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Forecast Improvement of Electricity Load Using a Model Integrating ARIMA and ANN

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ABSTRACT

A model combining seasonal autoregressive integrated moving average (SARIMA) and artificial neural network (ANN) methodology is developed to simulate the dynamics and to forecast stable electrical energy supply in power system by using the input of historical daily electricity load data, weather data, and holiday effect variables. An integrated SARIMA-ANN method is to process the strong seasonality and periodic characteristics of load data. Simulation results show that the proposed model is more effective than ANN model, ARIMA model, SARIMA model and ARIMA-ANN model in prediction and forecasting. The technical factors are attenuated by using the model to yield better forecasting results.

Keywords: Artificial Neural Network, Autoregressive Integrated Moving Average, Short-term load forecasting

1. Introduction

Electricity load forecasting is key to effective operation and planning of power systems. The forecasting accuracy has significant impacts on electric utilities and regulators. Overestimation of electricity demand will lead to conservative operation, where too many startup units supplying unnecessary level of reserve or substantial poor investment in power facilities. Conversely, underestimation may result in a risky operation and unmet demand and make the system vulnerable to disturbance. Electricity power generated from power plants or independent generators is difficult to be effectively stored with today's technology. An accurate load forecasting to provide favorable references is thus essential for ensuring stable national economy.

The issue of power supply has received more and more attention with increasing power demand for economy growth. Renewable energy has been the focus in pursuing sustainable future. However, renewable capacity additions cause several challenges: increasing power grid complexity for energy distribution, volatile load swings, frequency and voltage for management that require fast reacting grid control and adaptive assets. An accurate short-term load forecasting is therefore important to balance the demand and supply sides. Load forecasting is usually concerned with the prediction of hourly, daily, weekly, and annual values of the system demand and peak

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demand. Such forecasts are sometimes categorized as short-term, medium-term, and long-term forecasts, depending on the time horizon. In terms of forecasting outputs, load forecasts can also be categorized as point forecasts (i.e., forecasts of the mean or median of the future demand distribution), and density forecasts (providing estimates of the full probability distributions of the possible future values of the demand). Long-term forecasts usually require more than merely an extrapolation of the seasonality or trend evident in the historical data. A forecasting tool can not only derive a forecast from outside explanatory variables, such as economic or demographic information, but also help account for changes in the historical data and be a predictor in the forecast period. For instance, in electric load forecasting, short-term forecasts are influenced by weather conditions (driving air conditioning loads and heating use), whereas long-term forecasts are dominated by economic development and political decisions (building offshore wind parks yields different load distributions than those yielded by power plants). The forecasting model presented in this paper is suitable for short-term forecasts; therefore, there are few available socio–economic variables, which are different from the variables used in most methods that are used for long-term forecasts. There is no common basis to compare the prediction performance of models. Even for short-term forecasts, it is difficult to predict electrical loads because of many influencing social, weather, and seasonal factors. Social factors include human activities such as attending work or school, and they may affect the electricity supply. Weather factors include temperature and humidity, and these influence residential load. Seasonal factors include the trend of the four seasons and yearly power demand growth. The production of too much energy is wasteful and increases operational cost. Conversely, the insufficiency of electricity directly and severely affects the national economy. Thus, a robust short-term load forecasting model is crucial to precisely dispatch power during transmission and distribution.

In recent year, the issue of power supply has received more attention with increased power demand on renewable energy. However, the addition of renewable energy capacity can face challenges in the complexity of distributed energy systems. Yet expanding total generator capacity is difficult due to the limitation of resources and land development. With the deregulations of energy industries, a robust electricity load forecasting model is necessary to effectively strike the balance between power demand and supply, and is also essential for making decisions that prevent overloading. It also provides references on optimally scheduling electricity energy resources in advance by predicting future demand of one-day or one-week ahead. Recent reviews on energy forecasting provide detailed accounts of the existing forecasting models and their classification. Zhao and Magoules (2012) reviewed the existing methods for building energy consumption prediction into five categories. Hippert *et al*. (2001) presented a review on short-term load forecasting. Suganthi and Samuel (2012) presented a review on energy demand models for demand forecasting. Fumo (2014) presented a review on building energy estimation and also studied now estimation models are classified. Martinez-Alvarez *et al*. (2015) presented a survey on data mining for time series forecasting of electricity. Qamar Raza and Khosravi (2015) presented a review on short-term load forecasting techniques based on artificial intelligence (AI) techniques. A recent study by Mat Daut *et al*. (2017) presented a review on building electrical energy consumption forecasting analysis using conventional and AI methods (Ahmad *et al*., 2014; Wang & Srinivasan, 2017; Deb *et al*., 2017). All these reviews provide vital information on energy forecasting models on different scales and summarize the performance of the models. A forecasting model can either be based on static data that usually fits a dependent variable to a set of independent variables, or it can make use of a single or parallel time series data.

Data analytics by applying artificial intelligence is said to revolutionize all knowledge-based aspects. Many prediction techniques in either linear techniques such as autoregressive moving average (ARMA) and autoregressive integrated moving average (ARIMA) (Ohtsuka *et al*., 2010; Huang & Shih, 2003), or nonlinear techniques such as artificial neural networks (ANNs) and genetic algorithm (GA) have been proposed in literature for forecasting electricity load (Chuang *et al*., 2013; Sarangi *et al*., 2009; Yalcinoz & Eminoglu, 2005). Ohtsuka *et al*. (2010) applied a regressive Bayesian spatial ARMA model to forecast regional electricity consumption in Japan. Narayan and Smyth (2005) showed that electricity consumption, employment, and real income are cointegrated in Australia. Erdogdu (2007) proposed an ARIMA model with cointegration analysis for electricity demand forecasting in Turkey. Many works have been using ARIMA model for time series analysis, and the key lies in its inherent statistical characteristics. As a result of linear correlation structure among the time series, no nonlinear pattern can be captured by the ARIMA model. The intrinsic complexity of electrical loads and the nonlinearity of the power systems may require better forecasting methods (Ferreira & Da Silva, 2007). Chuang *et al*. (2013) compared the short- to long-term load forecasting accuracy of univariable and multivariable ARIMA and ANN models and showed that energy consumption and the amount of exports are the two essential factors for predicting short-term energy consumption. Yalcinoz and Eminoglu (2005) modeled mid-term load forecasting (MTLF) in monthly forecast step and short-term load forecasting (STLF) in daily forecast step using multi-layered perceptron neural network. Ferreira and Da Silva (2007) extended the support vector machines learning algorithm in an autonomous ANN-based electric load forecasters.

