsuthi et al. [12] studied seasonal leptospirosis transmission and the association with rainfall and temperature by using ARIMAX model showing that factoring in rainfall (with an 8-month lag) yields the best model for the northern region. The above forecasting methods are obviously effective in dealing with mutation structures and intelligent algorithms. However, they are not ideal in practical operation due to the limitation of data and laboratory equipment. The generalization capability is also weak. Traditional time series forecasting methods highlight the time role, without considering the external factor effects. Thus, the forecasting accuracy of time series methods is poor, with obvious defect [13, 14]. Based on the above research, an improved ARIMAX model

is proposed here by combining the traditional time series with regression analysis to forecast short-term electric load, which has a strong practice value in the short-term power load forecasting field. This model fills the gaps of external effects on electric load. The prediction result showed that the improved ARIMAX model has a smaller model information amount than AR(p) or ARMA(p, q) [15, 16].

2. Sigmoid-Function ANN Model

ANN (Artificial Neural Network) is very practical forecasting technology in short-term electric load forecasting fields, especially for those nonlinear data. The basic concepts about ANN are shown as

$$\text{Sigmoid function: } f(\text{Net}_{kj}) = \frac{1}{1 + e^{-\text{Net}_{kj}}}, \quad (1)$$

where Net_{kj} is the state of network unit u_j . Consider

$$\begin{aligned} \text{The output unit: } o_{kj} &= \frac{1}{1 + \exp(-\sum_i \omega_{ji} o_{ki} - \theta_j)} \\ &= \frac{1}{1 + e^{-\text{Net}_{kj}}}. \end{aligned} \quad (2)$$

Through the operating of first-order derivative to output unit, $f'(\text{Net}_{kj})$ is obtained as follows:

$$\begin{aligned} f'(\text{Net}_{kj}) &= \frac{\delta o_{kj}}{\delta \text{Net}_{kj}} = o_{kj}(1 - o_{kj}), \\ \text{Output layer unit: } \delta_{kj} &= (t_{\partial j} - o_{kj}) o_{kj}(1 - o_{kj}), \end{aligned} \quad (3)$$

$$\text{Hidden layer unit: } \delta_{kj} = o_{kj}(1 - o_{kj}) \sum_m \delta_{km} \omega_{mj},$$

$$\text{Weight tuning function: } \Delta \omega_{ji}(t+1) = \eta \delta_{kj} o_{kj}.$$

The specific algorithm of Sigmoid-Function ANN model is shown as follows:

- (1) The initial value of weight or threshold is defined as $\omega_{ji}(0)$, while $\theta_j(0)$ is small random number.
- (2) Training samples are input vector X_k , ($k = 1, 2, \dots, P$); expectation output d_k , ($k = 1, 2, \dots, P$). Steps from (3) to (5) are carried out for each input sample.
- (3) Computing actual output and the state of hidden units in network

$$o_{kj} = f_j \left(\sum_i \omega_{ji} o_{ki} + \theta_j \right). \quad (4)$$

- (4) Calculation training error

$$\begin{aligned} \text{Output layer: } \delta_{kj} &= (t_{\partial j} - o_{kj}) o_{kj}(1 - o_{kj}), \\ \text{Hidden layer: } \delta_{kj} &= o_{kj}(1 - o_{kj}) \sum_m \delta_{km} \omega_{mj}. \end{aligned} \quad (5)$$

- (5) Correcting weights and thresholds

$$\begin{aligned} \omega_{ji}(t+1) &= \omega_{ji}(t) + \eta \delta_j o_{ki} + \alpha [\omega_{ji}(t) - \omega_{ji}(t-1)], \\ \theta_{ji}(t+1) &= \theta_{ji}(t) + \eta \delta_j + \alpha [\theta_{ji}(t) - \theta_{ji}(t-1)]. \end{aligned} \quad (6)$$

- (6) When index k is located at P , judging if $E \leq \varepsilon$.

3. Time Series Theory

Time series is a typical time-domain analysis method. It can be used to reveal the internal laws of the sequences from the perspective of autocorrelation.

Typical time-domain analysis steps are the following:

- (1) Observing sequence features.
- (2) Selecting the appropriate fitted model according to the features computed by SAS.
- (3) Model testing and optimization process.
- (4) Using fitted model to infer the nature of sequence.

Core contents of time series analysis method are proposed by American statistician George E. P. Box and United Kingdom statistician Gwilym M. Jenkins in their book *Time Series Analysis Forecasting and Control*, in which it is called autoregressive moving average model (ARIMA). Some important concepts are displayed here.

Stationarity. $\{x_t\}$ is set as time series, and $m \in \mathcal{E}^*$, (\mathcal{E}^* is positive integer) $t_1, t_2, \dots, t_m \in T, \forall \tau \in \mathcal{E}$, (\mathcal{E} is integer), $\exists F_{t_1, t_2, \dots, t_m}(x_1, x_2, \dots, x_m) = F_{t_1+\tau, t_2+\tau, \dots, t_m+\tau}(x_1, x_2, \dots, x_m)$, named $\{x_t\}$ for strictly stationary time series.

