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A Study of the Hybrid Recurrent Neural Network Model for Electricity Loads Forecasting

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Abstract *In the electric industry, electricity loads forecasting has become more and more important, because electricity demand quantity is a major determinant factor in electricity supply strategy. Furthermore, accurate regional electricity loads forecasting is one of the principal factors for the electric industry to improve the energy management performance. Recently, statistical methods and artificial intelligence have been developed for electricity loads forecasting. However, there are two drawbacks in the past electricity loads forecasting models: (1) conventional statistical methods, such as regression models are unable to deal with the nonlinear relationships well, because electricity loads forecasting are known to be the nonlinear relationships; and (2) artificial intelligence technologies (i.e., support vector machines (SVM) and convention artificial neural networks (ANNs)) do not take into account time series causality for regional electricity loads forecasting. Based on these reasons above, this study proposes a new electricity loads forecasting model, which incorporates one step-ahead concept into recurrent neural network (RNN) to build a hybrid RNN model. The time series method considered from RNN model, which can be fitted to time series electricity loads datasets, and the neural network in hybrid RNN model can deal with the nonlinear relationships. For evaluating electricity loads forecasting performance, six different electricity loads forecasting models (RSVMG, ANN, Regression, HEFST, ANFIS and AR(2)) are used as comparison models. The research results indicate that the proposed electricity loads forecasting model is superior to the listing comparison models in terms of mean absolute percentage errors (MAPE).*

Key words Electricity loads, artificial neural networks, recurrent neural network, mean absolute percentage errors, nne step-ahead

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1. Introduction

The electrical energy is undoubtedly the primary source of energy consumption in any modern household, and the demand of electrical energy constantly increases. In general, the electricity loads have the following characteristics: (1) Time dependence: Electricity loads change according to different hours in one day. In one year, there are two load peaks; one is in summer and the other is in winter; (2) Region dependence: In different areas, even at the same time, the electricity loads are different. It is caused by the different consumption structure at each region; and (3) Temperature dependence: In different climate conditions, high or low temperature would result in high electricity demand. In high temperature, the electricity demand is high because a great part of the electricity is consumed to turn on cooling electrical equipment. Similarly, in low temperature, the electricity demand increases because much electricity is utilized for heating. Because of the economy growth, people hope to have a high quality life and the affluence growth in electricity instrument ownership, the demand of electrical energy constantly increases. Consequently, more power plants are built to meet users' demands and forecasting electricity demand is one of important topics in energy system planning and operation. Further, researchers also focus the topics of power production optimization and power scheduling (Nowak *et al.*, 2005; Nürnberg and Römisch, 2002). Accurate electricity loads forecasting can avoid producing too much electrical energy (energy waste), but insufficient electrical energy will bring users' dissatisfaction and complaints.

Various techniques have been developed during the past years for electricity load forecasting (Hippert *et al*., 2001; Taylor and Buizza, 2003; Taylor and McSharry, 2008), most of which are based on time series analysis. Time series is a sequence of data point, measured at successive times, spaced at uniform time interval. The attempt of time series analysis is to understand the underlying context of the data points. A time series model will generally reflect the fact that observations close together in time will be more closely related than observations further apart. From these mentions above, the sequence annual electricity loads would be belong to one kind of time series model. The statistical models are firstly adopted for the load forecasting problem, which include linear regression model (Haida and Muto, 1994), and autoregressive moving average (ARMA) model (Huang and Shih, 2003). However, the distributions of electricity loads data do not obey these statistic assumptions, and the conventional time series models are unable to properly be applied in electricity loads data. Further, one-step ahead forecast method has been applied to time series forecasting (Enders, 2015), and in many engineering problems, one-step-ahead prediction using neural networks has been performed and reported with satisfactory results (Chang *et al*., 2010). Recently, Pino *et al*. (2008) used one-step ahead forecast method within experimental procedure with encouraging results. There are some of other forecasting models which apply one step-ahead method in electricity market (Gonzales *et al*., 2005; Zareipour *et al*., 2006; Zhang and Luh, 2005; Mandal *et al*., 2006). To achieve a one step-ahead forecast, the learning strategy simply introduces the current value as the predicted value of the signal. The problems to be dealt with when predicting the future value is how many steps (time delays) are appropriate for obtaining the best performance. In time series forecasting techniques, one-step-ahead or multi-step-ahead prediction is frequently used. One-step-ahead or multi-step-ahead prediction implies that the predictor utilizes the available observations to forecast one value or multiple values at the definite future time.