In recent years, several studies of hybrid models have been implemented in load forecasting. Kavousi Fard and Akbari-Zadeh (2013) proposed a hybrid correction method integrating ARIMA model, wavelet transform and ANN to reach reliable load forecasting model. Khashei and Bijar (2011a) proposed a hybrid of ANN and ARIMA model for time series forecasting. In spite of all the above research, there is yet notable prediction error due to periodic, nonlinear and chaotic load data. In fact, it is time-consuming to analyze different characteristics of load data in real power systems. To overcome this situation, the seasonal, hybrid methodology that includes both linear and nonlinear short-term load modeling techniques can be pragmatic.

This paper proposes an integrated ARIMA-ANN seasonal method to process the strong seasonality and periodic characteristics of load data. An ARIMA model assumes that the present data are a linear function of past data and residuals, and it has been a popular linear model in time series prediction of energy price (Tan, *et al*., 2010), energy consumption (Do, *et al*., 2016), water quality (Faruk, 2010) and airline passenger forecasting (Chen, *et al*., 2012). It is effective when the time series is stationary without missing data and with a strong linear characteristic; however, it is futile to data with nonlinearity. By comparison, ANN with interconnected artificial neurons can reflect the nonlinear input and output by the parallel-distributed processors (Liu, *et al*., 2013). ANNs have been applied to model economic indicator and weather factors (Do, *et al*., 2016) and load forecasting (Ekonomou, 2010). Real-world time series are rarely pure linear or nonlinear. Hence integrating ARIMA and ANN model for time series forecasting have been shown better than any individual ARIMA model or ANN model (Zhang, 2003; Khashei & Bijar, 2011b). A seasonal integrating model based on ARIMA and ANN is proposed in this work to treat data with periodic and seasonal properties. By selecting suitable input variables, including historical daily electricity load data, weather data and holiday effect variables, the integrating model is shown effective for electricity load forecasting.

2. ARIMA and ANN Model

2.1 Autoregressive Integrated with Moving Average

The stationarity of a stochastic process for time series analysis can be described in two senses—strict or strong and wide or weak. For practical purposes, the second is of interest to us, in which the stationarity is characterized by the following properties: the expected values or means of the random variables do not depend on time (are constant), the variances do not depend on time either and are finite and, the covariances (the autocovariance) between two different periods of time only depend on the time lapse between these two periods (Chavez, *et al*., 1999). Their mathematical expressions are respectively

$$E(y(t)) = E(y(t+k)) \text{ for all } k \tag{1}$$

$$Var(y(t)) = Var(y(t+k)) \text{ for all } k \tag{2}$$

$$Cov(y(t), y'(t)) = Cov(y(t+k), y'(t+k)) \tag{3}$$

If the predictions are performed in non-stationary time series, and the problem of spurious regression is often generated in model estimation. Since ARIMA can only be used in stationary time series data, it is often necessary to convert non-stationary data into stationary data.

Decomposition of time series is an important technique for all types of time series analysis, especially for seasonal adjustment. It seeks to construct, from an observed time series, a number of component series (that could be used to reconstruct the original by additions or multiplications) where each of these has a certain characteristic or type of behaviour. For example, time series are usually decomposed into: $T(t)$ is the trend component at time t, which reflects the long-term progression of the series (secular variation). A trend exists when there is a persistent increasing or decreasing direction in the data. The trend component does not have to be linear. $C(t)$ is the cyclical component at time t, which reflects repeated but non-periodic fluctuations. The duration of these fluctuations is usually of at least two years. $S(t)$ is the seasonal component at time t, reflecting seasonality (seasonal variation). A seasonal pattern exists when a time series is influenced by seasonal factors. Seasonality occurs over a fixed and known period (e.g., the quarter of the year, the month, or day of the week). $I(t)$ is the irregular component (or noise) at time t, which describes random, irregular influences. It represents the residuals or remainder of the time series after the other components have been removed. Hence a time series using an additive model can be thought of as

$$y(t) = T(t) + C(t) + S(t) + I(t), \tag{4}$$

whereas a multiplicative model would be

$$y(t) = T(t) \times C(t) \times S(t) \times I(t). \tag{5}$$

An additive model would be used when the variations around the trend does not vary with the level of the time series whereas a multiplicative model would be appropriate if the trend is proportional to the level of the time series. Sometimes the trend and cyclical components are grouped into one, called the trend-cycle component. The trend-cycle component can just be referred to as the trend component, even though it may contain cyclical behavior.