White Noise. Time series $\{x_t\}$ meet the condition (1) $\forall t \in T, \exists EX_t = \mu$ (2) $\forall t, s \in T$; then

$$\gamma(t, s) = \begin{cases} \sigma^2, & t = s \\ 0, & t \neq s \end{cases} \quad (7)$$

named $\{x_t\}$ for white noise sequence or displayed as

$$X_t \sim \text{WN}(\mu, \sigma^2). \quad (8)$$

Definition 1. The model is named *autoregressive moving average model*, if it contains the following structures, abbreviated as ARMA(p, q) :

$$\begin{aligned} x_t &= \phi_0 + \phi_1 x_{t-1} + \dots + \phi_p x_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \dots \\ &\quad - \theta_q \varepsilon_{t-q}, \quad \phi_p \neq 0, \theta_q \neq 0, \end{aligned}$$

$$E(\varepsilon_t) = 0, \quad (9)$$

$$\text{Var}(\varepsilon_t) = \sigma_\varepsilon^2,$$

$$E(\varepsilon_t \varepsilon_s) = 0, \quad s \neq t,$$

$$E(x_s \varepsilon_t) = 0, \quad \forall s < t.$$

Introduced delay operator B , it can also be presented as

$$\Phi(B)x_t = \Theta(B)\varepsilon_t. \quad (10)$$

Cointegration Theory. The cointegration theory was put forward by *Engle and Granger* in 2001 [17]. Model can be calculated without the requirement that all sequences are stationary, if the cointegration relationship is obvious. The typical cointegration test is *EG* test [18–20].

Definition 2. Supposing that the response variable $\{y_t\}$ and the input variable sequences $\{x_1\}, \dots, \{x_k\}$ are all stationary, the regression model is established in response to the input variable sequences and response sequences:

$$y_t = \mu + \sum_{i=1}^k \frac{\Theta_i(B)}{\Phi_i(B)} B^i x_{it} + \varepsilon_t, \quad (11)$$

$$\varepsilon_t = \frac{\Theta(B)}{\Phi(B)} a_t,$$

abbreviated as *ARIMAX model*.

In the actual modeling process, an *improved ARIMAX model* is proposed to forecast the short-term electric load. The specific process is displayed below.

4. The Improved ARIMAX Modeling Process

4.1. *Modeling Steps.* These are as follows

- (1) Perform logarithmic transformation on the original response sequence and the inputted sequences in order to meet the homogeneity of variance assumption.
- (2) Checking the stationarity of logarithmic transformation sequences,

$$\{\ln y_t\}; \{\ln x_1\}, \dots, \{\ln x_k\}. \quad (12)$$

If the sequences are stationary, move on to the next step; if not, conduct differential operation to the logarithmic sequences and testing stationarity again; then execute the second-order differential operation until the stationarity is satisfied.

- (3) Establishing the ARMA model about $\{\nabla^n \ln x_t\}$,

$$\nabla^n \ln x_{it} = \frac{\Theta_{xi}(B)}{\Phi_{xi}(B)} \varepsilon_{xit}. \quad (13)$$

$\{\nabla^n \ln x_t\}$ are N-order difference stationary inputted sequences.

- (4) Establishing the ARMA model about $\{\nabla^n \ln y_t\}$,

$$\nabla^n \ln y_{it} = \frac{\Theta_{yi}(B)}{\Phi_{yi}(B)} \varepsilon_{yit}. \quad (14)$$

$\{\nabla^n \ln y_t\}$ are the N-order difference stationary response sequences.

- (5) Exploring the correlation coefficient between the stationary N-order difference logarithmic sequences “ $\nabla^n \ln y_t$ ” and “ $\nabla^n \ln x_t$ ” to determine the structure of improved ARIMAX model. This step is the improved part for traditional ARIMAX model. Therefore, the revised ARIMAX model can be calculated as follows:

$$y_t^* = \mu + \sum_{i=1}^k \frac{\Theta_i(B)}{\Phi_i(B)} B^i x_{it}^* + \varepsilon_t. \quad (15)$$

- (6) Fitting residual sequence $\{\varepsilon_t\}$

$$\varepsilon_t = \frac{\Theta(B)}{\Phi(B)} a_t. \quad (16)$$

$\{a_t\}$ is a zero mean white noise sequence.

Based on the above steps the improved ARIMAX model can be applied into load forecasting process.

4.2. *Modeling Flowchart.* See Figure 1.

5. Load Forecasting with ARMA Model

5.1. *Load Data.* The table in the appendix shows the daily maximum power load data and the maximum temperatures in a city from 1st June to 14th August (see Table 12). In this paper, the data is used to explore the classical time series models and ANN models are used to firstly forecast load. In Section 6, an improved ARIMAX model is established to compare the prediction accuracy [21–23].

It can be seen in Figure 2 that load data has an upward trend and clear cyclical fluctuations by observing the sequences, showing that the sequences are nonstationary [24, 25].

