WT-ARIMA Combination Modelling for Short-term Load Forecasting

Jinxing Che, Huachao Zhai

Abstract—**Accurate load forecasting is of critical importance for the smart grid. However, power load forecasting accuracy is limited in the traditional ARIMA model due to the non-stationary power grid data. In this research, a combined forecasting model based on wavelet transform and ARIMA is proposed to improve the forecasting accuracy and increase the predictability of power load data. The non-stationarity of the load data is reduced, and the predictability of the load data is increased by decomposing the original data. Finally, the prediction result is a linear superposition of each subsequence's predicted value. The feasibility of the proposed comprehensive forecasting model is verified by an experiment with the actual load data in a county in Jiangxi Province. The experimental results demonstrate that the proposed WT-ARIMA model has good performance in terms of MAPE and RMSE. Compared with the traditional ARIMA model, the prediction accuracy of the WT-ARIMA model is more stable.**

***Index Terms*—Short-term Load Forecasting, Wavelet Transform, ARIMA, Decomposing**

I. Introduction

In today's society, electricity is an essential energy source. Personal lives and work are all influenced by electricity. Therefore, it is necessary to ensure the safe and stable operation of the power system. Load forecasting is an important part of power system design, and it is a group of forecasting activities considering the load [1-3]. For reliable operation of the power system, accurate load forecasting is an indispensable reference. Through load forecasting, we can have a good understanding of the electricity consumption of a specific area in a certain period in the future. It provides a benchmark for the dispatching of the power system. The higher the accuracy of load forecasting, the more reliable the reference value of forecasting results. Therefore, improving the accuracy of load forecasting is an important topic for experts and researchers. To improve the accuracy of prediction, researchers combine different methods to improve the accuracy of prediction. Lee and Ko predict the load data by using the lifting scheme and ARIMA [2]. An improved SVR model is proposed by Li et al., they use the chaotic quantum bat algorithm to optimize the SVR's parameters [11]. Lu uses ARIMA to predict the load data and utilizes the ANN model to forecast the residual data [3]. Up to now, the popular load forecasting model is mainly divided into three categories: time series forecasting, machine learning forecasting, and deep learning forecasting. For example, ARIMA [1-7], SVM [8-13], ANN [14-20], etc. The load data is a standard and non-static time series. ARIMA is commonly used for load forecasting since it can minimize the nonstationary of load data by difference procedures. The ARIMA model has strong explanatory power for the linear part of the time series. This has also been proved in the studies of [1] and [2]. Therefore, scholars focus on how to improve the prediction accuracy of nonlinear parts of time series.

In most studies, there is only one ARIMA model for the mixed model. Lu uses ARIMA to predict the load data and the residual data is forecasted by the ANN model [3]. Fard uses wavelet transform to decompose these residual data, and an artificial neural network is used to forecast the decomposed data. Finally, a more accurate load forecasting model is obtained by superimposing the nonlinear and linear forecasting results [4]. Al Amin uses the predictions of the SVM and ARIMA models through actual data and evaluates these two prediction models with MAPE and MSE [5]. Kavousi-Fard uses the combination of CSA-optimized support vector regression machine and ARIMA to get better prediction results [6]. Although the overall forecast result is reasonable, the diversity of time series components is not considered. The ARIMA model parameters of the correlation time series are inconsistent under different components. According to this theory, a variety of ARIMA models with different components of time series should be more accurate than a single ARIMA model in theory.

Therefore, this paper puts forward a WT-ARIMA model for short-term load forecasting. Before establishing the ARIMA model, wavelet transform and reconstruction are firstly carried out on load data to reduce the non-stationarity of the load data. After reconstruction, an ARIMA prediction model is created for each sub-sequence, and the model parameters for each sub-sequence are determined. Finally, the predicted values of each ARIMA model are superimposed to generate the final predicted result. The feasibility of this strategy has been verified in the research using a real data set. The WT-ARIMA model is also more effective than a single ARIMA model.

II. Methods

A. Autoregressive Integrated Moving Average (ARIMA)

The ARIMA model is a combination of the ARMA model and the differential operation. Unlike the ARMA model, the

Manuscript received August 24, 2021; revised 19 April 19, 2022. The research is supported by the National Natural Science Foundation of China (Grant No. 71971105), the National Statistical Science Research Project (Grant No. 2020LZ03).

Jinxing Che is an associate professor in the College of Science, Nanchang Institute of Technology, Nanchang 330099, Jiangxi, China (corresponding author, e-mail: jinxingche1@163.com).

Huachao Zhai is a postgraduate in School of Information Engineering, Nanchang Institute of Technology, Nanchang 330099, Jiangxi, China (corresponding author, e-mail: huachaozhai@163.com).

ARIMA model can handle non-stationary time series. In the ARIMA model, because of the difference operation processing, the non-stationarity of time series will successfully be minimized. After that, the smoothed time series obtained by the difference operation in the previous step can follow the modeling steps of the ARMA model for the subsequent forecasting work. The ARIMA model can fit and predict time series, whether it is a smooth series or not. In general, the ARIMA's fitting effect is quite impressive for the linear section. In 1970, BOX and Jenkins proposed the ARIMA model as a tool for time series prediction. Since its appearance, it or its variation is used in many time-series forecasts. The ARIMA is made up of three elements in general: Autoregressive (AR), Difference (D), and Moving Average (MA). An appropriate ARIMA model may only have one or two of the three parts due to data fluctuation, which is entirely normal.

AR stands for autoregression, which is one of ARIMA's three components. We can use Eq. (1) to express the function expression. The AR model describes the relationship between the variable's past data and the data at present. It's worth mentioning that the AR model is sensitive to data stationarity, necessitating the use of a stationary time series. The difference connection corresponds to difference operation processing. If the data under study is non-stationary, we can increase the stability of the data by performing multiple differencing operations on the data. Finally, the differencing process allows the data to meet the stationarity criteria of the model. The number of differences required to convert non-stationary data to stationary data is denoted by d, where d is an integer higher than or equal to 0.

