A Hybrid Model for Forecasting Time-Varying Reactive Power Load of Power Systems

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***Abstract*—While real power forecasting ensures the supply-demand balance, reactive power forecasting provides a crucial element to efficiently and reliably perform management of reactive resources and thus voltages. Traditionally, only active power load demand is forecasted while reactive load is roughly determined using a typical power factor band. This paper develops a model for systematically forecasting the time-varying reactive power load. An emerging artificial neural network (ANN) learning technique called extreme learning machine (ELM) and a simple data-mining approach *k*-nearest neighbor (*k*-NN) are combined together to constitute a hybrid forecasting model. For the ELM sub-model, ensemble strategy is applied. The developed model has been practically tested on a real-world distribution system data for active and reactive power forecasting. The results show that its accuracy is reasonably high and the learning speed is very fast, which can be used in future studies to improve the system voltage control.**

***Index Terms*—extreme learning machine, ensemble learning, hybrid model, *k*-nearest neighbor, reactive power load forecasting**

I. Introduction

LOAD forecasting plays a key role in power system operation and planning activities. Depending on different leading periods, *short-term* load forecasting aims to predict hourly load for a leading time ranging from one hour to several days, and the results are used by fundamental operating functions such as unit commitment, economic dispatch, and security assessment, etc.; *mid-term* and *long-term* load forecasting aims to predict the peak load demand of months and years in the future, and the results serve as the base for system expansion and investment planning.

Traditionally, the load forecasting is mainly focused on the active power demand [1]-[4], while the reactive power load is roughly determined using a typical power factor band. However, the fact is that reactive power demand is also a time-varying variable and not always corresponding to the active load. For illustration, Fig.1 shows the active and reactive load profiles along a whole year as well as the corresponding power factor of a real-world distribution network (the data is also used in the remaining of this paper), where it can be seen that the profile shapes of active and reactive load are not always matching, and the power factor varies significantly along the time.

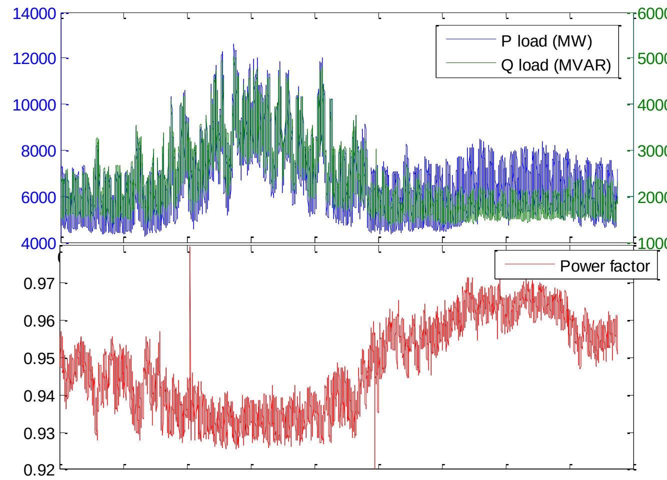

Fig.1 Active (P) and reactive (Q) power load profiles and corresponding power factor of a real-world distribution network in the U.S.

In practice, reactive power provides a crucial element to efficiently and reliably perform management of reactive resources and thus voltages. The transmission of excessive reactive power flow can result in higher network loss and the lack of reactive power support can lead to voltage problems such as under-voltage and even risk of voltage collapse [5]. Consequently, system planners and operators need to foresee the dynamic changes reactive power demands for appropriate reactive power compensation and control.

On the other hand, with the growing use of induction motors (e.g., air conditioners) and electronic devices such as inverters, the reactive power load has been increased continuously and its time-varying behavior can be even more complex, which implies that the conventional practices in determining the reactive load can become inadequate. Consequently, there is a pressing need for effective methods and tools to systematically forecast the reactive power load.

The contribution of this paper consists of developing an effective tool for short-term reactive power load forecasting, with such a tool the time-varying reactive load can be properly predicted (with a reasonable accuracy) for a leading time of one

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to seven days ahead. The forecasted reactive power demand can be used to 1) optimally schedule the reactive resources (e.g., switching shunt capacitor banks) to minimize the reactive power flow over transmission lines and therefore reduce the network power loss, 2) regulate voltage profiles more effectively, and 3) help system planners and operators to gain deeper insights into the reactive power load characteristics for better decision-making in planning and operating practices.