5.2. *Establishing ARMA Model.* After the time series analysis on the load data by SAS software, autocorrelation table is previously mentioned. Table 1 shows that the autocorrelation coefficients of the sequences are always positive [26–28]. It can be inferred that daily peak power load data is nonstationary series with a monotonic trend, which is shown in Figure 2.

At the same time, the partial autocorrelation table can be obtained. Table 2 shows that only the first-order partial autocorrelation coefficient is significantly greater than two-time standard errors [29]. The rest partial autocorrelation coefficients rapidly decline to zero, making random fluctuations within two-time standard deviation ranges. Thus it can be regarded as the first-order truncation.

According to white noise test, statistic P (probability) is less than 0.05; thus the sequence is nonwhite noise. Then, the AR(1) model is applied to forecast power load data. In residual autocorrelation coefficient test about AR(1) model, it is shown that statistic P is larger than 0.05; thus this model applies.

After the SAS processing, AR(1) model can be presented as

$$x_t = 2895.82 + \frac{\varepsilon_t}{1 - 0.90534 * B}. \quad (17)$$

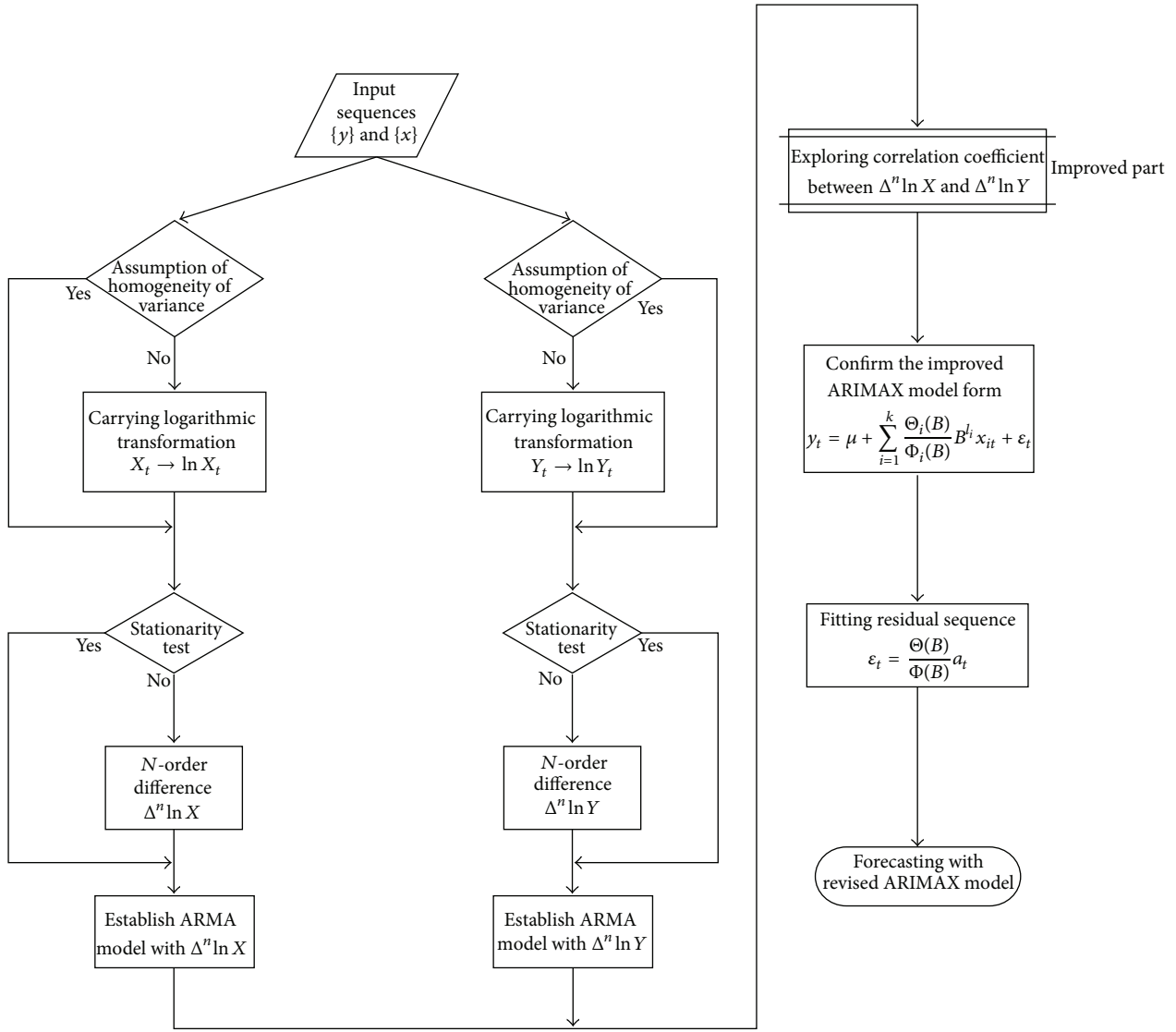


FIGURE 1: ARIMAX modeling flowchart.

TABLE 1: Autocorrelation table.