The functional formulation of difference operation is shown in Eq. (2). In practice, the real load data may have a certain periodicity. As a result, we can use the parameter c to adapt time series with periodicity. If the time series is not periodic, the default value is $c=1$.

The moving average (MA) model focuses on the error accumulation terms in the AR model. It is the final phase. Eq. (3) depicts the functional link.

$$X_t = c + \sum_{i=1}^{p} \varphi_i X_{t-i} + \varepsilon_t \tag{1}$$

$$(1-B)y = y_t - y_{t-c} \tag{2}$$

$$x_t = \mu + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots - \theta_q \varepsilon_{t-q} \tag{3}$$

$$\left(1-\sum_{i=1}^{p} \phi_i L^i\right)(1-L)^d X_t = \left(1+\sum_{i=1}^{q} \theta_i L^i\right)\varepsilon_t \tag{4}$$

The ARIMA model is a three-part integrated model with individual parameters for each part. Therefore, there are three parameters in the ARIMA model. AR, D, and MA are represented by the letters p, d, and q, respectively. The mathematical function expression of ARIMA is provided in Eq. (4). In the ARIMA model construction process, there is a negative feedback relationship. The flow chart of ARIMA is shown in Figure 1. ARIMA modeling steps are as below.

Step (a) Sequence stabilization.

If the time series is stationary, the data can be directly used for prediction without differential processing. However, if the time series is non-stationary, in that case, it is necessary to perform the differential operation on the data. By this means, the non-stationary data is transformed into a stationary time series.

Step (b) Randomness test.

White noise is a set of completely random data points from which no association can be drawn and has no analytical significance. As a result, it is critical to rule out the possibility that the stationary time series in question is a white noise series.

Step (c) Calculation of the parameters p, d, and q.

For this calculation process, Step (a) yields the value of parameter d. The p and q are found by inspecting the autocorrelation and partial correlation graphs of the stationary non-white noise data collected. Then, we can use the AIC information criteria to select the suitable ARIMA(p,d,q) model.

Step (d) Test for residuals.

For this test process, we should check that the residual sequence of the model is a white noise sequence, as estimated in Step (c). The model is considered satisfactory if the residuals are white noise sequences with no autocorrelation. Otherwise, autocorrelation exists, indicating that the model chosen in the previous stage is insufficient. In this case, the algorithm returns to Step (c) to select another model.

Step (e) Output the determined model.

After the final ARIMA(p,d,q) model is determined, the corresponding predicted value can be generated by inputting the corresponding value.

Whether the sequence is stationarity can be determined by performing an ADF unit root test on the sequence or observing the autocorrelation function (ACF) graph. If the P-value in the ADF test result is less than the given significance level, and the ACF gradually decreases to zero, it

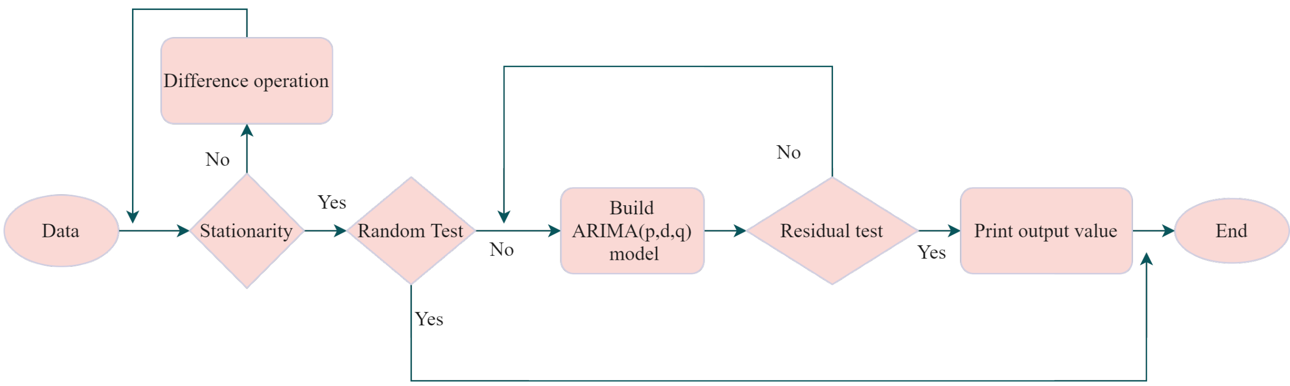

Fig. 1 ARIMA flow chart

means that the time series is stable. On the contrary, the sequence is non-stationary and requires a difference operation.

By calculating the ACF and the PACF of a stationary time series, we can obtain a set of data about the parameters p and q used in the ARMA model. Akaike's information criterion (AIC) is introduced for selecting suitable parameters to better fit the time series. AIC can weigh the bias and variance of the model and avoid the model being too complicated. Eq. (5) gives the calculation method of AIC.

$$\mathrm{AIC}(m) = \mathrm{Ln}\left(\sigma_a^2\right) + \frac{2m}{n} \tag{5}$$

B. Wavelet Transform

Load data is a typical type of time series data that changes over time and is frequently non-stationary. On the other hand, the wavelet transform may not only successfully reduce the non-stationary signal's instability, but it may also efficiently capture the signal's frequency shift as well as the associated time and location information. As a result, the wavelet transform can be applied in the non-stationary signal analysis. A wavelet is a signal with a fixed duration that increases or decays over time. Continuous wavelet transform and discrete wavelet transform are the two types of wavelet transform.