In the remaining parts of this paper, the forecasting techniques used in this paper are introduced in Section II; the proposed hybrid forecasting model is presented in Section III; the application results of the proposed model to a real-world distribution network reactive load forecasting are given in Section IV; the conclusion of the whole paper is drawn in Section V.

II. Forecasting Techniques

Among various short-term load forecasting techniques, artificial neural network (ANN) has received wide acceptance from academia and industry [1]-[4]. The principle behind ANN is to extract the complex non-linear relationship between the electricity load and the relevant parameters by learning on the historical load series. It has been shown in many previous works that ANN can provide a reasonable forecasting accuracy for practical use.

However, it can also be observed in the literature that most of the ANNs are based on the gradient-based learning algorithms such as back-propagation (BP) and its variations [1]-[4]. These algorithms can usually suffer from local optima and excessive training/tuning burden, which hinders their real applications to short-term load forecasting.

In this paper, a hybrid forecasting model combing an emerging learning algorithm called extreme learning machine (ELM) [6] and *k*-nearest neighbor (*k*-NN) method is designed for reactive power load forecasting. ELM is an ultra-fast learning algorithm which learns a database by randomly selecting the input parameters and analytically determines the output parameters. Compared with conventional ANNs, ELM is shown with much faster in learning speed and better in generalization performance on a number of benchmark and real-world problems [6]-[11]. However, a major pitfall of ELM is that its output is unstable due to the randomness in its training. To deal with this issue, a set of individual ELMs are combined as an ensemble for use. On the other hand, *k*-NN is a simple yet effective data-mining approach for time-series prediction, which can be a complementary to the ELM ensemble. The two forecasting methods are strategically combined.

A. Extreme Learning Machine

The ELM was proposed by Huang *et al* [6] as a novel learning technology for training generalized single-layer feed-forward neural networks (SLFNs). As illustrated in Fig.2, a SLFN consists of an input layer, a hidden layer, and an output layer.

Given a training data set with N instances in total, $\aleph_N = \left\{ \left(\mathbf{x}_j, \mathbf{t}_j \right) | \mathbf{x}_j \in R^n, \mathbf{t}_j \in R^m \right\}_{j=1}^{N}$, where $\mathbf{x}_j$ is the $n \times 1$ input vector and $\mathbf{t}_j$ is a $m \times 1$ target vector, the output function of the SLFN with $\tilde{N}$ hidden nodes is

$$f_{\tilde{N}}\left(\mathbf{x}_j\right) = \sum_{i=1}^{\tilde{N}} \beta_i \cdot \vartheta\left(\mathbf{w}_i \cdot \mathbf{x}_j + b_i\right) = \mathrm{t}_j, \quad j = 1, 2, \ldots, N \qquad (1)$$

where ϑ is the activation function, $\mathbf{w}_i$ is the weight vector connecting the i-th hidden node and the input nodes, β_i is the weight vector connecting the i-th hidden node and the output nodes, and b_i is the bias of the i-th hidden node, $\mathbf{w}_i \cdot \mathbf{x}_j$ denotes the inner product of $\mathbf{w}_i$ and $\mathbf{x}_j$.

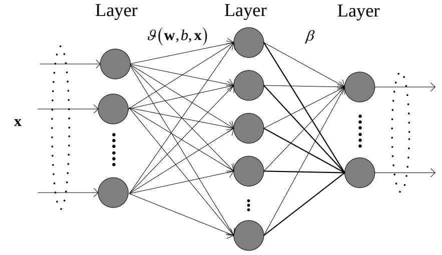

Fig. 2. Structure of a SLFN

ELM is completely different from traditional gradient-based ANN learning algorithm in that it learns via randomly selecting the input weights and biases for hidden nodes **w** and b, and analytically determining the output weights β via explicit matrix calculations [6].

According to ELM theory [6], (1) can be rewritten as a compact formulation as:

$$\mathbf{H}\beta = \mathbf{T} \qquad (2)$$

where **H** is named as the hidden layer output matrix of the network [6].

For a training data set, given the activation function and hidden node number, the ELM learning process can be briefly summarized as the following three steps:

Step 1) Randomly generate the input weights $\mathbf{w}_i$ and b_i, for $i = 1, \ldots, \tilde{N}$;

Step 2) Calculate the hidden layer output matrix **H**; and

Step 3) Calculate output weights matrix $\beta = \mathbf{H}^{\dagger}\mathbf{T}$.

where $\mathbf{H}^{\dagger}$ is the *Moor-Penrose generalized inverse* of **H**, and can be calculated by *singular value decomposition* for better generalization performance [6].