Lag	Correlation	-19 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1	Std. error
0	1	*****	0
1	0.93898	*****	0.114708
2	0.86458	*****	0.190683
3	0.81703	*****	0.236709
4	0.78057	*****	0.271289
5	0.74394	*****	0.299386
6	0.70116	*****	0.322794
7	0.66555	*****	0.342248
8	0.63503	*****	0.358874
9	0.60586	*****	0.373367
10	0.5797	*****	0.386086
11	0.54107	*****	0.397374

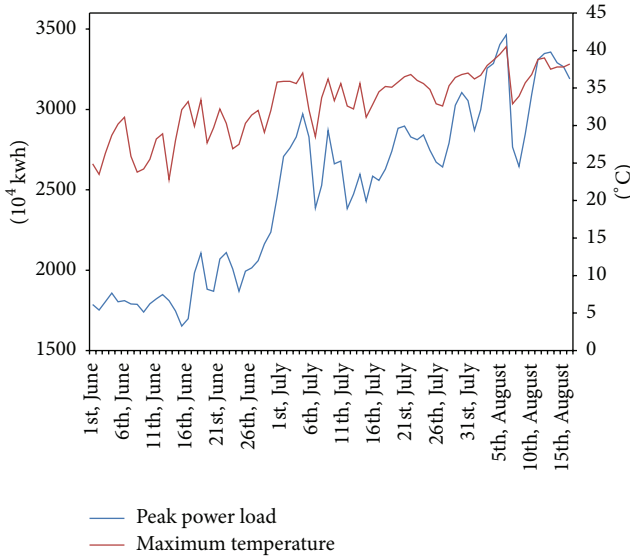


FIGURE 2: Load and temperature figure.

TABLE 2: Partial autocorrelation table.

Lag	Correlation	-1	9	8	7	6	5	4	3	2	1	0	1	2	3	4	5	6	7	8	9	1	
1	0.93898																						
2	-0.14458																						
3	0.2036																						
4	0.01297																						
5	0.01204																						
6	-0.05103																						
7	0.06133																						

In order to optimize the ARMA model, the minic option is used to detect the best order [30]. Setting ARMA(p, q) model as $x_t = \mu + (\Theta(B)/\Phi(B))\epsilon_t$, the option detects the ARMA(3, 2). The ARMA(p, q) model is presented as

$$x_t = 2949.334 + \frac{1 - 0.97485B + 0.3208B^2}{1 - 1.97331B + 1.49699B^2 - 0.52368B^3} \epsilon_t. \tag{18}$$

6. Load Forecasting with Improved ARIMAX Model

6.1. Testing Statistics. Regardless of the kinds of models, the P value of test statistic τ is significantly greater than 0.05 by ADF test. Daily maximum power load data series are markedly nonstationary. Therefore, the following analysis is conducted on nonstationary data sequence.

Firstly, performing logarithmic transformation on the original sequence,

$$x, y \longrightarrow \ln x, \ln y. \tag{19}$$

TABLE 3: Autocorrelation check for white noise.

To lag	Pr > ChiSq
12	0.1066
18	0.2526

TABLE 4: Augmented Dickey-Fuller unit root tests.

Type	Lags	Pr < Rho	Pr < Tau	Pr > F
Zero means	0	<0.0001	<0.0001	
	1	0.0001	<0.0001	
	2	0.0001	<0.0001	
Single mean	0	0.0007	0.0001	0.001
	1	0.0001	0.0001	0.001
	2	0.0002	0.0001	0.001

Thus the sequences can meet the homogeneity of variance. The white noise test of $\ln x$ sequence indicates that the $\ln x$ sequence is a nonwhite noise sequence. Unit root test shows that the P value of τ statistic is significantly greater than 0.05. It is suggested that $\ln x$ sequence is nonstationary. There is one unit root in $\ln x$ sequence at least. And the analysis on $\ln y$ sequence is similar to that of $\ln x$ [23–25].

Secondly, operating first-order differential operators to $\{\ln y_t\}$ and $\{\ln x_t\}$ sequences to get stationary $\{\Delta \ln y_t\}$ and $\{\Delta \ln x_t\}$,

$$\ln x_t, \ln y_t \longrightarrow \Delta \ln x_t, \Delta \ln y_t. \tag{20}$$

Thirdly, operate stationary test and white noise test to logarithmic sequence after first-order differential $\{\Delta \ln y_t\}$ and $\{\Delta \ln x_t\}$. The test result shows that the P value of white noise test is greater than 0.05, which means that $\{\Delta \ln y_t\}$ and $\{\Delta \ln x_t\}$ sequences are pure random white noise sequences [26]. And the P value of τ statistic is less than 0.05, showing that $\{\Delta \ln y_t\}$ and $\{\Delta \ln x_t\}$ sequences are stationary series. Until now, the test analysis has been finished.