To incorporate the nonlinearity, artificial neural networks (ANNs) have received much more attention recently (Hippert *et al.*, 2001; Fan *et al.*, 2005; Hsu and Chen, 2003). Neural networks have been shown to have the ability to learn the load series and reported good performance in load forecasting. In addition, machine learning techniques and fuzzy logic approaches have been used for load forecasting. Pai and Hong (2005) utilized recurrent support vector machines with genetic algorithms (RSVMG) model to forecast electricity loads. The hybrid ellipsoidal fuzzy systems for time series forecasting (HEFST) model were used to forecast regional electricity loads (Pai, 2006). However, the convention artificial intelligence models above do not take into account time series causality for regional electricity loads forecasting.

Based on the drawbacks above, this study proposes a new model, which incorporates one step-ahead concept into recurrent neural network (RNN) to build a hybrid RNN model. Further, in order to enhance the performance of time series forecasting, a ANN using time series concept are utilized in this study (RNN model), which can be fitted to time series electricity loads datasets. And then, the proposed electricity loads forecasting model optimizes the model parameters by neural network, which can avoid the limitations of statistical methods (data need obey some mathematical distribution).

2. Literature review

This section reviews related studies of different forecasting models on electricity loads, time series model and Elman neural network.

2.1. Different forecasting models on electricity loads

The increasing competition of an electricity market, therefore, accurate electricity loads forecasting is important to distribution system investments and the electricity loads planning and management strategies in the power industry. Hence, many researchers have presented different methods to deal with electricity loads forecasting problems. In 2003, back propagation (BP) neural network model to predict the regional peak load of Taiwan was presented by Hsu and Chen (2003). Further, Taylor and Buizza (2003) proposed the regression model using the distribution of the demand scenarios to estimate the demand forecast uncertainty. Then, a recurrent support vector machine with genetic algorithms (RSVMG) was proposed by Pai and Hong (2005) to forecast electricity loads. Pai (2006) developed a hybrid ellipsoidal fuzzy system for time series forecasting (HEFST) model and apply the HEFST model to forecast regional electricity loads in Taiwan. Recently, Ying and Pan (2008) presented an adaptive network based fuzzy inference system (ANFIS) model to forecast electricity loads.

2.2. The time series model

Time series data often arise when monitoring industrial processes or tracking corporate business metrics. Time series analysis accounts for the fact that data points taken over time may have an internal structure (such as autocorrelation, trend or seasonal variation) that should be accounted for (Chatfield, 2004). The financial and economic variables, such as stock price, there are correlation relationships between previous and present periods. Therefore, time series analysis is usually applied in estimating and forecasting the future price (Box *et al*., 2008). Box and Jenkins (1976) proposed the autocorrelation moving average (ARMA) model to find the relationships among time-series observations. The ARMA model is a combination of AR (autocorrelation) and MA (moving average) where time series variable is related to previous periods of residual. The model is usually then referred to as the ARMA (*p*, *q*) model where *p* is the order of the autoregressive part and *q* is the order of the moving average part (as defined below).

Given a time series of data y_t, the notation AR(*p*) refers to the autoregressive model of order *p*. The notation MA (*q*) refers to the moving average model of order *q*. The ARMA (*p*, *q*) model is defined as follow:

$$y_t = a_0 + \sum_{i=1}^{p} a_i y_{t-i} + \varepsilon_t + \sum_{i=1}^{q} b_i \varepsilon_{t-i} \tag{1}$$

Where a_1, …, a_p and b_1, …, b_p are the parameters of the model, ε_t is white noise. If q =0, the process is called a pure autoregressive process denoted by AR(*p*), and If p =0, the process is called a pure moving average process denoted by MA(*q*). Some constraints are necessary on the values of the parameters of this model in order that the model remains stationary. For example, processes in the AR(1) model with $|a_1| \geq 1$ are not stationary.