Depending on the specific database it learns, ELM can be applied to either categorical classification or numeric prediction, either single output or multi-output, and either batch learning or sequential learning [7]. Compared with traditional learning algorithms, the salient feature of the ELM is that it learns without iterative adjustment of network parameters which is burdensome and time-consuming, therefore its learning speed can be thousands times faster and requires much less computation memory. In the meantime, as proved in [6], ELM can not only reach the minimized training error $\left\|\mathbf{H}\beta - \mathbf{T}\right\|$ but also the smallest norm of output weights $\left\|\beta\right\|$, leading to better generalization performance. Another important merit of ELM is its efficient tuning mechanism: given an activation function, only the hidden neuron nodes number needs to be tuned, which can be efficiently achieved via a linear validation procedure [6]. Besides, ELM can avoid difficulties like stopping criteria, learning rate, learning epochs and local minima that can be commonly encountered by gradient-based algorithms. More mathematical details, theoretical justifications and proof behind ELM could be found in [6]-[8].

In the literature, ELM has been comprehensively validated on a number of benchmark datasets, showing much faster learning speed and better generalization capacity over some competing methods [6]-[8]. In power engineering, ELM has been successfully applied for non-technical loss analysis [9] and real-time dynamic security assessment [10],[11]. A comprehensive survey of ELM can be found in [8].

B. *k-Nearest Neighbor*

The *k*-NN is a simple yet effective data-mining approach originally designed for classification purpose. Its principle is that it finds an uneven number of nearest (in a specified distance space, e.g., *Euclidean* space) neighboring training samples and assigns the object value (class label) of the unknown sample to the most frequent class among the nearest samples.

For regression problems, i.e., when the object value is continuous, the object of the unknown sample $(x, \hat{y})$ can be determined by the average value of the nearest samples:

$$\hat{y} = \frac{1}{k}\sum_{i=1}^{k} y_i \tag{3}$$

where y_i is the object value of the *i*-th nearest neighboring sample of $(x, \hat{y})$.

It should be noted that the distance can be evaluated by other criterion. For power system load forecasting, the nearest sample of a load point can be the one with *same* hour index (e.g., 0-24) and weekday index (Monday to Sunday) and *most similar* weather index. The selection of the nearest neighbour of a sample $(\hat{H}, \hat{D}, \hat{W}, \hat{L})$ can be formulated as follows:

$$\min \quad \left\| W_i - \hat{W} \right\| \tag{4}$$

$$\text{s.t.} \quad H_i = \hat{H}, D_i = \hat{D} \qquad i \in \Theta \tag{5}$$

where *H*, *D*, *W*, and *L* denote hour index, weekday index, weather index, and load demand of a hour, respectively; Θ denotes the set of historical days.

Other nearest neighbouring samples can be selected sequentially according to (4) and (5). The computation speed of k-NN is very fast.

III. Proposed Model for Reactive Power Forecasting

A. *Model Structure*

It is usually found that a single forecasting technique can only achieve a limited accuracy. According to *ensemble learning* theory [12], different individual learners can be combined together to make a plurality decision, in doing so, the single learners can compensate for each other, and the whole ensemble can reduce aggregated variance and tend to increase accuracy over the individuals.

As already introduced, ELM has a strong non-linear modelling capacity which can effectively capture the complex mapping relationship between the load demand and relevant parameters. *k*-NN, on the other hand, has a simple forecasting mechanism, which can reflect the straightforward coupling relationship between load demand of similar days. Hence, the two methods can be ideal candidates to complement to each other. Following this, this paper designs a hybrid model as shown in Fig. 3.

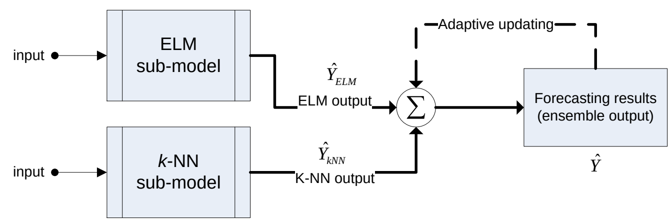

Fig. 3. Structure of the hybrid model

For the hybrid model, after appropriate training, the ELM sub-model and *k*-NN sub-model can forecast their individual forecasting result given the required input, and the final forecasting result is the weighted summation of the two:

$$\hat{Y} = \alpha \times \hat{Y}_{ELM} + (1-\alpha) \times \hat{Y}_{kNN} \tag{6}$$

where α is the weighting factor that is subjected to a pre-tuning process.