For an autoregressive integrated with moving average model, the notation AR(p) model refers to the autoregressive model of order p. The future value of a variable is assumed to be a linear function of the past observations and random errors. The output data $y(k)$ at any given time k is written

$$y(k) = c + \sum_{i=1}^{p} ø_i\, y(k-i) + \varepsilon(k) \tag{6}$$

where $Ø_1$, ...$Ø_p$ are the model AR(p) parameters, c is a constant, and the random variable $\varepsilon(k)$ is white noise. The notation MA(q) refers to the moving average model of order q:

$$y(k) = \mu + \varepsilon(k) + \sum_{i=1}^{q} \theta_i\, \varepsilon(k-i) \tag{7}$$

where $\theta_1,\ldots\theta_q$ are the parameters of the model MA(q), μ is the expectation of $y(k)$ and the $\varepsilon(k)$, $\varepsilon(k-1)$, …, $\varepsilon(k-i)$ is white noise error. The notation ARMA(p, q) refers to the model with p autoregressive terms and q moving-average terms,

$$y(k) = c + \varepsilon(k) + \sum_{i=1}^{p} ø_i\, y(k-i) + \sum_{i=1}^{q} \theta_i\, \varepsilon(k-i) \tag{8}$$

or

$$y(k) = c + Ø_1 y(k-1) + Ø_p y(k-p) + \varepsilon(k) + \theta_1 \varepsilon(k-1) + \ldots \theta_q \varepsilon(k-q) \tag{9}$$

An ARIMA process generates a nonstationary series of order D is denoted $I(D)$, where the nonstationary process can be made stationary by taking D differences is the so called difference-stationary or unit root processes. A stationary ARMA(p, q) process after differenced D times is denoted by ARIMA(p, D, q). The form of the ARIMA(p, D, q) model is

$$\Delta^D y(k) = c + Ø_1 \Delta^D y(k-1) + Ø_p \Delta^D y(k-p) + \varepsilon(k) + \theta_1 \varepsilon(k-1) + \ldots \theta_q \varepsilon(k-q) \tag{10}$$

where $\Delta^D y(k)$ denotes a D^{th} difference time series. In lag operator notation $B^i y(k) = y(k-i)$, the ARIMA(p, D, q) model becomes

$$Ø^*(B)y(k) = Ø(B)(1-B)^D y(k) = c + \theta(B)\varepsilon(k) \tag{11}$$

where $Ø^*(B) = Ø(B)(1-B)^D$ is an unstable AR operator with D unit roots, $Ø(B) = 1 - Ø_1(B) - \ldots - Ø_p B^p$ is a stable degree p AR lag operator (with all roots lying outside the unit circle), and similarly, $\theta(B) = 1 + \theta_1(B) + \ldots + \theta_q B^q$ is an invertible degree q MA lag operator.

Many time series exhibit a seasonal trend, meaning there is a relationship between observations made during the same period in successive period. In addition to this seasonal property, there can also be a relationship between observations made during successive periods. The multiplicative ARIMA model is an extension of the ARIMA model that addresses seasonality and potential seasonal unit roots. For a series with periodicity s, the multiplicative ARIMA(p, D, q) × (p_s, D_s, q_s)$_s$ is

$$Ø(B)\Phi(1-B)^D(1-B^s)^D y(k) = c + \theta(B)\,\Theta(B)\,\varepsilon(k) \tag{12}$$

where the stable, degree p, AR and $\Phi(B)$ is a stable, degree p_s, AR operator. The seasonal ARIMA can be expressed as SARIMA$(p, D, q) \times (p_s, D_s, q_s)_s$.

An iterative three-stage ARIMA model includes model identification, parameter estimation and diagnostic checking (Box & Jenkins, 1976). In model identification stage, when the observed time series presents trending and heteroscedasticity, transformation, differencing and seasonal differencing are applied to the data to remove its trend and stabilize the variance before fitting data into an ARIMA model. In model parameters estimation, the order can be identified by observing an autocorrelation function and a partial autocorrelation function. By using the maximum likelihood estimation, the ARIMA parameters can be determined to best fit the load data characteristics. In diagnostic checking, the residuals are assumed to follow the assumptions for a stationary unit root process in white noise drawings from a fixed distribution with a constant mean and variance. If these assumptions are not satisfied, one needs to go back to the first stage to fit a more appropriate model.

2.2 Artificial Neural Network (ANN)

An artificial neural network consists of simple nodes with high interconnections, called neurons, and each carries an activation function for transferring the input signals as illustrated in Figure 1(a). The transfer function f is for converting the weighted summation to get the output value. The schematic diagram of a three-layer ANN is shown in Figure 1(b), in which the input signals are passed from the input layer to the hidden layer, and then to the output layer. A traditional perceptron model can be used as activation function to solve linear classification, but load prediction belongs to linear inseparability most of the time. Hamzacebi (2007) used the sigmoid function as activation function in the hidden-layer to handle linear

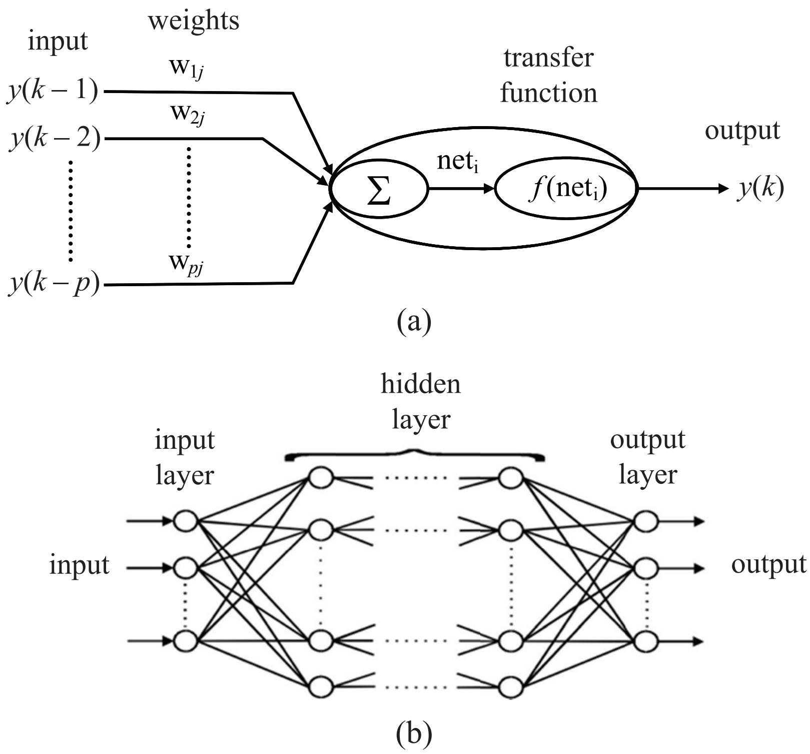

Fig. 1. (a) The structure of an artificial neuron and (b) the schematic of a feedforward neuron network model (by authors).