In practical stock markets, most time-series variables are non-stationary. However, the Box-Jenkins model assumes the time series is stationary. Therefore, Box and Jenkins recommend differencing non-stationary series one or more times to achieve stationary and an auto-regressive integrated moving average model (ARIMA) was produced which is capable of describing certain types of non-stationary (Chatfield, 2004). An ARIMA (*p*, *d*, *q*) process is obtained by integrating an ARMA(*p*, *q*) process. That is given as follows:

$$\Delta^d y_t = a_0 + \sum_{i=1}^{p} a_i \Delta^d y_{t-i} + \varepsilon_t + \sum_{i=1}^{q} b_i \varepsilon_{t-i} \tag{2}$$

Where *d* is a positive integer that controls the level of differencing (or, if *d* = 0, this model is equivalent to an ARMA model).

2.3. The Elman neural network

The Elman neural network (Elman NN) is a single recursive neural network that has a context layer as an inside self-referenced layer (as shown in Figure 1). Both current input from the input layer and previous state of the hidden layer saved in the context layer activate the hidden layer during operation. There exists an energy function associated with the hidden layer, context layer, and input layer (Liou and Lin, 2006; Liou, 2006). In training, the connection weights can load the temporal relations in the training word sequences.

The context layer carries the memory. The hidden layer activates the output layer and refreshes the context layer with the current state of the hidden layer. The back-propagation learning algorithm is commonly used to train the weights in order to reduce the difference between the output of the output layer and its desired output (Rumelhart and McClelland, 1986). Let L_o, L_h, L_c and L_i be the number of neurons in the output layer, the hidden layer, the context layer, and the input layer, respectively. In the Elman NN, L_h is equal to L_c, that is, $L_h=L_c$. In this study, the number of neurons in the input layer is equal to that in the output layer and is also equal to the number of total features, that is, $R=L_0=L_i$.

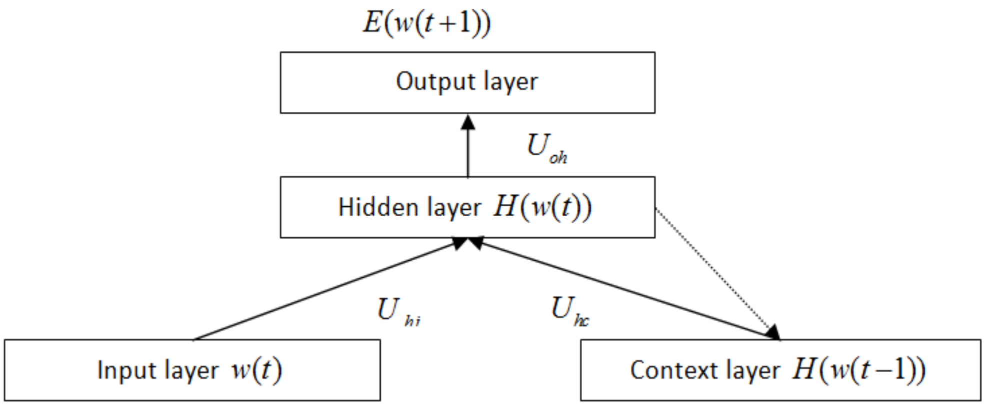

Figure 1. The Elman neural network

Let the three weight matrices between layers be U_{oh}, U_{hc} and U_{hi}, where U_{oh} is an L_h by L_o matrix, U_{hc} is an L_c by L_h matrix, and U_{hi} is an L_i by L_h matrix, as shown in Figure 1. The output vector of the hidden layer is denoted as *H(w(t))* when *w(t)* is fed to the input layer. *H(w(t))* is an L_h by 1 column vector with L_h elements. Let *E(w(t+1))* be the output vector of the output layer when *w(t)* is fed to the input layer. *E(w(t+1))* is an L_o by 1 column vector. The function of the network is:

$$H(w(t)) = \varphi(U_{hi}w(t) + U_{hc}H(w(t-1)) \tag{3}$$

Where φ is a sigmoid activation function that operates on each element of a vector (Rumelhart and McClelland, 1986). In Elman's experiment, the first step is to update the weights, U_{hi}, U_{hc} and Uo_h, through training. The second step is to encode words with a tree structure. All the attempts are aimed at minimizing the error between the network outputs and the desired outputs to satisfy the prediction. Further, in the case of comparison with other type of multilayered network, the most important advantage of Elman's network is a robust feature extraction ability, which provides feedback connections from the hidden layer to a context layer (Serhat-Şeker *et al*., 2003).

$$w(t+1) \approx E(w(t+1)) = \varphi(U_{oh}H(w(t))) \tag{4}$$

3. The Proposed Hybrid Recurrent Neural Network Model

From the literature review, there are two drawbacks in those forecasting models: (1) most statistical methods rely upon some assumptions about the variables and data used, so it is not to be fitted to all datasets; (2) most artificial intelligence technologies do not take into account time series causality for forecasting regional electricity loads. In order to solve these drawbacks above, the proposed hybrid RNN model considers time series method to fit to time series electricity loads datasets. Further, the proposed model uses neural network to optimize the proposed model parameters, which can avoid the limitations of statistical methods.