Eq. (6) and Eq. (7) are the formulas for the continuous wavelet transform and the discrete wavelet transform, respectively.

$$\mathrm{CWT}(a,b) = \int_{-\infty}^{\infty} \psi_{a,b}(t) \cdot x(t)dt \tag{6}$$

$$\mathrm{DWT}(m,n) = 2^{\left(-\frac{m}{2}\right)} \sum_{t=0}^{T-1} f(t)\phi\left(\frac{t}{2^m} - n\right) \tag{7}$$

Compared to discrete wavelet transform, continuous wavelet transform takes a lot longer and requires more memory. The discrete wavelet transform shortens processing time while ensuring precision in the decomposed signal. Using the N-level wavelet transform technique, we will obtain one low-frequency approximation component and N high-frequency detail components from initial data. In contrast to the Fourier transform, the wavelet transform can preserve temporal scale. The frequency change of the data may be seen through the time change because the decomposed data is still a time series. Figure 2 displays a schematic diagram of a wavelet transform, which represents the decomposed time series, represents the approximate composition of the layer, and represents the detail component of the layer. The decomposed time series is the sum of the approximate components of the last layer and the detail components of all layers. Eq. (8) expresses the mathematical relationship between the original sequence and the decomposed subsequence.

$$S_n = A_n + D_{n-1} + D_{n-2} + \ldots + D_1 \tag{8}$$

Figure 2 shows the three-level wavelet transform structure diagram of a signal. According to Eq. (8), Eq. (9) can be obtained.

$$Data = A_3 + D_3 + D_2 + D_1 \tag{9}$$

Because continuous wavelet transform consumes more data and produces more information, it is not suitable for subsequent time-series data analysis. Thus, the discrete wavelet transform method is utilized in this experiment.

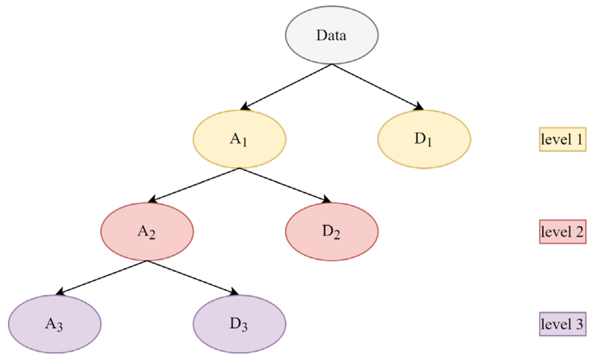

Fig. 2 schematic diagram of wavelet transform.

C. WT-ARIMA Model

A single ARIMA model is not perfect when fitting load data, where load data is a non-stationary time series in the classical sense. In this study, a combination forecasting model is proposed. It includes wavelet transform and ARIMA, called the WT-ARIMA model, which overcomes the drawback that the single ARIMA model does not fit the load data well. In this model, the non-stationary load data is decomposed by discrete wavelet transform, and the decomposed data is reconstructed by inverse wavelet transform to produce the relevant approximate and detail components. The processed component series of discrete wavelet have better steady-state levels than the original data without decomposition. We use the ARIMA model to fit each reconstructed sequence and output the predicted value from each ARIMA model. The predictions of the WT-ARIMA model are calculated by computing the predicted values of all the ARIMA models. The flow chart of WT-ARIMA is shown in Figure 3. There are three stages in this WT-ARIMA model: reconstruction and wavelet transform; building prediction models; obtaining the predicted outcomes.

Stage 1: Reconstruction and wavelet transform.

The appropriate number of decomposition layers is determined based on the number of selected experimental samples. The time series are separated into appropriate approximate and detailed components using wavelet transform, and n is the number of decomposition layers.

D_n and A_n denotes the detail and approximation components of each layer, respectively. The detail components of each layer ($D_n, \ldots, D_1$) and the approximate composition (A_n) of the final layer will be reconstructed to keep the temporal scale constant with the original data.

Stage 2: Building the prediction models.

An independent ARIMA prediction model will be built for each time series obtained after the reconstruction, n+1 in total, respectively.

Stage 3: Obtaining the predicted outcomes.

After each subseries is successfully modeled with ARIMA predictions, it can be used to output the corresponding prediction results. Ultimately, by calculating the arithmetic sum of all the subseries predictions, a set of values can be obtained, which are the predicted values of the WT-ARIMA model for the load data at the corresponding time points.