6.2. Computing $\Delta \ln y_t$ and $\Delta \ln x_t$ Sequences Model. Firstly, the $\Delta \ln y$ model is established. The test shows that $\Delta \ln y$ is a stationary white noise sequence; thus the fitting model is

$$\Delta \ln y = \epsilon_t. \tag{21}$$

Secondly, the $\Delta \ln x$ model is established (see Table 6). The test results obtained by SAS from Tables 3 to 5 show that $\Delta \ln x$ is a stationary white noise sequence (the P value in Table 3 is larger than 0.05, while the P value in Table 4 is smaller than 0.05). The best order for ARMA(p, q) model is [AR(0), MA(4)]. Therefore, the fitting model is ARMA(0, 4) or MA(4) model. The constant term is not significant, using the noint option to remove the intercept. The final fitting model is shown as [31]

$$\Delta \ln x_t = (1 - 0.45098B^4) \epsilon_t. \tag{22}$$

TABLE 5: Minimum information criterion.

Lags	MA(0)	MA(1)	MA(2)	MA(3)	MA(4)	MA(5)
AR(0)	-5.14349	-5.22355	-5.48448	-5.51557	-5.51716	-5.51704
AR(1)	-5.13228	-5.19252	-5.42776	-5.4607	-5.4677	-5.48567
AR(2)	-5.35327	-5.40243	-5.37285	-5.41553	-5.41986	-5.46426
AR(3)	-5.3958	-5.42964	-5.39755	-5.36473	-5.3641	-5.41041
AR(4)	-5.40213	-5.42436	-5.39489	-5.36661	-5.30905	-5.37159
AR(5)	-5.4457	-5.422	-5.40418	-5.3893	-5.33506	-5.32363

Minimum table value: BIC(0,4) = -5.51716

TABLE 6: Fitting parameter of $\Delta \ln x$ model.

Parameter	Estimate	Standard error	t-value	Approx. Pr > t	Lag
MA(1, 1)	0.45098	0.10373	4.35	<0.0001	1

TABLE 7: Relationship number table of $\Delta \ln y$ and $\Delta \ln x$.

Lag	Correlation	-1	9	8	7	6	5	4	3	2	1	0	1	2	3	4	5	6	7	8	9
-3	0.05145		.	*	.																
-2	-0.24894								****		.										
-1	-0.17628								.****		.										
0	0.49787		.		*****																
1	0.15016		.		***.																
2	-0.02468		.		.																
3	-0.05311		.		*		.														

TABLE 8: Parameter estimates of REG procedure.

Variable	Dependent variable	Parameter estimates	Standard error	t-value	Pr > t
$\Delta \ln x$	$\Delta \ln y$	0.37098	0.07442	4.98	<0.0001

TABLE 9: Autocorrelation check of residuals.

To lag	Pr > ChiSq
6	0.0578
12	0.0687
18	0.1588

TABLE 10: Crosscorrelation check of residuals with input $\ln x$.

To lag	Pr > ChiSq
5	0.0581
11	0.0634
17	0.0732

6.3. Computing Load Data with Improved ARIMAX Model.

The above model is used to filter input variable sequence $\{\Delta \ln x_1\} \cdots \{\Delta \ln x_k\}$ and the response variable sequence $\{\Delta \ln y_t\}$. The mutual relationships numbers between the independent variables and the response variable are calculated after filtration by ARIMA analysis process.

It can be found in Table 7 that only the 0-order delay mutual relationship number is significantly nonzero, which

means that there is no hysteretic effect between response sequence and input sequences. Therefore, the model should be treated in the same period.

The regression analysis in Table 8 shows that the final regression coefficient is 0.37098.

The statistics test is carried out on residual sequence, showing that the residual sequence is stationary white noise sequence (Pr > 0.05). The fitted model for residual sequence is $\varepsilon_t = a_t$, and a_t is zero mean white noise sequence [32–35].

It is known that there is significant correlation in the zero-order between the two sequences in Table 7. The same period model is established between $\Delta \ln y$ and $\Delta \ln x$, based on the parameter estimates in Table 8 and tests in Tables 9~10. The P value in Table 9 is larger than 0.05; thus the autocorrelation check of residuals shows that the model is effective for forecasting loads:

$$\Delta \ln y_t = 0.37098 \Delta \ln x_t + \varepsilon_t, \tag{23}$$

$$\varepsilon_t = a_t.$$

The load from 15th to 31st is forecasted according to the improved ARIMAX model.

TABLE 11: Predictions of different models.

Obs.	Actual power load data	Prediction value of improved ARIMAX	Prediction value of AR(1)	Prediction value of ARMA(3, 2)	Prediction value of Sigmoid-Function ANN
16	2685	2678	2648	2699	2698
17	2833	2820	2810	2855	2844
18	2924	2930	2917	2934	2934
19	3112	3122	3128	3130	3128
20	2393	2400	2428	2441	2412
21	2570	2600	2650	2661	2598
22	2689	2709	2723	2741	2699
23	2730	2788	2796	2801	2812
24	2597	2638	2654	2687	2611
25	2216	2219	2225	2258	2215
26	1935	1929	1971	1995	1952
27	1826	1822	1910	1984	1857
28	1897	1850	1927	1968	1904
29	1945	1926	2018	2100	1965
30	2244	2230	2101	2154	2264
31	2261	2258	2177	2137	2274
AIC Criterion		-72.7	381.4	433.8	78.6
SBC Criterion		-71.5	383.9	436.6	79.2
MAE		0.0037	0.0389	0.0494	0.0185

By operating logarithm to the forecasting results “ln y,” the next 15-day maximum load can be obtained, which is shown in Table 11.