inseparability problem. This work applies back-propagation network (BP). Xiao *et al*. (2009) proposed to integrate BP and rough set for short-term load forecasting. Steepest descent method is also commonly used in BP network (Su *et al*., 2011) with slower convergence. Catalao *et al*. (2007) proposed Lavenberg-Marquardt Algorithm (LM) as the training algorithm to achieve faster convergence for a three-layer feed-forward neural network when predicting one-week ahead electricity price with more accurate results.

The relation between the output $y(k)$ and the input $y(k-1), y(k-2), ..., y(k-P)$ is:

$$y(k) = w_0 + \sum_{j=1}^{Q} w_j g\left(w_{0j} + \sum_{i=1}^{P} w_{ij} y(k-i)\right) + \alpha(k) \tag{13}$$

where w_{ij} ($i = 0, 1, 2, \ldots, P, j = 1, 2, \ldots, Q$) and w_j ($j = 0, 1, 2, \ldots, Q$) are the model parameters often called the linking weights, $\alpha(k)$ is random error, P is the number of input nodes, and Q is the number of hidden nodes. The sigmoid function is the hidden layer transfer function,

$$g(x) = [1 + \exp(-x)]^{-1} \tag{14}$$

where x is the input. An ANN model performs a nonlinear operative mapping from the previous observations to the future value $y(k)$ by a function f defined by the network formation and correlation weights.

$$y(k) = f(y(k-1), y(k-2), \ldots, y(k-P), \tilde{W}) + \alpha(k) \tag{15}$$

where $\tilde{W}$ is a vector of all parameters. Simple network framework with a small number of hidden layer neurons often performs well in out-of-sample forecasting. To avoid over-fitting, the network should not input too many free parameters, which may allow the network to fit the training data well, leading to poor generalization.

3. The Integrated Seasonal ARIMA–ANN Model

The SARIMA model, as an extension of the ARIMA model, is the linear approach for predicting future time-series to improve prediction accuracy by removing the characteristics of seasonal variation through seasonal differences. For example, electricity load series shows a strong seasonality on weekly order, and may observe some disturbance due to temperature fluctuation, weather condition, and/or holidays. In this study, the SARIMA model can be implemented to remove the characteristics of seasonal variation and to improve the prediction accuracy of future electricity load.

Both ARIMA and ANN models have achieved successes in linear and nonlinear forecasting domains respectively; however, neither is a universal model suitable for all circumstances. In real world, the given data may have both linear and nonlinear components,

$$y(k) = L(k) + N(k) \tag{16}$$

where $L(k)$ denotes the linear and $N(k)$ the nonlinear component. Assume that the linear and nonlinear patterns exist in a system can be modeled separately, and the relation between linear and nonlinear components is addictive. An ARIMA model is well defined and the residuals carry only the nonlinear relationship. The seasonal integrated ARIMA–ANN model is shown in Figure 2. Instead of decomposing data into linear and nonlinear components, real load data of the past are directly fit into linear ARIMA model in the first stage with the advantage of effectively identifying and magnifying existing the linear structure in data. The residuals of past data $e(k-1), e(k-2), \ldots, e(k-p)$ obtained from the linear model are the nonlinear

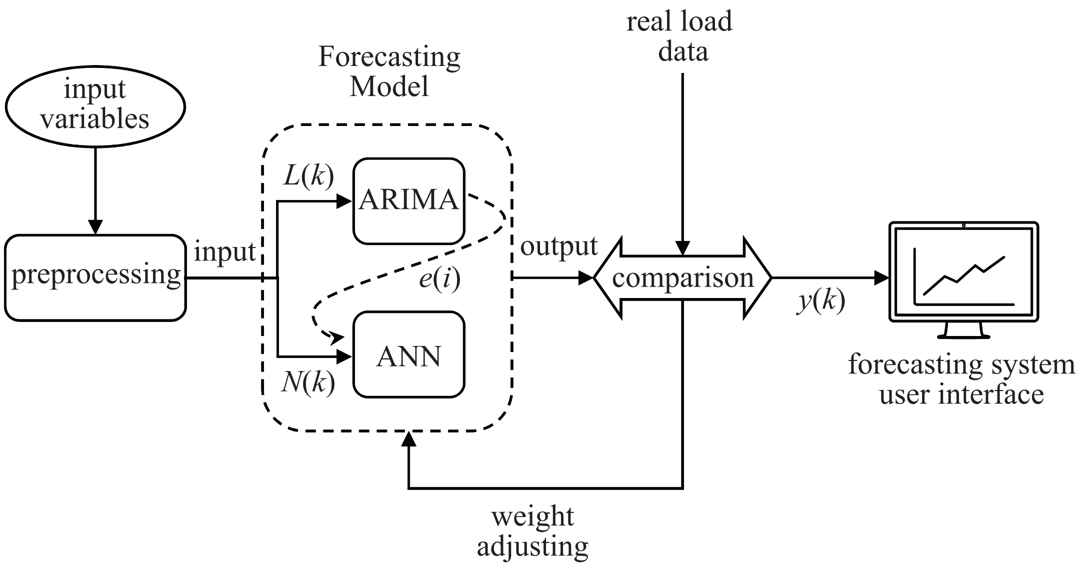

Fig. 2. The proposed model integrating ARIMA and ANN for the strong seasonality and periodic characteristics in electricity load forecasting (by authors).

components. Since ARIMA cannot be utilized to produce an accurate model for forecasting nonlinear time series, load data can be express as the sum of linear and nonlinear components,

$$\hat{L}(k) = y(k) - e(k) \tag{17}$$

where the cap notation indicates the forecast value. The residuals should pass the diagnostic statistics and show no linear correlation left in the residuals.