The tuning of the weighting factor α is to adjust its value to achieve the highest forecasting accuracy. Besides, it is important to note that the weighting factor α should be updated during the on-line application phase to track the change of the load patterns. Typically, the updating can be performed after a specified period of operation, e.g., 3 months.

B. *Ensemble-based ELM*

As already introduce, the ELM learns by randomly selecting the input layer parameters and analytically determine the output layer parameters. Although this can lead to much faster learning speed and better generalization performance, a disturbing pitfall of a single ELM is that the output is usually unstable due to the randomness in its training. To mitigate this, ensemble learning can be used. In [13], several single ELMs are connected in parallel and the outputs of the ELMs are averaged as the final result, it is shown that the stability and accuracy of the single ELM is improved effectively. In [11], an ensemble learning rule and decision-making rule are designed for dynamic security assessment of power system, and it is shown that the accuracy can be enhanced significantly.

For the ELM sub-model in the proposed hybrid forecasting model, the ensemble-based ELM is used. Specifically, a large set of single ELMs are individually trained, and given the same input vectors, the single ELMs export individual outputs, the final output is the *median* value of the individual outputs. It should be noted that the use of *median* value rather than *average* value as the whole model output can be more robust in practical use [4].

C. Input Selection for ELM sub-model

Appropriate selection of the input is paramount to the accuracy of the ANN-based forecasting model. Generally, this step aims to select the most relevant parameters as input to forecast the load demand of next period of interest. However, it should be noted that given different systems, the load pattern can vary significantly, hence the selection of inputs should be performed case-by-case combining engineering experience.

For the proposed model, the inputs consist of three vectors, which are load-related vector, weather-related vector, and day index-related vector.

1) Load-related vector

Since there is an inherent quasi-linear relationship between active and reactive power consumption, the active load P should be selected as the input to forecast the reactive load Q.

Given the historical load database, the following load-related inputs are selected to forecast the hourly reactive load Q of day D:

- Hourly reactive load of day D-1: $Q_{D-1}(1), Q_{D-1}(2), \ldots, Q_{D-1}(24)$
- Hourly active load of day D: $P_D(1), P_D(2), \ldots, P_D(24)$
- Hourly active load of day D-1: $P_{D-1}(1), P_{D-1}(2), \ldots, P_{D-1}(24)$

Consequently, to forecast the reactive load, it is necessary to forecast P first. To forecast P of day D, the hourly active load of day D-1 is used as the load-related vector.

2) Weather-related vector

Power load has a strong coupling relationship between weather variables. After some preliminary correlation studies on the historical load database, the following weather variables are selected for P and Q forecasting, respectively.

- Hourly temperature of day D: $T_D(1), T_D(2), \ldots, T_D(24)$
- Hourly temperature of day D-1: $T_{D-1}(1), T_{D-1}(2), \ldots, T_{D-1}(24)$

3) Day index-related vector

This vector is to distinguish different day types in a week. The weekday index of day D D_D is coded as 0.1 to 0.7 for Monday to Sunday, and 0.6 for public holiday.

Consequently, for active power forecasting, a total of 73 variables are used, and for reactive power forecasting, a total of 121 variables are used.

The structure of the ELM ensembles for load forecasting is shown in Fig.4.

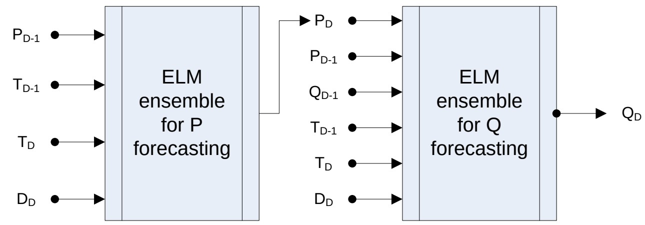

Fig. 4. ELM ensemble for load forecasting

IV. APPLICATION RESULTS

The developed load forecasting model has been practically tested on a realistic power load dataset of a distribution network in the U.S.

To measure the accuracy, the mean absolute percentage error (MAPE) and mean absolute error (MAE) are used, the measures are calculated as follows:

$$MAPE(\%) = \frac{1}{N} \cdot \sum_{i=1}^{N} \frac{\left| P_k(i) - \hat{P}_k(i) \right|}{\left| P_k(i) \right|} \times 100 \tag{7}$$

$$MAE = \frac{1}{N} \cdot \sum_{i=1}^{N} \left| P_k(i) - \hat{P}_k(i) \right| \tag{8}$$

where $P_k(i)$ and $\hat{P}_k(i)$ are respectively the real and forecasted value of electricity load, N is the total number of the points being forecasted.