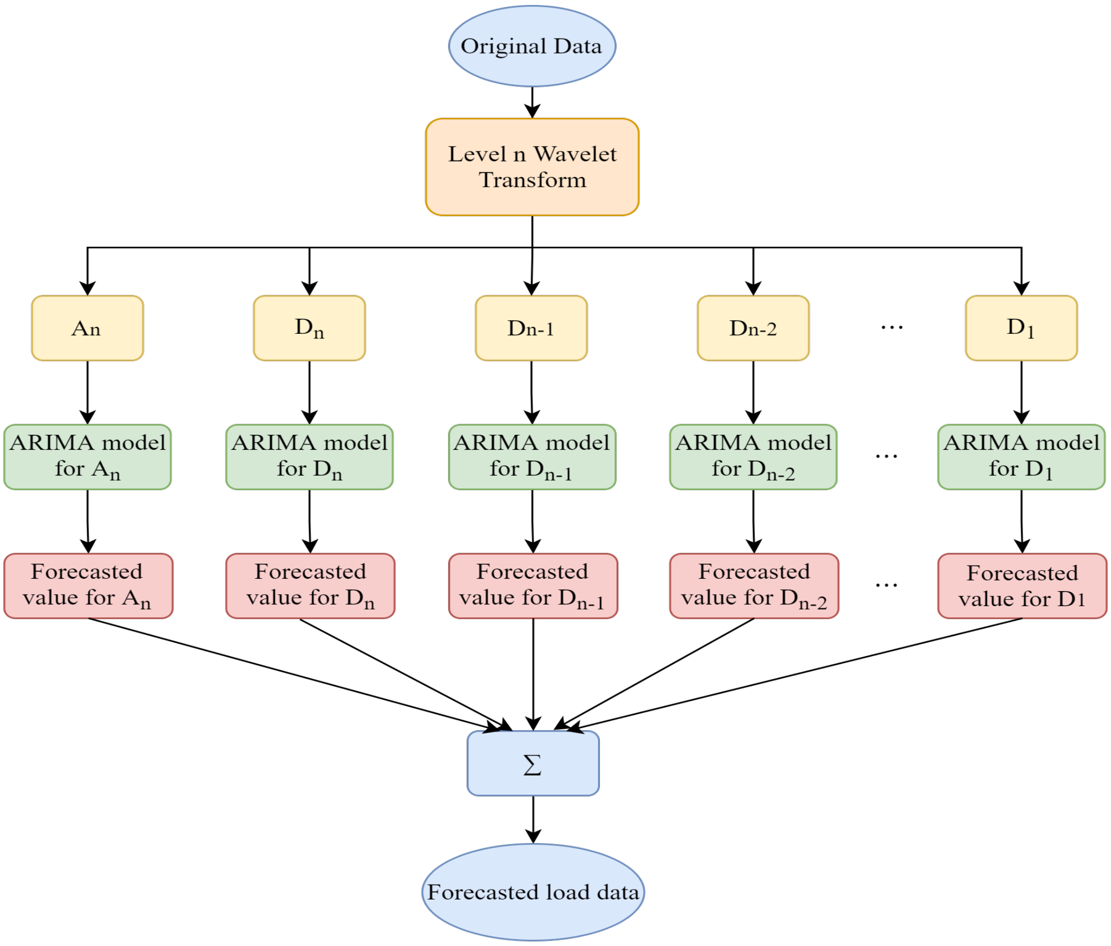

Fig. 3 WT-ARIMA flow chart.

III. Experiment

A. Data Set Introduction

In this study, real load data are used for the experiment. The source of the experimental data is the actual peak load data of a county in Jiangxi province in 2013. The data are sampled from the equipment at 24-hour intervals, and the sample values are the historical maximum load data within the day, i.e., the peak load data. The line graph of the load data is shown in Figure 4. In Figure 5, we draw the ACF plot and PACF plot corresponding to the initial peak load data. By observing the ACF plots in Figure 5, it is easy to see that this data set is a set of non-smooth time series data.

B. Load Data Processing by Wavelet Transform

We choose to use discrete wavelet transform with the inverse transform for the data processing of load data. Among the many wavelet functions, db4 is selected as the wavelet function in the experiment, and the number of the decomposition layers depends on the length of the load data. Figure 6 shows the result of the initial load data after the discrete wavelet transform and the reconstruction data by the inverse transform. After decomposing and reconstructing the data, we obtained six subseries data containing one approximate component and five detail components. In other words, the load data are decomposed into five layers. If we use capital D for the detail component and capital A for the approximate component, then the six subsequences are A_5, D_5, D_4, D_3, D_2, and D_1. Assuming that capital Y represents the original load data, then we have the equation:

$$Y = A_5 + D_5 + D_4 + D_3 + D_2 + D_1 \tag{10}$$

The maximum decomposable level of a data set is directly related to the data length of the data set itself and the length of the selected wavelet function. Eq. (11) describes the mathematical relationship among them.

$$\max\_level = \log_2\left(\frac{data\_len}{filter\_len - 1}\right) \tag{11}$$

, where the result of the calculation is usually taken as an integer.

C. Model Building and Prediction Results

We apply the ARIMA model to the original load data and the reconstructed data for each sub-series separately. After building the ARIMA model corresponding to each time-series data, we can get the prediction results of each series in the ARIMA model. Now, according to Eq. (8), we can obtain Eq. (12).

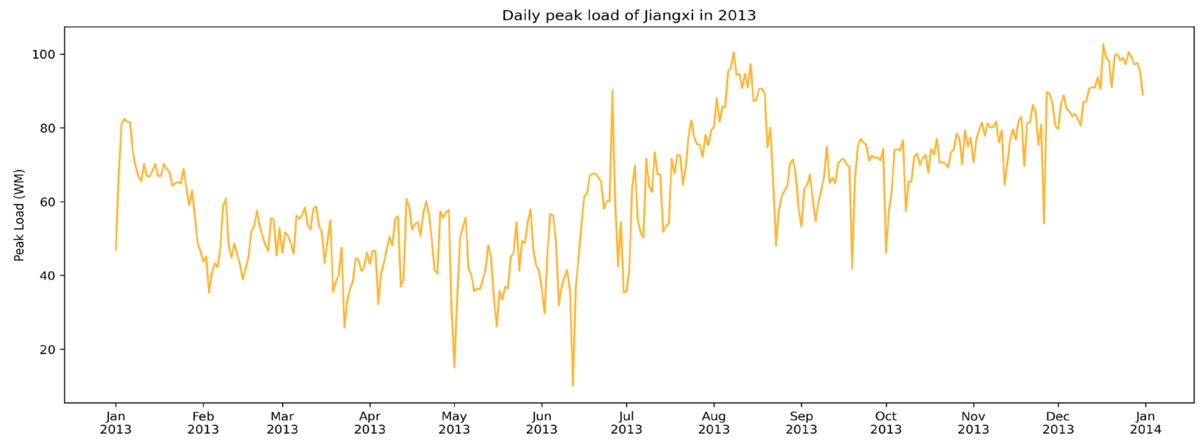

Fig. 4 Load value of a county in Jiangxi Province in 2013.