To enhance electricity loads forecasting performance, this study applies one-step ahead forecast method to the proposed model. The one-step ahead method can utilize current accuracy value to get the next period forecast. Based on the advantages above, this study proposes novel electricity loads forecasting model which includes two facets: (1) build a hybrid RNN model which incorporates one step-ahead concept into RNN; (2) use neural network to optimize the proposed model parameter. To summarize the proposed procedure, the overall flowchart of the proposed model is shown as Figure 2. For understanding the proposed electricity loads forecasting model procedure easily, the proposed algorithm is introduced step by step in the following.

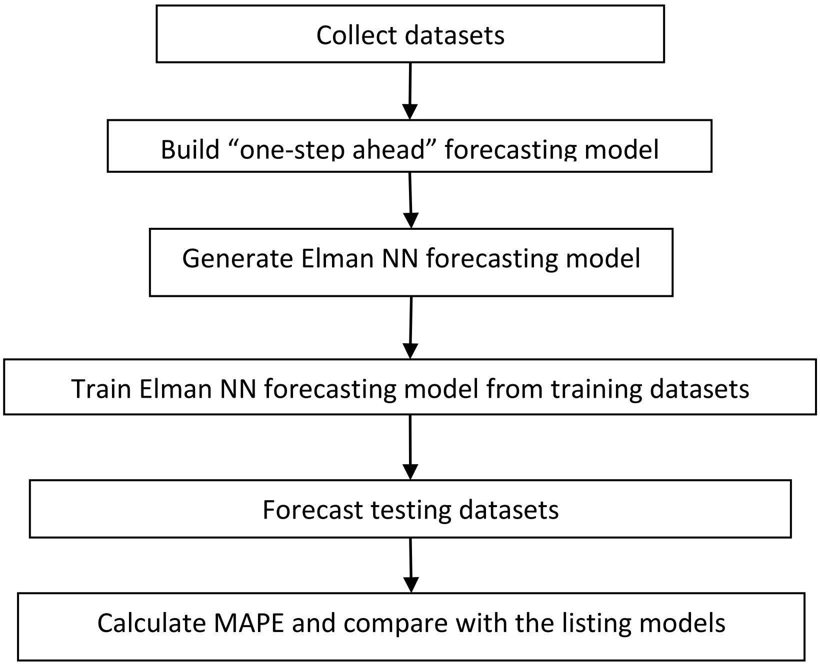

Figure 2. Flowchart of the proposed electricity loads forecasting model procedure

Step 1: Collect datasets

In this step, the annual regional electricity loads data in Taiwan are collected as research data (Table 1) (Hsu and Chen, 2003). The training data are selected and used for testing in each region.

*Table 1***.** The regional electricity loads of Taiwan (from 1981 to 2000)

Year	Northern region	Central region	Southern region	Eastern region
1981	3388	1663	2272	122
1982	3523	1829	2346	127
1983	3752	2157	2494	148
1984	4296	2219	2686	142
1985	4250	2190	2829	143
1986	5013	2638	3172	176
1987	5745	2812	3351	206
1988	6320	3265	3655	227
1989	6844	3376	3823	236
1990	7613	3655	4256	243
1991	7551	4043	4548	264
1992	8352	4425	4803	292
1993	8781	4594	5192	307
1994	9400	4771	5352	325
1995	10254	4483	5797	343
1996	10719	4935	6369	363
1997	11222	5061	6336	358
1998	11642	5246	6318	397
1999	11981	5233	6259	401
2000	12924	5633	6804	420

Step 2: Build "one-step ahead" forecasting model

In this step, the "one-step ahead" forecasting method (as in Equation 5) (Enders, 2015) is applied to the proposed electricity loads forecasting model. From Equation 5, the real data up to the time period prior to forecast data are used as the condition attribute.