A. Tuning Parameters

For the best performance, several parameters are to be tuned, including the hidden node number of single ELMs, the number of nearest neighbors used for *k*-NN algorithm, and the weighting factor in (6). Besides, for the ELM ensemble, a total of 200 single ELMs are used.

For tuning, the training data can be divided into two exclusive sets, one serves as training set and the other as validation set. The optimal parameters can be selected as the one that leads to lowest validation error. In this study, a whole year's historical P and Q data is used for tuning.

For illustration, the tuning profiles for 1 day ahead forecasting are shown below.

The tuning profile of hidden nodes of ELM ensemble for P and Q forecasting are shown in Fig.5 and Fig.6, respectively. It can be observed that the optimal hidden node number is 180 for both P and Q forecasting, and the lowest validation errors are 3.24% and 4.69%, respectively.

Besides, it is worth mentioning that the training speed of single ELM is very fast, with 180 hidden nodes, the learning time of a single ELM on the training data takes only 0.08 s, and the ELM ensemble (with 200 single ELMs) costs around 16 s, which is very computationally efficient for on-line use.

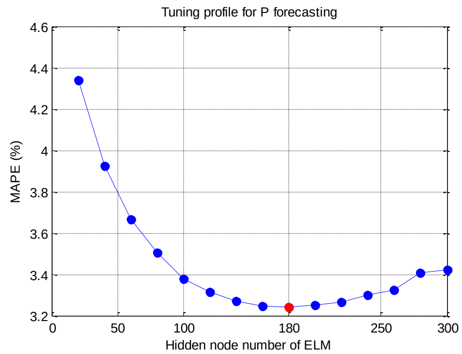

Fig. 5. Hidden node V.S. MAPE in P forecasting

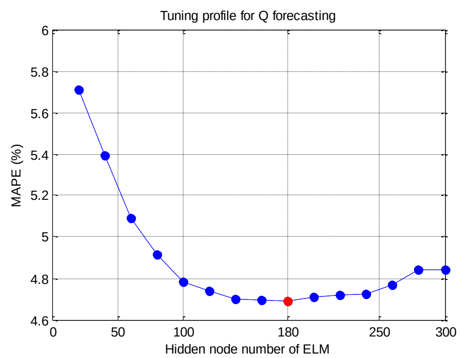

Fig. 6. Hidden node V.S. MAPE in Q forecasting

The tuning profiles of *k* for *k*-NN approach for P and Q forecasting are shown in Fig.7 and Fig.8, respectively. It can be seen that for P forecasting, the best k is 6 for both P and Q forecasting, and the corresponding MAPE are 3.85% and 6.52%, respectively.

It should be noted that the forecasting accuracy of *k*-NN is lower than that of ELM ensemble, since k-NN is much simpler in the forecasting mechanism, while ELM is more powerful in capturing the non-linear relationship between the load and the relevant inputs.

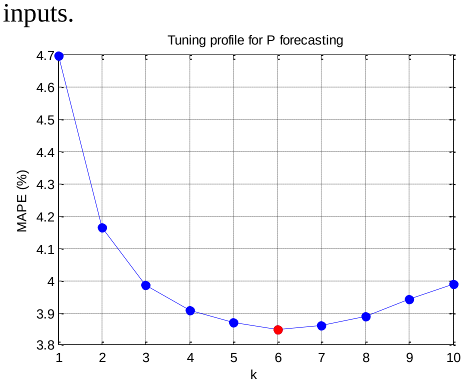

Fig. 7. k V.S. MAPE in P forecasting

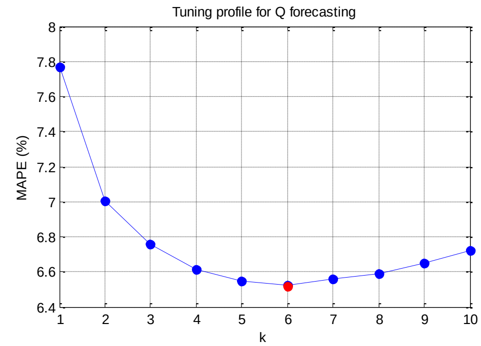

Fig. 8. k V.S. MAPE in Q forecasting

Fig.9 and Fig.10 show the weighting factors for P and Q forecasting, respectively. It can be seen that, the best factors are 0.65 and 0.55 for P and Q, respectively, and the corresponding MAPE are 2.34% and 3.83%, respectively.