MAE (Mean Absolute Error) is computed as follows:

$$MAE = \sum_t \frac{|\hat{y}_t - y_t|}{T}, \tag{24}$$

where \hat{y}_t is the prediction value, y_t is the actual value, and T is the sample size.

It can be seen in Table 11 that the MAE of the improved ARIMAX model is the minimum, Sigmoid-Function ANN ranked second small, followed by AR model, and ARMA model is the maximum. It means that the improved ARIMAX model is better than S-ANN, AR, or ARMA model according to the AIC and SBC Criterion in Table 11. The revised ARIMAX model is more effective, by which more accurate load results can be obtained.

It can be seen in Figure 3 that the blue line is the actual daily maximum power load data, while the red line is the forecasting data of improved ARIMAX. The difference between improved ARIMAX model and actual power load data is the minimum among these models. Residual stationarity and white noise test show that the residual is stationary white noise sequence, showing that $\varepsilon_t = a_t$. There is second-order delay correlation between ln y and ln x. The final fitting model is

$$\ln y_t = 2.86647 + 1.41495 \ln x_{t-2} + \varepsilon_t, \tag{25}$$

$$\varepsilon_t = a_t.$$

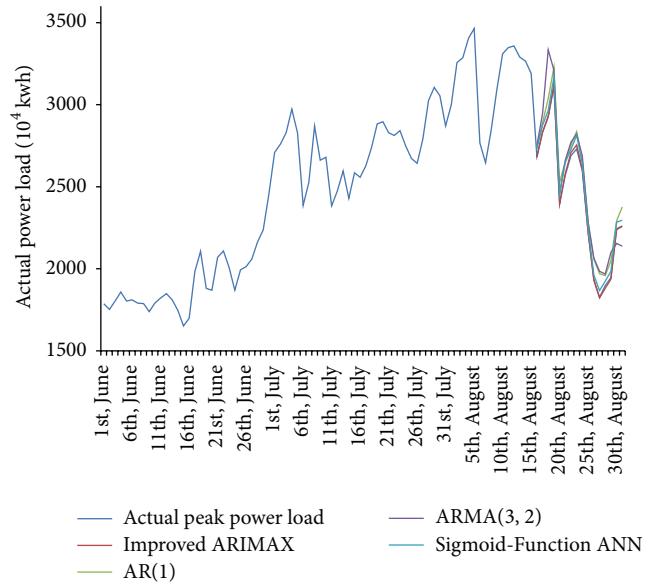


FIGURE 3: Forecasting graphics.

7. Conclusion

Based on the above analysis, the improved ARIMAX model can effectively dig up self-related information of load data. As an effective method for short-term load forecasting, the model can get a more accurate prediction result than traditional time series models. Prediction accuracy of this

TABLE 12: Daily maximum power load and temperature data in some city in 2010.

Time	Peak power load	Maximum temperature	Time	Peak power load	Maximum temperature
1st Jun.	1787	24.9	9th Jul.	2662	33.3
2nd Jun.	1752	23.5	10th Jul.	2679	35.6
3rd Jun.	1804	26.3	11th Jul.	2383	32.6
4th Jun.	1858	28.7	12th Jul.	2473	32.2
5th Jun.	1804	30.2	13th Jul.	2596	35.6
6th Jun.	1810	31.1	14th Jul.	2429	31.1
7th Jun.	1790	25.9	15th Jul.	2585	32.8
8th Jun.	1788	23.8	16th Jul.	2558	34.5
9th Jun.	1739	24.2	17th Jul.	2628	35.2
10th Jun.	1791	25.5	18th Jul.	2739	35.1
11th Jun.	1822	28.2	19th Jul.	2883	35.8
12th Jun.	1848	28.9	20th Jul.	2896	36.5
13th Jun.	1811	22.8	21st Jul.	2829	36.8
14th Jun.	1746	28	22nd Jul.	2812	36
15th Jun.	1652	32.1	23rd Jul.	2841	35.6
16th Jun.	1698	33.2	24th Jul.	2746	34.8
17th Jun.	1983	29.9	25th Jul.	2672	32.9
18th Jun.	2106	33.4	26th Jul.	2642	32.6
19th Jun.	1881	27.7	27th Jul.	2791	35.3
20th Jun.	1869	29.7	28th Jul.	3026	36.4
21st Jun.	2069	32.2	29th Jul.	3105	36.8
22nd Jun.	2109	30.3	30th Jul.	3054	37
23rd Jun.	2007	26.9	31st Jul.	2870	36.2
24th Jun.	1869	27.5	1st Aug.	2999	36.7
25th Jun.	1994	30.3	2nd Aug.	3256	38
26th Jun.	2014	31.4	3rd Aug.	3286	38.7
27th Jun.	2059	32	4th Aug.	3404	39.5
28th Jun.	2163	29.1	5th Aug.	3464	40.5
29th Jun.	2237	32	6th Aug.	2766	32.9
30th Jun.	2456	35.8	7th Aug.	2646	33.9
1st Jul.	2708	35.9	8th Aug.	2847	35.7
2nd Jul.	2760	35.9	9th Aug.	3094	36.8
3rd Jul.	2829	35.6	10th Aug.	3310	38.8
4th Jul.	2972	37	11th Aug.	3348	39
5th Jul.	2829	32.1	12th Aug.	3357	37.5
6th Jul.	2387	28.5	13th Aug.	3290	37.8
7th Jul.	2528	33.7	14th Aug.	3265	37.8