$$S_t = (X_{t-1}, X_{t-2}, X_{t-3}, X_{t-4}, \ldots),$$
$$S_{t+1} = (X_t, X_{t-1}, X_{t-2}, X_{t-3}, \ldots) \qquad (5)$$
$$\ldots$$

Where $S_t = (X_{t-1}, X_{t-2}, X_{t-3}, X_{t-4}, \ldots)$ denotes if X_{t-1} (electricity load in period *t*-1) and X_{t-2} (electricity load in period *t*-2) and X_{t-3} (electricity load in period *t*-3) and X_{t-4} (electricity load in period *t*-4)…. and X_{t-16} (electricity load in period *t*-16) then S_t (electricity load in period *t*) (i.e., use 16 data to build one step ahead model), X_{t-1} represents the real electricity load value for period *t*-1, S_t represents the electricity load forecasting value for period *t*.

Step 3: Generate Elman NN forecasting model

In this step, we set one hidden-layer hyperbolic tangent sigmoid transfer function (tansig) and the numbers of neurons are 1 to 15 and a single log sigmoid transfer function (logsig) output layer. For each training step, the error is back propagated to find gradients of errors for each weight and bias.

Step 4: Train Elman NN forecasting model from training datasets

In this study, we set epoch as 10000 and error converges is 0.00001 for the training stopping criterion (the training model is executed for the predetermined fixed number (10000) of iterations unless it terminates while the training error converges).

Step 5: Forecast testing datasets

The parameters for Elman NN model are determined when the stopping criterion is reach from Step 4, and then the generated models are used to forecast the corresponding testing dataset. With determined parameters, the future electricity load forecasting at time, *t*+1, can be obtained by the electricity loads forecasting model.

Step 6: Calculate MAPE and compare with the listing models

Calculate MAPE values in testing datasets by Equation (6). Then the MAPE is taken as evaluation criterion to compare with the listing electricity loads forecasting models.

$$\text{MAPE} = \frac{1}{n}\sum_{t=1}^{n} \left| \frac{actual(t) - forecast(t)}{actual(t)} \right| \times 100\% \qquad (6)$$

Where *actual*(*t*) denotes the real electricity loads value, *forecast*(*t*) denotes the electricity loads forecasting value and *n* is the number of data.

4. Experiment analysis and discussions

This section provides electricity loads forecasting model estimation and performance comparison. To verify the proposed model, the experimentation, using the annual four regional (north, center, south and east) electricity loads data in Taiwan from 1981 to 2000 is implemented (Hsu and Chen, 2003). The sub-datasets for previous 16-years are used as training and those from 1997 to 2000 are selected for testing.

Furthermore, the performance of the proposed electricity loads forecasting model is compared with the listing electricity loads forecasting model: recurrent support vector machines with genetic algorithms (RSVMG) model (Pai and Hong, 2005), back propagation (BP) neural network model (Hsu and Chen, 2003), regression model (Taylor and Buizza, 2003), hybrid ellipsoidal fuzzy systems for time series forecasting (HEFST) model (Pai, 2006), ANFIS model (Ying and Pan, 2008), and AR(2) model (Box and Jenkins, 1976). The forecasting performance of the listing models and the proposed model for four regional electricity loads in

Taiwan are listed in Table 2, and the performance of the proposed model outperforms the listing models in three regions (center, south and east). Furthermore, the average forecasting performance of the listing models and the proposed electricity loads forecasting model for four regions are listed in the last column of Table 2, which shows that the proposed model performance outperforms the listing models.

Table 2. The comparison of different models for different regional electricity loads in Taiwan

Models	Region				
	North	Center	South	East	Average
RSVMG	0.76	1.31	1.71	1.87	1.41
ANN	1.06	1.34	2.34	3.23	1.99
Regression	2.54	8.52	8.29	4.1	5.86
HEFST	0.35	0.94	1.85	1.46	1.15
ANFIS	0.04[a]	0.19	0.99	1.32	0.64
AR(2)	3.87	3.17	3.53	5.14	3.93
Proposed model	0.053	0.118[a]	0.053[a]	0.052[a]	0.069[a]

Note : [a] The best performance among seven models

Further, we conduct non-parametric statistic method, Friedman test (Friedman, 1937), to verify whether the proposed model is superior to the listing models. Using the data of Table 2, the statistic test, Chi-Square is utilized to test the hypothesis: H_o: equal performance. The results of Chi-Square (p= 0.001) for hypothesis, which reject H_o = 0 (as shown in Table 3). Table 4 shows the mean rank of Friedman test and we can see that the proposed model performance (mean rank = 1.25) outperforms the listing models. From Tables 3 and 4, the difference in the performance is significant.

