AN APPROACH TO SHORT TERM LOAD FORECASTING USING MARKET PRICE SIGNAL

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ABSTRACT

With the worldwide deregulation of the power industry, load forecasting is becoming more important, not only for system operators, but also for market operators, transmission owners, and other market participants, so that adequate energy transactions can be scheduled, and appropriate operational plans and bidding strategies can be established. In this new context, high forecasting accuracy and speed are required for reliable system operation, minimum operational costs and enhanced electric market efficiency. The system load-forecasting model is a critically important decision support tool for operating the electric power system securely and economically. In this paper, a new Radial Basis Function Neural Network (RBFN) called Generalized Regression Neural Network (GRNN) has been used for short-term load forecasting using hour and day indicators, weather temperature data and electric price signal as inputs. Results show that the proposed Neural Network method is able to forecast accurate future loads using price and temperature as inputs.

INTRODUCTION

A precise short-term load forecasting method plays a key role in the economic and secure operation of a power system [1]. Economic and secure operations allow electric utilities to optimize resources for better energy prices. In vertically integrated (also called regulated) electric utilities, the basic operations such as unit commitment, hydro-thermal co-ordination, interchange evaluation, and security assessments require a reliable short-term load forecast. Future introduction of different tariff periods will make short-load forecasting much more important, not only for large utilities, but also for the medium and small ones. Load forecasting in a power system can normally be segregated into the following categories.

- Very short-term forecasting of up to a few minutes ahead,
- Short-term forecasting with a lead time of up to a few days ahead,
- Medium-term forecasting over a six month or one year period,
- Long-term forecasting of the power system.

More efforts have been put, mainly, on short-term forecasting since it plays a vital role in optimum unit commitment, start-up and shut-down of thermal plants, control of spinning reserve and buying and selling of power in inter connected systems.

In recent years, artificial neural networks (ANNs) have been applied to many areas of power system analysis and control. These include load forecasting [2], static and dynamic security assessment, dynamic load modeling, and alarm processing and fault diagnosis [3] etc. These applications take advantage of the powerful mapping ability of ANNs and their inherently parallel and distributed processing characteristics for performing ultra high-speed computation. Artificial neural networks (ANNs), whose operation is based on certain known properties of biological neurons, comprise various architectures of highly interconnected processing elements that offer an alternative to conventional computing approaches. They can achieve complicated input-output mappings without explicit programming and extract relationships (both linear and nonlinear) between data sets presented during a learning process. Furthermore, the redundancy of their inter connections ensures robustness and fault tolerance, and they can be designed to self adapt and learn [4,5].

The application of ANNs to the short-term load forecasting has gained a lot of attention. Dillon et al. [6] used adaptive pattern recognition and self-organizing techniques for short term load forecasting. Later, they used an adaptive neural network for short term load forecasting [7]. The availability of historical load data on the utility databases makes this area highly suitable for ANN implementation. ANNs are able to learn the relationship among past, current, and future weather variables and loads combining both time series and regression approaches. As in the time series approach, the ANN traces previous load patterns and predicts (i.e., extrapolates) a load pattern using recent load data. The ANN is able to perform non-linear modeling and adaptation. Their ability to perform better than traditional methods especially during rapidly changing weather conditions and the short time required to their development, have made ANN based load forecasting models very attractive for on-line implementation in energy control centers.

The most important work in building an ANN load forecasting model is the selection of input variables. In the present emerging market, the interdependence between price and load is very critical issue in load forecasting modeling. The price-load relationship is neither linear nor stationary in time but can be expected to be relatively stable over shorter periods of time. In contrast to load forecasting, where there are relatively well-understood load patterns (weekdays vs. holidays and weekends, unusually hot weather, and so on), the volatile electricity prices in power markets are a new phenomenon that needs to be examined. Since the relationship between electricity price and load is complex and dynamic, further research is needed to study how different customers' price response characteristics and locations affect load forecasting. The most important input variables, which affect the load forecasting, are weather temperature and price as these are having a strong correlation with load.

In this paper, an investigation on the use of ANNs for short-term load forecasting has been explored using hour and day indicators, weather temperature data and pricing signal as inputs. A new Radial Basis Function Neural Network (RBFN) [9], known as Generalized Regression Neural Network (GRNN) having a radial basis layer and a special linear layer, has been used. The effectiveness of the proposed method has been tested and results show that the proposed method is able to forecast accurate future loads.

NEURAL NETWORK INPUT VARIABLES

The most important work in building an ANN load forecasting model is the selection of input variables. There is no general rule that can be followed in this process. It depends on engineering judgment and experience and is carried out almost entirely by trial and error. However, some statistical analysis can be very helpful in determining which variables have significant influence on the system load. In general, three types of variables are used as inputs to the neural network: (a) hour and day indicators, (b) weather related inputs and (c) historical loads, (d) market pricing signal.

Hour indicator H(k)

Load varies through out the day which can be seen from Fig. 1. There may be several peak loads and valley loads during a day and there is a significant difference in load magnitudes at different time of a day or a week. Therefore, an hour indicator H (k) (where k changes from 1 to 24) is very helpful in short term load forecasting.

Day indicator D(k)

Load also changes from day to day during a week. Fig. 1 shows an average daily load for a typical winter week. It is clear that power consumption is different on different days. As a result, a day indicator D(k) (where k changes from 1 to 7) is helpful in load forecasting.

Weather variables

Temperature, which is considered in this work, is the most important weather variable. Other weather variables (wind velocity, cloud cover, humidity etc.) are not taken in the present work, as they have less effect.