In the second stage, ANN is used model nonlinear part and probable relationships existing in residuals and nonlinear components of the original data.

$$\begin{aligned}\hat{N}(k) = h(&e(k), e(k-1), \ldots, e(k-l), z(k), z(k-1),\\ &\ldots, z(k-m), z_s(k)\, z_s(k-1), \ldots, z_s(k-n),\\ &\hat{L}(k), p(k))\end{aligned} \tag{18}$$

where $h(k)$ is the nonlinear function determined by the neural network, $e(k)$ is the residual from time step k to to $k-1$, and $z(k)$ and $z_s(k)$ are the non-seasonal and seasonal differencing operator from time step k to $k-m$ and time step k to $k-n$. Here s notation indicates the seasonal term, and l, m, and n are numbers of steps for each term. The last input for non-linear function, $p(k)$, includes weather variables and holiday effect variable of time step k.

$$z(k) = \Delta^d(y(k)-\mu) \tag{19}$$

$$z_s(k) = \Delta_s^D \Delta^d(y(k)-\mu) \tag{20}$$

where d and D are non-seasonal and seasonal differencing order. In this stage, two examples are provided to compare the performance with the proposed ARIMA-ANN model in next section. One is the Zhang's (2003) ARIMA-ANN model, where ANN is used model nonlinear part and probable relationships existing in residuals and nonlinear components of the original data, $\hat{N}(k) = h(e(k), e(k-1), \ldots, e(k-l), p(k))$. In the Khashei and Bijar's (2011b) ARIMA-ANN model, the nonlinear function determined by the neural network is $\hat{N}(k) = h(e(k), e(k-1), \ldots, e(k-l), z(k), z(k-l), \ldots, z(k-m), \hat{L}(k), p(k))$.

The proposed seasonal hybrid model integrates two algorithms for prediction: the seasonal ARIMA for the linear part of electricity load forecasting and the ANN for the residuals. Several past residuals steps, non-seasonal differencing terms and seasonal differencing terms are selected, where the number of steps for each term is determined by trial and error and empirical research as the input to the ANN model. The additional factors are weather variables and holiday effect variable, and the output from the ANN can be used as the forecast values of the nonlinear part and be added onto the linear results obtained from ARIMA model.

$$\hat{y}(k) = \hat{L}(k) + \hat{N}(k) \tag{21}$$

4. Technical Analysis

Figure 3(a) is the load series over 730 days in 2015 and 2016, and Figure 3(b) displays the load fluctuation over 31 days in March 2016, where the electricity load series shows a strong seasonality of weekly order. The disturbance may also include temperature fluctuation, weather condition, and holiday effect. In this study, seasonality is chosen as $s = 7$ as shown in Eq. (11), since electricity load series shows a strong weekly seasonality. Thus the seasonal ARIMA model is determined as SARIMA $p = 1, D = 1, q = 1, p_7 = 1, D_7 = 1, q_7 = 1$. To comprehensively model the load data, there are three important factors in electricity load forecasting: daily maximum temperature of major cities, daily precipitation of major cities and holiday effect variables. It cannot be denied that the daily maximum temperature in a subtropical zone is most important to influence the power usage of air conditioner, which significantly influence the total electricity load. The second factor, daily precipitation, indirectly affects the local electricity demand. If one considers the extreme weather