model is greatly improved, which is of high value in engineering application area. It is verified by relative error analysis of ARMA and the improved ARIMAX that the revised model has higher prediction accuracy than usual forms.

Notation

Net_{kj} : The state of network unit u_j
 o_{kj} : Output unit
 δ_{kj} : Output (hidden) layer unit
 $\omega_{ji}(0)$: Initial value of weight or threshold

X_k : Training samples
 ε : Accuracy requirements
 $\{x_t\}$: Time series
 EX_t : Mean of time series $\{x_t\}$
 ϕ_p : Autoregressive coefficient
 θ_q : Random interference coefficient
 $\Phi(B)$: Q-order moving average coefficient polynomials
 $\Theta(B)$: Residual sequence moving average coefficient polynomials
 B : Delay operator
 σ : Standard deviation.

Conflict of Interests

The authors declare no conflict of interests.

Acknowledgment

The authors gratefully acknowledge the financial support from the National Natural Science Fund of China (no. 71471061).

References

- [1] S.-M. Chen, "Forecasting enrollments based on fuzzy time series," *Fuzzy Sets and Systems*, vol. 81, no. 3, pp. 311–319, 1996.
- [2] J. L. Torres, A. García, M. De Blas, and A. De Francisco, "Forecast of hourly average wind speed with ARMA models in Navarre (Spain)," *Solar Energy*, vol. 79, no. 1, pp. 65–77, 2005.
- [3] R. G. Kavasseri and K. Seetharaman, "Day-ahead wind speed forecasting using f-ARIMA models," *Renewable Energy*, vol. 34, no. 5, pp. 1388–1393, 2009.
- [4] M. Tamimi and R. Egbert, "Short term electric load forecasting via fuzzy neural collaboration," *Electric Power Systems Research*, vol. 56, no. 3, pp. 243–248, 2000.
- [5] L. Suganthi and A. A. Samuel, "Energy models for demand forecasting—a review," *Renewable and Sustainable Energy Reviews*, vol. 16, no. 2, pp. 1223–1240, 2012.
- [6] K. Huarng and H.-K. Yu, "A dynamic approach to adjusting lengths of intervals in fuzzy time series forecasting," *Intelligent Data Analysis*, vol. 8, no. 1, pp. 3–27, 2004.
- [7] J. Ramón Cancelo, A. Espasa, and R. Grafe, "Forecasting the electricity load from one day to one week ahead for the Spanish system operator," *International Journal of Forecasting*, vol. 24, no. 4, pp. 588–602, 2008.
- [8] H. S. Hipperta, D. W. Bunn, and R. C. Souza, "Large neural networks for electricity load forecasting: are they overfitted?" *International Journal of Forecasting*, vol. 21, no. 3, pp. 425–434, 2005.
- [9] L. Felipe Amarala and R. Castro Souza, "A smooth transition periodic autoregressive (STPAR) model for short-term load forecasting," *International Journal of Forecasting*, vol. 24, no. 4, pp. 603–615, 2008.
- [10] N. Amjady and F. Keynia, "A new neural network approach to short term load forecasting of electrical power systems," *Energies*, vol. 4, no. 3, pp. 488–503, 2011.
- [11] K. Wangdi, P. Singhasivanon, T. Silawan, S. Lawpoolsri, N. J. White, and J. Kaewkungwal, "Development of temporal modelling for forecasting and prediction of malaria infections using time-series and ARIMAX analyses: a case study in endemic districts of Bhutan," *Malaria Journal*, vol. 9, article 251, 2010.
- [12] S. Chadsuthi, C. Modchang, Y. Lenbury, S. Iamsirithaworn, and W. Triampo, "Modeling seasonal leptospirosis transmission and its association with rainfall and temperature in Thailand using time-series and ARIMAX analyses," *Asian Pacific Journal of Tropical Medicine*, vol. 5, no. 7, pp. 539–546, 2012.
- [13] U. Yolcu, E. Egrioglu, V. R. Uslu, M. A. Basaran, and C. H. Aladag, "A new approach for determining the length of intervals for fuzzy time series," *Applied Soft Computing Journal*, vol. 9, no. 2, pp. 647–651, 2009.
- [14] K. Kandananond, "Forecasting electricity demand in Thailand with an artificial neural network approach," *Energies*, vol. 4, no. 8, pp. 1246–1257, 2011.
- [15] C.-C. Hsu and C.-Y. Chen, "Regional load forecasting in Taiwan—applications of artificial neural networks," *Energy Conversion & Management*, vol. 44, no. 12, pp. 1941–1949, 2003.
- [16] J. Yoo and K. Hur, "Load forecast model switching scheme for improved robustness to changes in building energy consumption patterns," *Energies*, vol. 6, no. 3, pp. 1329–1343, 2013.