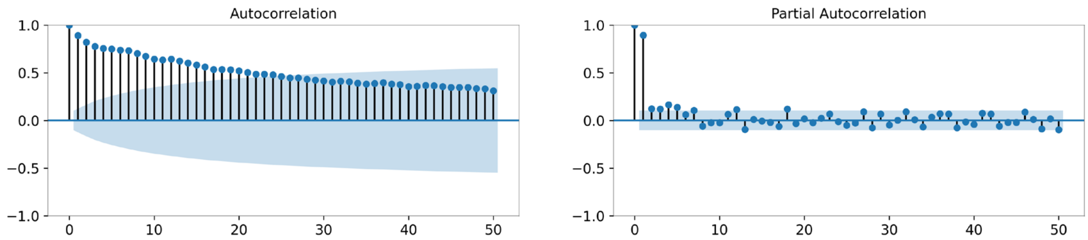

Fig. 5 Load data ACF (left) graph and PACF (right) graph.

$$Y^* = A_5^* + D_5^* + D_4^* + D_3^* + D_2^* + D_1^* \tag{12}$$

In Eq. (12), the superscript with a star indicates the predicted data.

Figures 7 shows the fit of the test dataset decomposed and reconstructed for all the subseries under the ARIMA model. From these figures, we can see that the fit of the individual component data is quite good. With the above three stages, we can obtain the corresponding ARIMA model for each individual component data, and the combined WT-ARIMA model for the actual load data, respectively. The predictions of the two models are shown in Figure 8. In this experiment, the load data from December 17 to December 31 are used as test data. In order to compare these test data more clearly, the subgraph of Figure 8 shows the comparison performance of these data points.

D. Model Evaluation

Although it is intuitive to observe the model fit from the subgraph of Figure 8, one or more evaluation metrics can better assess the prediction accuracy from a scientific point of view. In this experiment, we use two metrics, MAPE and RMSE, to evaluate the experimental performance. Eq. (13) and Eq. (14) show the mathematical formulas for these two metrics.

$$MAPE = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{\hat{y}_i - y_i}{y_i}\right| \tag{13}$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2} \tag{14}$$

Among these, $\hat{Y}_i$ is the predicted value of the model output, Y_i is the true value of load data.

TABLE I

THE ACTUAL LOAD VALUE AND FORECASTING VALUE BY ARIMA AND WT-ARIMA, AND THE EVALUATION OF TWO MODELS.

DATE	LOAD	ARIMA	WT-ARIMA	MAPE WT-ARIMA	MAPE ARIMA	RMSE WT-ARIMA	RMSE ARIMA
2013/12/17	102.7540	91.0974	103.1750	**0.4097**	11.3442	**0.4210**	11.6566
2013/12/18	99.0830	100.7056	98.3250	**0.7651**	1.6376	**0.7580**	1.6226
2013/12/19	98.1660	99.7030	98.1483	**0.0181**	1.5658	**0.0177**	1.5370
2013/12/20	91.0110	98.3207	93.7802	**3.0427**	8.0316	**2.7692**	7.3097
2013/12/21	99.6390	92.2158	98.5030	**1.1402**	7.4501	**1.1360**	7.4232
2013/12/22	99.9750	98.1668	98.9112	**1.0641**	1.8086	**1.0638**	1.8082
2013/12/23	98.2520	99.9179	99.2963	**1.0629**	1.6955	**1.0443**	1.6659
2013/12/24	99.0020	98.5449	99.5786	0.5825	0.4617	0.5766	0.4571
2013/12/25	97.2120	98.8745	98.4130	**1.2354**	1.7102	**1.2010**	1.6625
2013/12/26	100.4740	97.5164	100.6627	**0.1878**	2.9436	**0.1887**	2.9576
2013/12/27	99.2170	99.9185	98.0537	1.1725	0.7070	1.1633	0.7015
2013/12/28	97.1870	99.4312	96.7122	**0.4885**	2.3092	**0.4748**	2.2442
2013/12/29	97.6110	97.5327	98.8045	1.2227	0.0802	1.1935	0.0783
2013/12/30	95.5680	97.5388	95.5634	**0.0048**	2.0622	**0.0046**	1.9708
2013/12/31	88.9470	95.9160	87.8290	**1.2570**	7.8350	**1.1180**	6.9690

Table I provides the prediction results of each forecast point and the matching actual load data to compare the prediction accuracy of the two models more intuitively. At the same time, Table I also shows the MAPE and RMSE of each predicted sample point. By comparing the evaluation indexes of the two models, it is not difficult to see that the WT-ARIMA model adopted in this paper is superior to the ARIMA model in most cases. Although the WT-ARIMA model is not superior to the ARIMA model in all the predicted sample points, there is significant difference in the prediction error between the two models. Moreover, compared with the ARIMA model, the prediction error of the WT-ARIMA model is more stable.