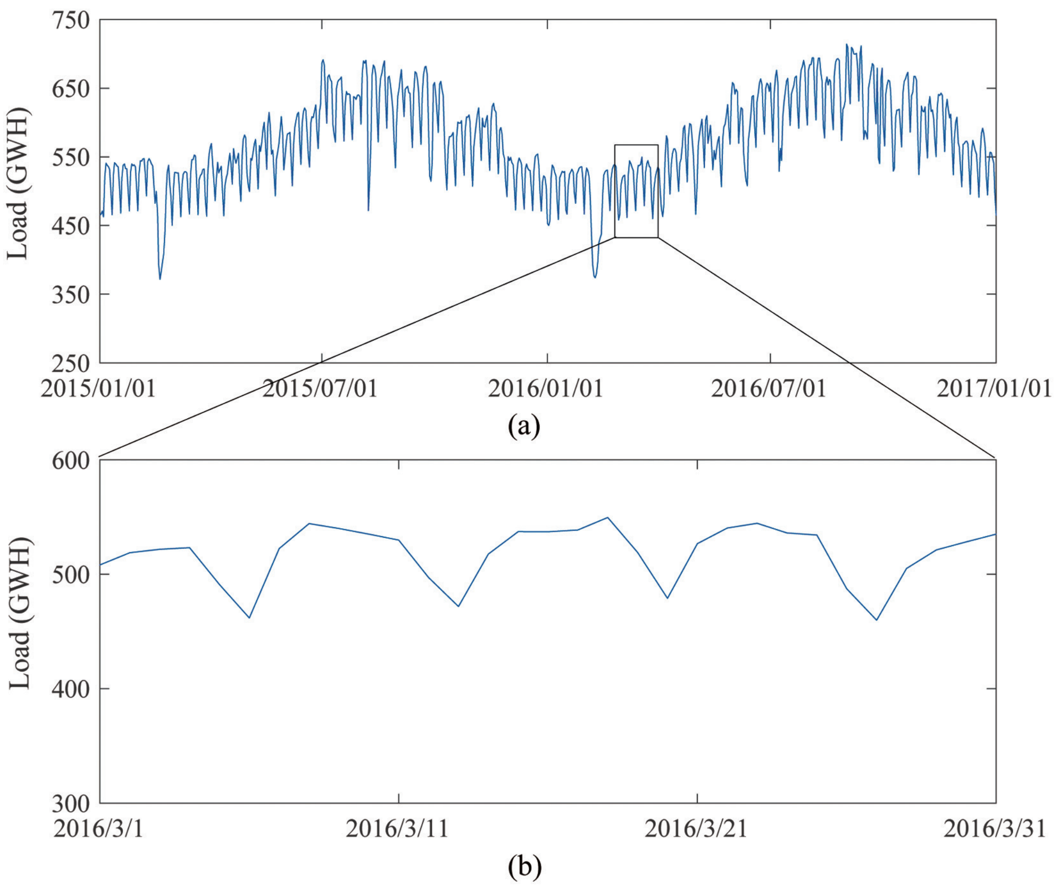

Fig. 3. (a) Daily electricity load in year 2015 and 2016 and (b) in March, 2016 (by authors).

condition, such as typhoon, the economic activities may result in different load profiles. The last one is the holiday effect variable critical to national economic activities. The above three factors are selected as the inputs to an integrated seasonal electricity load forecasting model.

Data with 882 observations from the period of 2015/1/1 to 2017/5/31are provided by the Taiwan Power Company. Consider five distinct periods of time: the normal summer week, the normal winter week, the 3- /4-day holiday week, the long holiday week, and the extreme weather condition week. The out-of-sample approach is selected to test the forecasting accuracy. Of those 882 data, only length of 730 data are selected to train the model for forecasting daily load of the next day and the following week. The prediction results are validated by the real load. Consider the integrated model of SARIMA $p = 1, D = 1, q = 1, p_7 = 1, D_7 = 1, q_7 = 1$ and a nine input neurons, eight hidden layer neurons and one output neuron [9-8-1] ANN. With 9 input variables, including four daily weather variables, which are Taipei highest temperature (T_1), Kaohsiung highest temperature (T_2), Taipei precipitation (P_1), and Kaohsiung precipitation (P_2), one dummy variable for holiday effect and four historical variables, which are residuals of $k - 1$, differencing terms of $k - 1$, $k - 2$ and seasonal differencing terms of $k - 1$. Both linear and nonlinear models have been applied to these data sets, and the performance of the proposed model will be compared with ANN, ARIMA, SARIMA, ARIMA-ANN model, Zhang (2003) and Khashei and Bijar (2011b).

The results of one-day ahead and one-week ahead in five conditions are shown in Figure 4 and 5. In normal summer week and the normal winter week, the data has strong linear relation and ARIMA model has better performance than ANN. While in the 3- /4-day holiday week and the long holiday week, the data has strong non-linear relation and instead the ANN model has better performance than ARIMA. With strong weekly seasonality for the electricity load as shown in Figure 3, the SARIMA-ANN model has best performance than ARIMA-ANN. The integrated SARIMA-ANN model can accommodate on modeling both linear and nonlinear properties, thus outperforms the other models with smaller errors in forecasting.

The performance of the proposed model on electricity load forecasting is validated by the five models: ANN, ARIMA, SARIMA, ARIMA-ANN model, Zhang (2003) and Khashei and Bijar (2011b), as given in Table 1 and 2. The Mean Absolute Percentage Error (MAPE) and Root Mean Squared Error (RMSE) are employed as performance indicators.

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|(y_i - \hat{y}_1)/y_i\right| \tag{22}$$

$$\text{RMSE} = \sqrt{\tfrac{1}{n}\textstyle\sum_{i=1}^{n}(y_i - \hat{y}_1)^2} \tag{23}$$

where n is the number of observed data, y_i is the real value and $\hat{y}_i$ is the forecast value. The proposed model has the best performance over these models for all of the five interested conditions. In normal summer week, this work outperforms the other five models with RMSE = 1, while the other models have RMSE = 13, 6, 6, 37, 8 and 7, respectively. All of the above simulation results show that the integrated seasonal autoregressive integrated moving average and neural network model has better performance in modeling, prediction and forecasting.