- [17] R. F. Engle and C. W. J. Granger, "Co-integration and error correction: representation, estimation, and testing," in *Essays in Econometrics*, pp. 145–172, Harvard University Press, Cambridge, Mass, USA, 2001, <http://dl.acm.org/citation.cfm?id=781849>.
- [18] H. Zhang, Z. Wang, and D. Liu, "Global asymptotic stability of recurrent neural networks with multiple time-varying delays," *IEEE Transactions on Neural Networks*, vol. 19, no. 5, pp. 855–873, 2008.
- [19] X.-G. Liu, R. R. Martin, M. Wu, and M.-L. Tang, "Global exponential stability of bidirectional associative memory neural networks with time delays," *IEEE Transactions on Neural Networks*, vol. 19, no. 3, pp. 397–407, 2008.
- [20] A. Azadeh, S. F. Ghaderi, and S. Sohrabkhani, "A simulated-based neural network algorithm for forecasting electrical energy consumption in Iran," *Energy Policy*, vol. 36, no. 7, pp. 2637–2644, 2008.
- [21] M. Espinoza, J. A. Suykens, and B. de Moor, "Fixed-size least squares support vector machines: a large scale application in electrical load forecasting," *Computational Management Science*, vol. 3, no. 2, pp. 113–129, 2006.
- [22] M. G. Karlaftis and E. Vlahogianni, "Statistical methods versus neural networks in transportation research: differences, similarities and some insights," *Transportation Research Part C: Emerging Technologies*, vol. 19, no. 3, pp. 387–399, 2011.
- [23] H. Niska, T. Hiltunen, A. Karppinen, J. Ruuskanen, and M. Kolehmainen, "Evolving the neural network model for forecasting air pollution time series," *Engineering Applications of Artificial Intelligence*, vol. 17, no. 2, pp. 159–167, 2004.
- [24] Z. Ma, J. Xing, M. Mesbah, and L. Ferreira, "Predicting short-term bus passenger demand using a pattern hybrid approach," *Transportation Research Part C: Emerging Technologies*, vol. 39, pp. 148–163, 2014.
- [25] W. Wang, J. Jin, and Y. Li, "Prediction of inflow at three Gorges dam in Yangtze River with wavelet network model," *Water Resources Management*, vol. 23, no. 13, pp. 2791–2803, 2009.
- [26] K. Afshar and N. Bigdeli, "Data analysis and short term load forecasting in Iran electricity market using singular spectral analysis (SSA)," *Energy*, vol. 36, no. 5, pp. 2620–2627, 2011.
- [27] B. Premanode and C. Toumazou, "Improving prediction of exchange rates using differential EMD," *Expert Systems with Applications*, vol. 40, no. 1, pp. 377–384, 2013.
- [28] X. H. Yang, D. X. She, Z. F. Yang, Q. H. Tang, and J. Q. Li, "Chaotic bayesian method based on multiple criteria decision making (MCDM) for forecasting nonlinear hydrological time series," *International Journal of Nonlinear Sciences & Numerical Simulation*, vol. 10, no. 11-12, pp. 1595–1610, 2009.
- [29] S. Razavi and B. A. Tolson, "A new formulation for feedforward neural networks," *IEEE Transactions on Neural Networks*, vol. 22, no. 10, pp. 1588–1598, 2011.
- [30] A. Alvarez, A. Orfila, and J. Tintore, "DARWIN: an evolutionary program for nonlinear modeling of chaotic time series," *Computer Physics Communications*, vol. 136, no. 3, pp. 334–349, 2001.
- [31] H. Kantz and T. Schreiber, *Nonlinear Time Series Analysis*, Cambridge University Press, Cambridge, UK, 1997.

- [32] M. Ardalani-Farsa and S. Zolfaghari, "Residual analysis and combination of embedding theorem and artificial intelligence in chaotic time series forecasting," *Applied Artificial Intelligence*, vol. 25, no. 1, pp. 45–73, 2011.
- [33] Y.-H. Chen and F.-J. Chang, "Evolutionary artificial neural networks for hydrological systems forecasting," *Journal of Hydrology*, vol. 367, no. 1-2, pp. 125–137, 2009.
- [34] K. A. de Oliveira, A. Vannucci, and E. C. da Silva, "Using artificial neural networks to forecast chaotic time series," *Physica A: Statistical Mechanics and Its Applications*, vol. 284, no. 1, pp. 393–404, 2000.
- [35] G. G. Szpiro, "Forecasting chaotic time series with genetic algorithms," *Physical Review E—Statistical Physics, Plasmas, Fluids, and Related Interdisciplinary Topics*, vol. 55, no. 3, pp. 2557–2568, 1997.



Hindawi

Submit your manuscripts at
<http://www.hindawi.com>