*Table **3.*** Results of Friedman Test

Parameter	
n	4
Chi-Square	22.929
df	6
Asymp. Sig.	.001

Note: *n* is the number of data, df denotes degree of freedom

Table 4. Mean rank of Friedman Test

Models	Mean Rank
RSVMG	3.75
ANN	5
Regression	6.50
HEFST	3.25
ANFIS	1.75
AR(2)	6.50
Proposed model	1.25

Note: the smaller mean rank denotes high performance

After model verification and comparison, the proposed method performance outperforms the listing methods. However, some viewpoints can be further discussed in this section: (1) the results (see Tables 2 and 4) show that the proposed model outperforms the listing models; and (2) only simply one hidden-layer is set to forecast electricity loads which would reduce calculation complexity. From model verification in section 4, we can see that the proposed model performance outperforms the listing models. From the experimental results, there are three findings in this study as follows:

(1) According to Tables 2 and 4, it is evidence that the proposed electricity loads forecasting model is superior to the listing methods in terms of MAPE. The main reason is that the proposed model takes into

account "one-step ahead" method, and this study uses time series and neural network (in Elman NN procedure) to optimize the forecasting model for electricity loads forecasting.

(2) The experimental results indicate that the proposed model outperforms AR(2) and regression models significantly in terms of forecasting accuracy. The superior performance of the proposed model has two causes. First, the proposed model has nonlinear mapping capabilities and thus can more easily capture electricity load data patterns than the AR(2) and regression models. Second, the Elman NN can continually capture data patterns from the output layer with past values into the hidden layer.

(3) From Table 2, the proposed model performs outstandingly when electricity loads is in high demand regions (North (MAPE=0.053) and South region (MAPE=0.053)) or low demand region (East (MAPE=0.052)). These performance evaluations prove that the proposed electricity loads forecasting model can extract tinier fluctuations in different region than the other models.

5. Conclusions

To forecast regional load accurately is helpful for power facilities construction location planning and important for the economy development of an island country lack of energy such as Taiwan. The historical electricity load data of each region in Taiwan shows a strong growth trend, particularly in northern region. Although this is a common sense in developing countries, overproduction or underproduction electricity loads influences the sustainable economy development a lot. One step-ahead Elman NN model has been proposed for the electricity loads forecasting to investigate its feasibility in forecasting annual regional electricity loads in this study. Furthermore, the proposed electricity loads forecasting model is compared with six different electricity loads forecasting models (RSVMG, ANN, Regression, HEFST, ANFIS and AR(2)) to evaluate the forecasting performance. This proposed electricity loads forecasting model mainly uses input variables of annual electricity loads data in Taiwan to forecast the next electricity loads for electricity managers. To illustrate the proposed model, annual four regional (north, center, south and east) electricity loads data in Taiwan are used in this empirical experiment, which all consist datum from 1981 to 2000 (20 years in total). Each dataset including data of 20 years is spilt into 4 sub datasets based on region respectively. Sub dataset of each year for the first 16-year, 1981 to 1996, is used for training and the last 4-year, 1997 to 2000, is used for testing. From Table 2, the experimental results of four datasets indicate that the proposed electricity loads forecasting model outperforms the listing electricity loads forecasting models in terms of MAPE. Moreover, the results of this study are useful and viable for electricity managers, decision makers and future researches. We deem that electricity managers can utilize this electricity loads forecasting model to discover the superior target of energy investment with benefits in electricity management. For subsequent research, we can use other national electricity loads datasets such as China, Japan and America to further validate the proposed model. In future work, there are two methods suitable to integrate into the proposed electricity loads forecasting model, which will improve the forecasting accuracies: (1) use data discretization in preprocessing step which granulates (partitions) attributes to enhance the performance of the proposed electricity loads forecasting model; (2) validate the generated model by expert group to improve accuracy.

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