5. Conclusions

1. Accurate electricity load forecasting is important

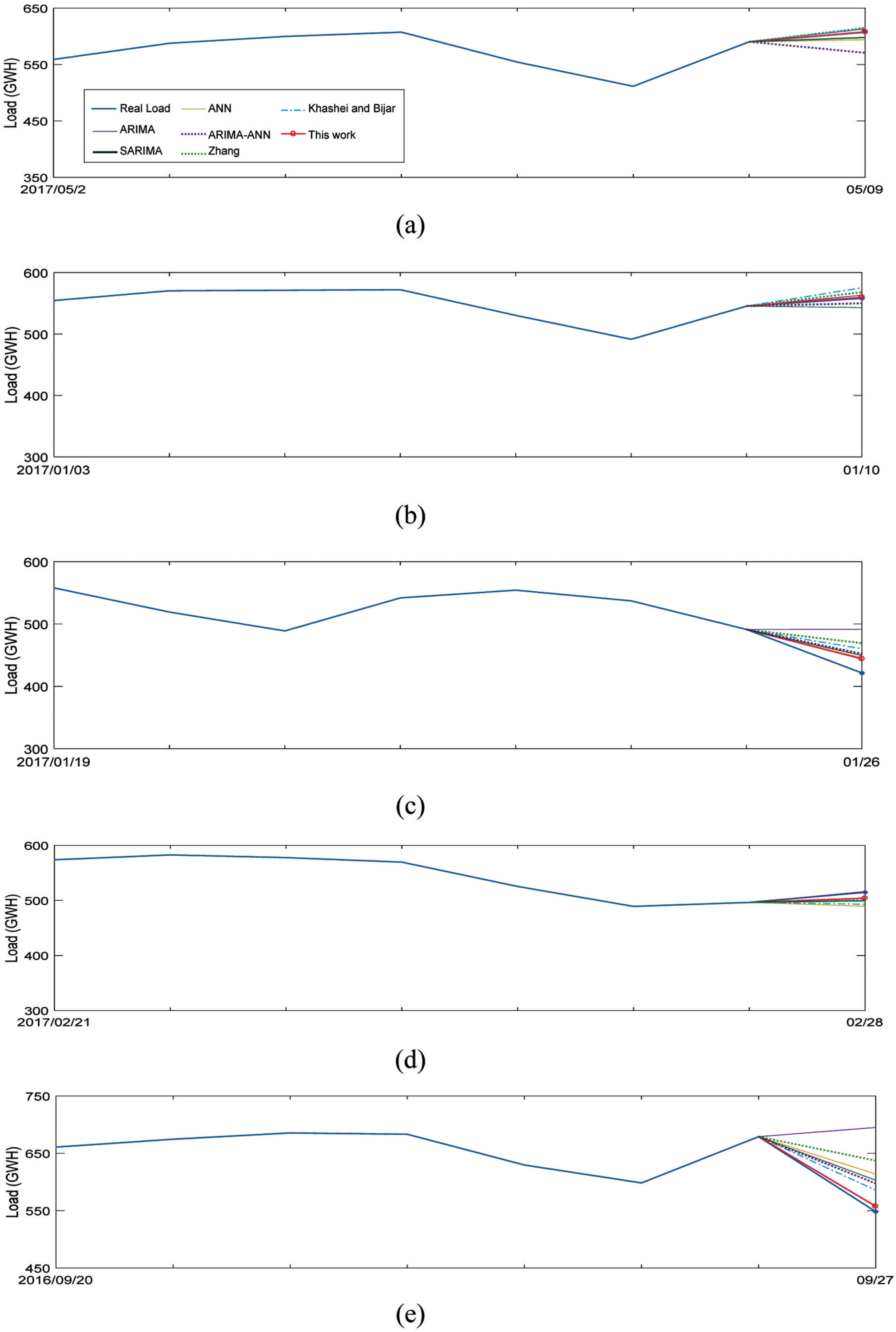

Fig. 4. One-day ahead electricity load forecasting in five conditions: (a) normal summer week, (b) normal winter week, (c) long holiday week- Chinese New Year, (d) 3-day/4-day holiday week and (e) extreme weather condition (by authors).