The tuning performance is summarized in Table I. It is important to note that by combing the two sub-models, the forecasting accuracy has been increased significantly over each of the two. This is because the two sub-models can effectively complement to each other.

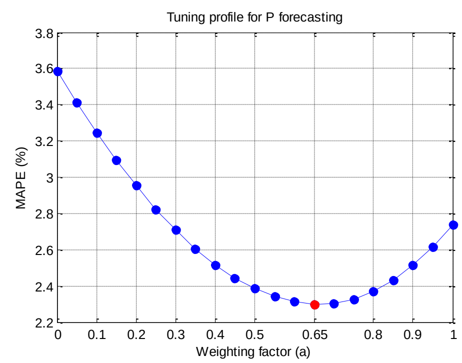

Fig. 9. Weighting factor V.S. MAPE in P forecasting

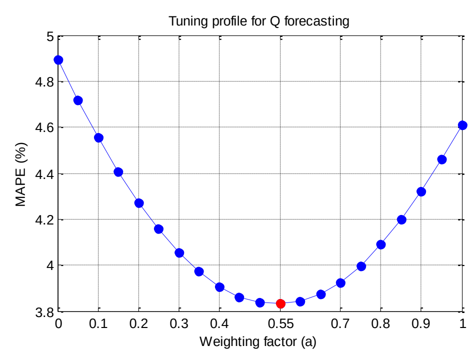

Fig. 9. Weighting factor V.S. MAPE in Q forecasting

TABLE I
TUNING RESULTS

Model	MAPE for P	MAPE for Q
ELM sub-model	3.24%	4.69%
k-NN sub-model	3.85%	6.52%
Hybrid model	2.34%	3.83%

B. Generalization Performance

With the optimal selected parameters, the hybrid model is tested on another load dataset of a whole year, which is different from the one used in tuning.

The leading time ranges from one to seven days ahead, and the corresponding performance is listed in Table II.

TABLE II
GENERALIZATION TEST RESULTS

Leading day	P forecasting		Q forecasting	
	MAPE	MAE (MW)	MAPE	MAE (MVar)
1	2.24%	160.5	3.7%	83.1
2	2.92%	204.7	4.6%	102.4
3	3.09%	216.8	4.7%	107.0
4	3.19%	223.8	5.1%	114.3
5	3.20%	225.6	5.2%	118.4
6	3.35%	236.5	5.5%	125.9
7	3.56%	250.1	5.8%	135.0

According to Table II, for P forecasting, the MAPE is 2.24% to 3.56 % for one to seven days ahead, which is quite accurate for practical use. And for Q forecasting, the MAPE is 3.7% to 5.8% for one to seven days ahead, which, although higher than that of the P forecasting, is reasonable considering the complex variations of reactive power consumption behavior in modern electricity networks.

C. *Comparisons with State-of-the-Art ANN Algorithms*

The superiority of the proposed model is compared with two state-of-the-art ANN algorithms: radial basis function neural network (RBFNN) and back-propagation neural network (BPNN). The average forecasting errors (1-7 days) of the three models are given in Table III. It can be seen that the proposed hybrid model is much more accurate over the compared.

TABLE III
AVERAGE FORECASTING ERRORS (1-7 DAYS) OF 3 MODELS

Model	P forecasting		Q forecasting	
	MAPE	MAE (MW)	MAPE	MAE (MVar)
Proposed	3.08%	216.9	4.94%	112.3
RBFNN	5.74%	417.8	12.5%	289.7
BPNN	6.26%	449.0	8.45%	201.7

V. CONCLUSION

Traditional load forecasting is mainly focused on active power demand, while reactive power load is roughly determined using a typical power factor band. However, with growing use of induction motors and electronic devices, the time-varying behavior of reactive power demand becomes increasingly complex. This paper develops a hybrid model for systematically forecasting the time-varying reactive power load. In the hybrid model, an emerging ANN learning technique called ELM and a simple yet effective data-mining approach *k*-NN are combined together. For the ELM sub-model, the ensemble strategy is used. Key parameters are then tuned through a validation process. The developed model has been practically tested on a real-world distribution system for active and reactive power forecasting. The results validate that by combing the two forecasting approaches, the accuracy can be significantly improved. The studies on the real system's data have shown the proven success of the reactive power forecasting, and the results can be used to improve the system efficiency and voltage control.

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