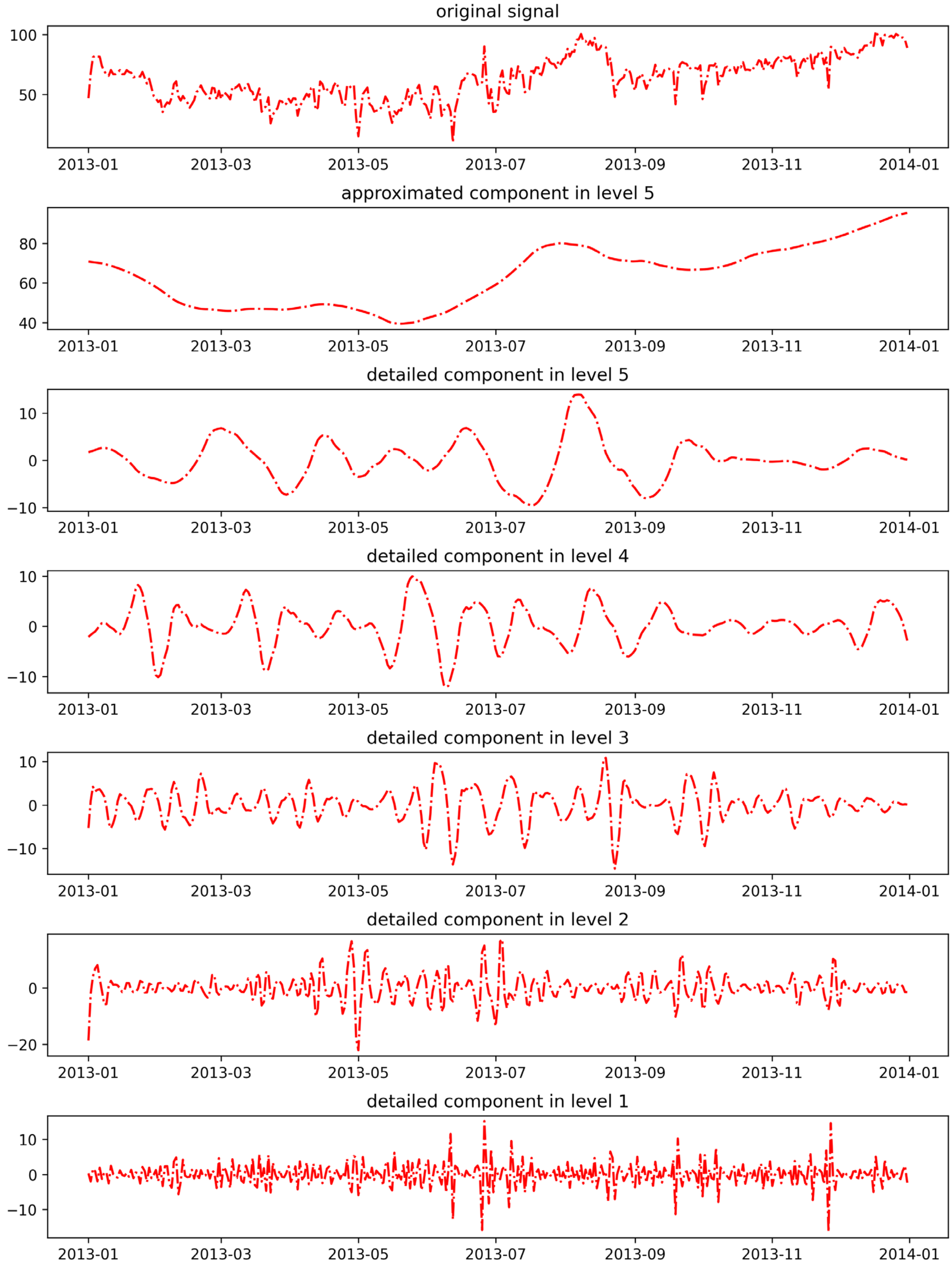

Fig. 6 The result after wavelet transform and reconstruction of load data.

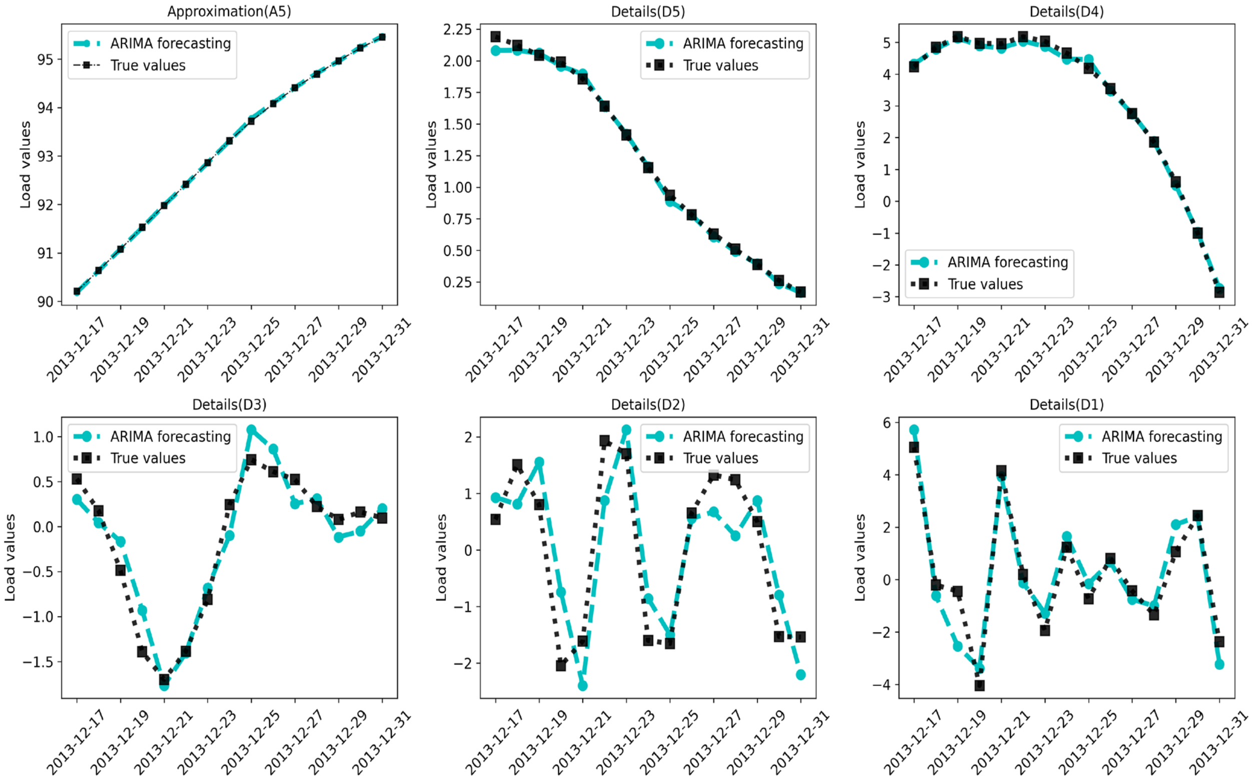

Fig. 7 Comparison of the actual and forecasting values of A_5, D_5, D_4, D_3, D_2, and D_1 component of the test dataset by WT-ARIMA.