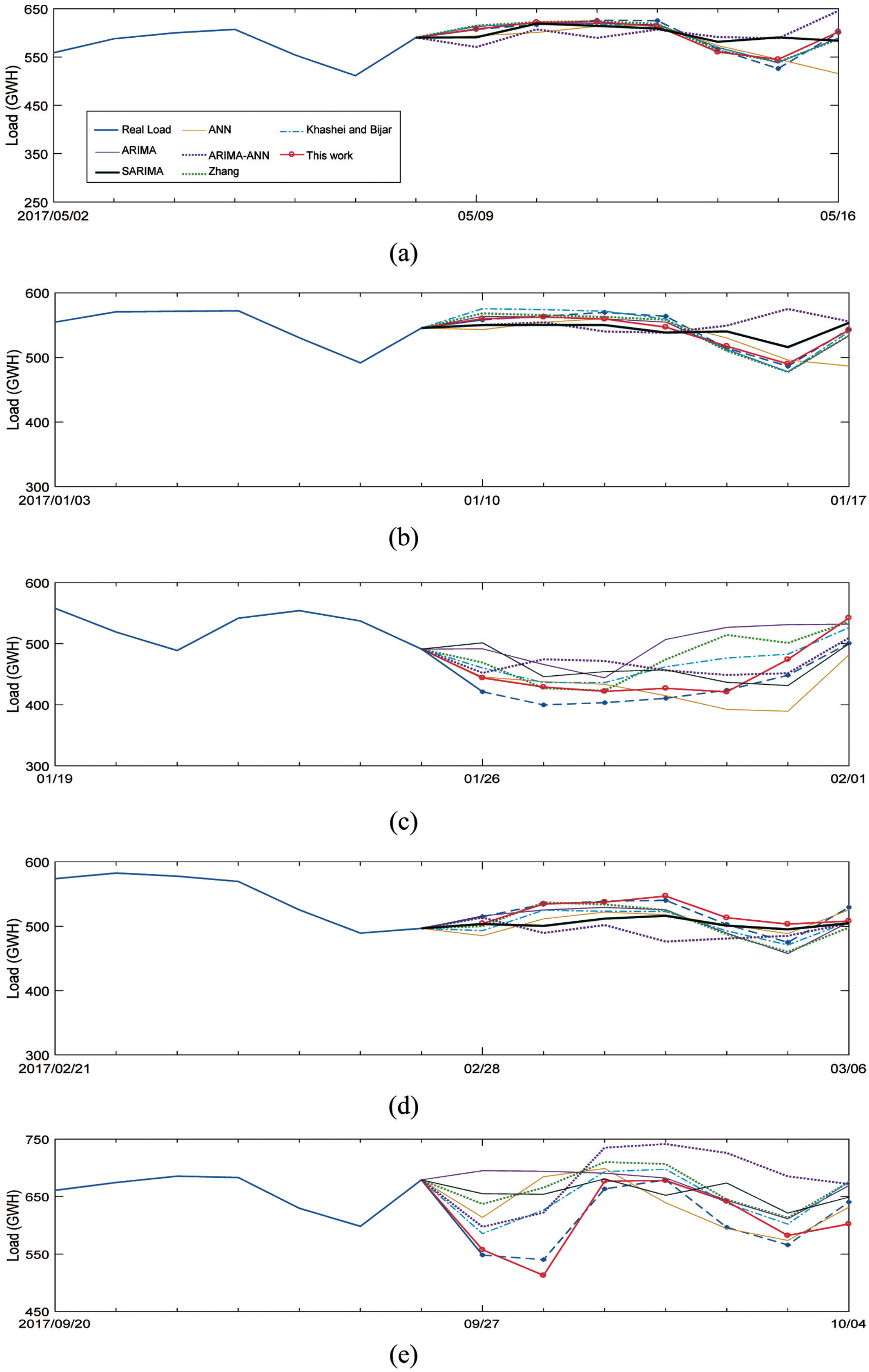

Fig. 5. One-week ahead electricity load forecasting in five conditions: (a) normal summer week, (b) normal winter week, (c) long holiday week- Chinese New Year, (d) 3-day/4-day holiday week and (e) extreme weather condition (by authors).

Table 1. One-step ahead forecasting result and performance of the proposed model and the other models – RMSE (GWH) (by authors)

		Real data	ANN	ARIMA	SARIMA	ARIMA-ANN	Zhang (2003)	Khashei and Bijar (2011b)	This work
Normal summer week	GWH	607.4	594	613.2	601.6	570.9	615.1	614	607.9
	RMSE	--	13	6	6	37	8	7	1
Normal winter week	GWH	558.2	543	563.4	560.3	550.1	568.2	575.4	559.8
	RMSE	--	15	5	2	8	10	17	2
Long holiday	GWH	421.3	445.6	491.6	441.5	452.2	469.2	460.4	444.2
	RMSE	--	21	17	20	31	15	14	10
Holiday	GWH	514.8	489.6	516.1	501.5	513.4	500.1	493.1	504.1
	RMSE	--	25	1	13	1	15	22	11
Extreme weather condition	GWH	548.3	613.8	695.1	603.1	597.4	637.3	585.6	557.5
	RMSE	--	65	147	55	49	89	37	9

Table 2. One-week ahead forecasting performance of the proposed model and the other models (GWH) (by authors)

		ANN	ARIMA	SARIMA	ARIMA-ANN	Zhang (2003)	Khashei and Bijar (2011b)	This work
Normal summer week	MAPE (%)	3.9	1.3	2.7	5.8	1.2	1.4	1.1
	RMSE	35	8	16	37	9	9	9
Normal winter week	MAPE (%)	3.3	1.2	1.4	5.7	1.2	1.3	1
	RMSE	24	7	8	39	7	9	8
Long holiday	MAPE (%)	6.3	7.3	10.1	8.9	5.6	5.7	5.2
	RMSE	33	46	56	45	32	33	34
Holiday	MAPE (%)	4.9	0.3	2.2	5.5	2.9	4.2	2.1
	RMSE	25	1	11	35	15	22	11
Extreme weather condition	MAPE (%)	7.6	11.5	11.7	13.1	10.3	7	3.6
	RMSE	63	85	92	85	68	45	26

yet often a difficult task for decision making. As in many other time series, electricity load forecasting cannot be easily expressed in linear relations and/or nonlinear relations, and thus an integrated model is developed to generalize the time series in two stages: the first linear modeling by SARIMA and then the nonlinear modeling by ANN, is most successful to improve prediction accuracy.

2. The integrated seasonal model includes SARIMA of $(1,1,1) \times (1,1,1)_7$ with seasonality of 7 and one degree in each autoregressive, differencing, and moving average terms and a [9-8-1] ANN model with nine input neurons, eight hidden layer neurons and one output neuron for electricity load forecasting. With 9 input variables, including four daily weather variables, one dummy variable for holiday effect and four historical variables, it is shown that the model has a mean absolute percentage error (MAPE) less than 3%.
3. In regard to time series seasonality, an SARIMA should be selected for data with seasonal terms, and differencing operators should be replaced by seasonal differencing operators to obtain more accurate and robust short-term load forecasting. The integrated model with a seven-day seasonality SARIMA is selected to be integrated with ANN model. By conquering the nonlinear and chaotic electricity data with seasonality, the proposed seasonal ARIMA-ANN electricity load forecasting model has the best performance over the 5 models in references.
4. In future work, the period of the historical data will be lengthened and used to provide a reference of the power system planning for the proposed model in the medium-term and long-term load forecasting. The seasonal short-term forecast results will be added to the seasonal or annual forecasts. The prediction errors outside the sample will be compared to confirm that the proposed model in this paper is indeed superior to other models.

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整合自我迴歸移動平均與類神經網路於電力負載之預測改善

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摘　要

本文發展一整合季節性自我迴歸移動平均(SARIMA)和類神經網路(ANN)演算法之預測模型，利用歷史電力負載數據、氣象數據和假日效應之變量當作輸入參數，模擬電力系統動態及電能供應穩定性之預測。整合的SARIMA-ANN方法可用於預測顯著的季節性及周期性特徵之電力負載系統數據。研究模擬結果顯示，此模型應用在預測能力方面比ANN模型、ARIMA模型、SARIMA模型和ARIMA-ANN模型更有效，藉由使用此預測模型可減少技術性因子的影響並能產生更好的預測結果。

關鍵詞：類神經網路，自我迴歸移動平均，短期負載預測

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