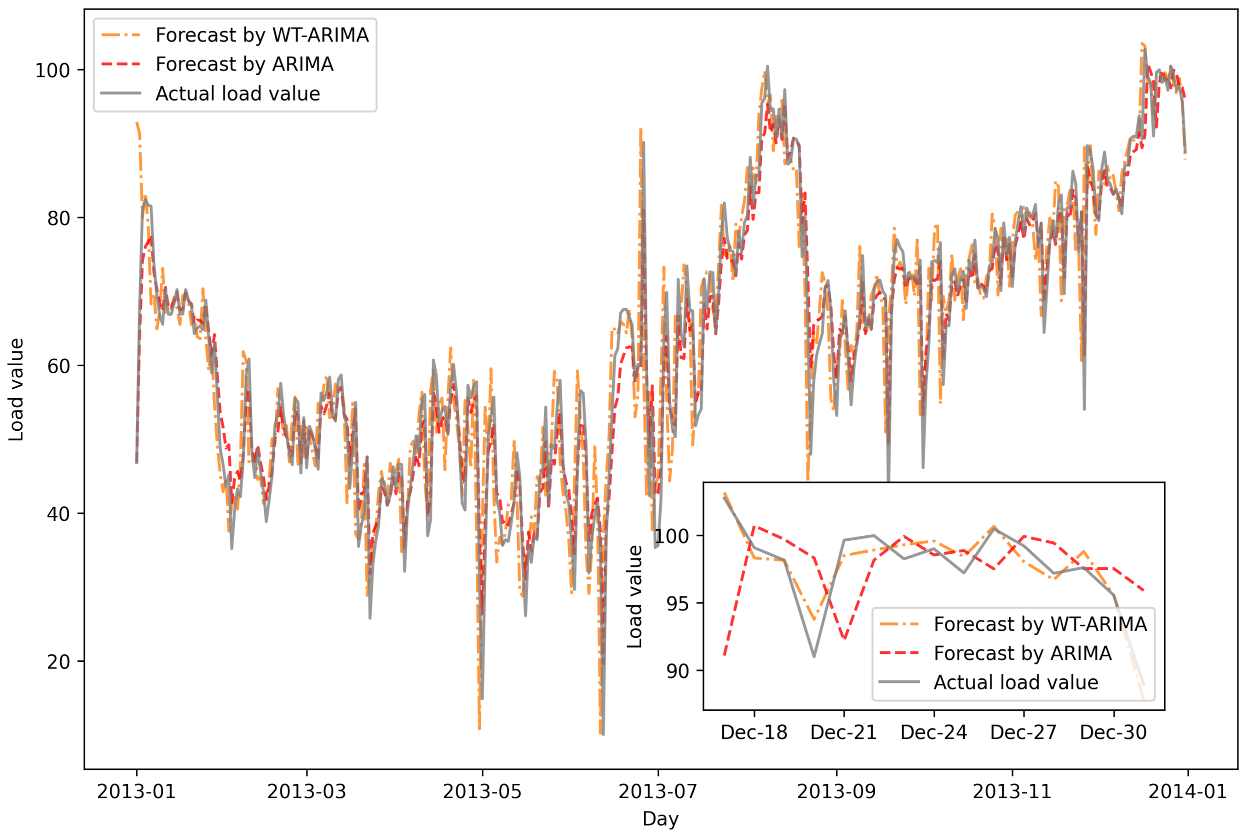

Fig. 8 Comparison of the actual and forecast values of load values by ARIMA and WT-ARIMA.

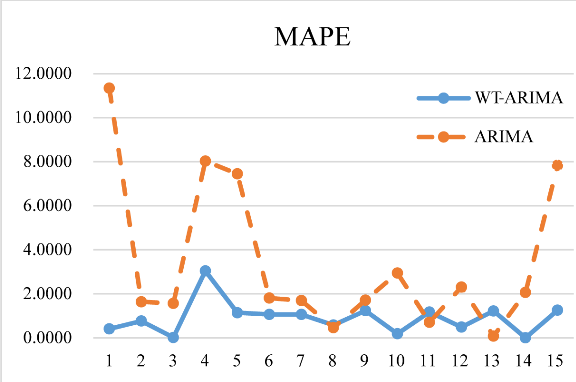

Fig. 9 MAPE evaluation of the prediction results of the two models

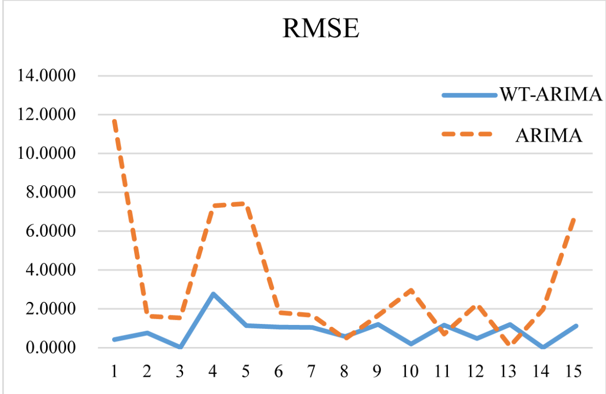

Fig. 10 RMSE evaluation of the prediction results of the two models

To get a more intuitive sense of the predictive power of the two prediction models, we evaluate its error indices of the test dataset. The predicted errors are shown in Figure 9 and Figure 10. The comparison of the above two plots indicates that the WT-ARIMA model described in this study is more stable than the classical ARIMA model in actual prediction.

IV. Conclusion

Due to the strong non-stationarity of load data, the prediction error of a single ARIMA model in short-term load forecasting is unstable. The combined prediction method of wavelet transform and ARIMA is proposed for short-term power load prediction to solve this problem. The load data is decomposed by wavelet to reduce the non-stationary of the original load data, which makes the data more suitable for the ARIMA model. Specific experiments on actual load data show that this method can effectively improve the prediction accuracy of ARIMA, and the prediction error of each sample point is more stable than that of a single ARIMA model. In terms of prediction accuracy and error stability, the WT-ARIMA model suggested in this study outperforms the single ARIMA model. On the other hand, load data is not only a time series, but also a nonlinear variable that is susceptible to a range of external factors. In future research, we will take into account the nonlinear nature of load data to further investigate and explore a more accurate prediction model.

References

[1] Nie H, Liu G, Liu X, et al. Hybrid of ARIMA and SVMs for short-term load forecasting[J]. Energy Procedia, 2012, 16: 1455-1460.

[2] Lee C M, Ko C N. Short-term load forecasting using lifting scheme and ARIMA models[J]. Expert Systems with Applications, 2011, 38(5): 5902-5911.

[3] Lu J C, Niu D X, Jia Z Y, " A study of short-term load forecasting based on ARIMA-ANN," Proceedings of 2004 International Conference on Machine Learning and Cybernetics (IEEE Cat. No. 04EX826), IEEE, 2004, no.5, pp. 3183-3187.

[4] Fard A K, Akbari-Zadeh M R. A hybrid method based on wavelet, ANN and ARIMA model for short-term load forecasting[J]. Journal of Experimental & Theoretical Artificial Intelligence, 2014, 26(2): 167-182.

[5] Al Amin M A, Hoque M A, "Comparison of ARIMA and SVM for Short-term Load Forecasting," The 9th annual information technology, electromechanical engineering and microelectronics conference (IEMECON), IEEE, 2019, pp. 1-6.

[6] Kavousi-Fard A, Kavousi-Fard F. A new hybrid correction method for short-term load forecasting based on ARIMA, SVR and CSA[J]. Journal of Experimental & Theoretical Artificial Intelligence, 2013, 25(4): 559-574.

[7] Tan Z, Zhang J, He Y, et al. Short-term load forecasting based on integration of SVR and stacking[J]. IEEE Access, 2020, 8: 227719-227728.

[8] Fan G F, Peng L L, Zhao X, et al. Applications of hybrid EMD with PSO and GA for an SVR-based load forecasting model[J]. Energies, 2017, 10(11): 1713.

[9] Yang Y, Che J, Deng C, et al. Sequential grid approach based support vector regression for short-term electric load forecasting[J]. Applied energy, 2019, 238: 1010-1021.

[10] Li Y, Che J, Yang Y. Subsampled support vector regression ensemble for short term electric load forecasting[J]. Energy, 2018, 164: 160-170.

[11] Li M W, Geng J, Wang S, et al. Hybrid chaotic quantum bat algorithm with SVR in electric load forecasting[J]. Energies, 2017, 10(12): 2180.

[12] Hong W C, Fan G F. Hybrid empirical mode decomposition with support vector regression model for short term load forecasting[J]. Energies, 2019, 12(6): 1093.

[13] Zhang Z, Hong W C, Li J. Electric load forecasting by hybrid self-recurrent support vector regression model with variational mode decomposition and improved cuckoo search algorithm[J]. IEEE Access, 2020, 8: 14642-14658.

[14] Nalcaci G, Özmen A, Weber G W. Long-term load forecasting: models based on MARS, ANN and LR methods[J]. Central European Journal of Operations Research, 2019, 27(4): 1033-1049.

[15] Aly H H H. A proposed intelligent short-term load forecasting hybrid models of ANN, WNN and KF based on clustering techniques for smart grid[J]. Electric Power Systems Research, 2020, 182: 106191.

[16] Elgarhy S M, Othman M M, Taha A, et al., "Short term load forecasting using ANN technique," The Nineteenth International Middle East Power Systems Conference (MEPCON), IEEE, 2017, pp. 1385-1394.

[17] Xu L, Wang S, Tang R. Probabilistic load forecasting for buildings considering weather forecasting uncertainty and uncertain peak load[J]. Applied Energy, 2019, 237: 180-195.

[18] Samuel I A, Adetiba E, Odigwe I A, et al. A comparative study of regression analysis and artificial neural network methods for medium-term load forecasting[J]. Indian Journal of Science and Technology, 2017, 10(10).

[19] Singh S, Hussain S, Bazaz M A, "Short term load forecasting using artificial neural network," The Fourth International Conference on Image Information Processing (ICIIP), IEEE, 2017, pp. 1-5.

[20] Mitchell G, Bahadoorsingh S, Ramsamooj N, et al., "A comparison of artificial neural networks and support vector machines for short-term load forecasting using various load types," IEEE Manchester PowerTech, IEEE, 2017, pp. 1-4.

Jinxing Che received his B. S. degree from Jiujiang University in 2007 and his M. S. degree in applied mathematics from Lanzhou University in 2010, as well as his Ph. D. degree in mathematical statistics from Xidian University, China in 2019. He is currently an associate professor and Master's Supervisor in the College of Science, Nanchang Institute of Technology, China. His main research interest is data analysis theory and application, hydrological information processing as well as prediction theory and method.

Huachao Zhai received a B. S. degree from Hebei University of Science and Technology in 2019. He is studying for a master's degree at the Nanchang Institute of Technology.