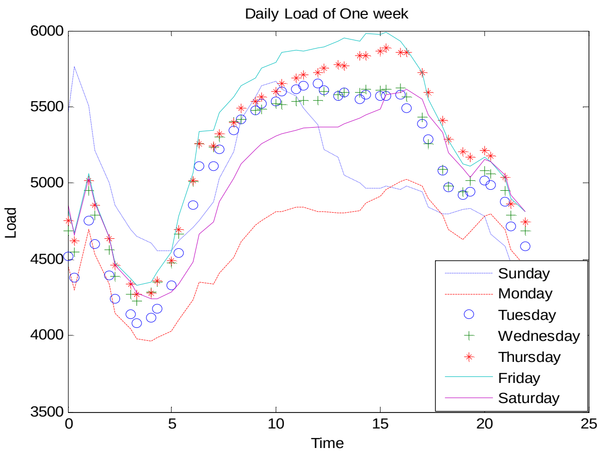

Fig. 1: Load curves during a day

Historical price

The price-load relationship is neither linear nor stationary in time but can be expected that price-load relationship is relatively stable over shorter periods of time. Volatile electricity prices in power markets are a new phenomenon that needs to be examined. It is clear from the Fig. 2 that there is a strong correlation between load and price; hence, price is a major deciding factor for load forecasting.

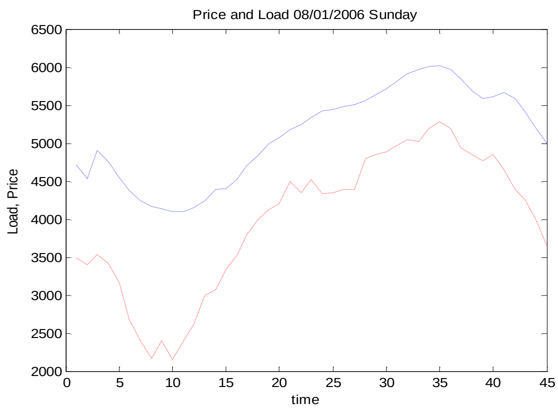

Fig. 2: Load and Price changes during the day

ANN USED: TYPE AND STRUCTURE

The well-known radial basis function network (RBFN) having special features is used here as a primary test in this application. A radial basis function (RBF) network consists of two layers, a hidden layer with nonlinear neurons and an output layer with linear neurons. Thus the transformation from the input space to the hidden unit space is non-linear whereas the transformation from the hidden unit space to the output space is linear.

Generalized regression neural network (GRNN), which is often used for function approximation, is having a radial basis layer and a special linear layer. The architecture for the GRNN is similar to the radial basis network, but has a slightly different second layer. The first layer has as many neurons as there are input/ target vectors. Each neuron's weighted input is the distance between the input vector and its weight vector. Each neuron's net input is the product of its weighted input with its bias. The output of each neuron is its net input passed through radial basis layer. The second layer also has as many neurons as input/target vectors. A larger spread (distance) leads to a large area around the input vector where layer-1 neurons will respond with significant outputs. Therefore, if spread is small, the radial basis function is very steep so that the neuron with the weight vector closest to the input will have a much larger output than other neurons. The network will tend to respond with the target vector associated with the nearest design input vector. As spread gets larger, the radial basis function's slope gets smoother and several neurons may respond to an input vector. The network then acts like taking a weighted average of target vectors whose design input vectors are closest to the new input vector. As spread gets larger, more and more neurons contribute to the average with the result that the network function becomes smoother.

ANN TRAINING: DATA AND ALGORITHM

To demonstrate the effectiveness of the proposed approach, publicly available data from the Australian national electricity market (NEMMCO) web site as been taken to forecast electricity prices and loads for the Victorian electricity market. The Australian national electricity market (NEM) is a deregulated electricity supply industry covering Victoria, New South Wales, Queensland, South Australia, and the Australian Capital Territory. The data of 2006 is divided into several windows where half of them (non-consecutive ones) are used for training and the other half is used for testing the ANN.

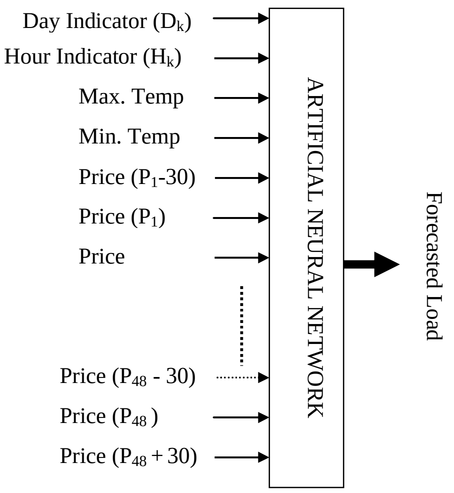

Fig. 3: The ANN model used in this application

More precisely, for each month, the first week and the third week are used for training, while the second and fourth weeks are left for testing the ANN. Training was done for all the data widows at the same time; i.e., the same ANN is trained to be used at any time during the year. All inputs and outputs are normalized before training. The inputs to the ANN as shown in Fig. 3 are:

H(k) hour indicator
D(k) day indicator
P(k) estimated temperature at hour k
P(k - 30) temperature at 30 minutes before hour k
P(k +30) temperature at 30 minutes after hour k
T(max) Maximum temperature of the day
T(min) Minimum temperature of the day

SIMULATION AND RESULTS

With the available data as discussed in previous section, the generalized regression neural network (GRNN) is trained and tested. Due to its special features as explained in the previous sections, the algorithm resulted in a very fast training, and the error was significantly reduced to very low value. Then, the performance of the developed ANN model for load profile forecasting was tested using windows of data that were not included in the training set. The forecasted hourly load for the several days was estimated but due to limited space, only two cases are presented here which gave more error compared to the other cases in the prediction. Fig. 4 shows the actual (data2) and forecasted load for January 14, 2006. It is clear from the results that forecasted load patterns are similar and matching to the actual one.

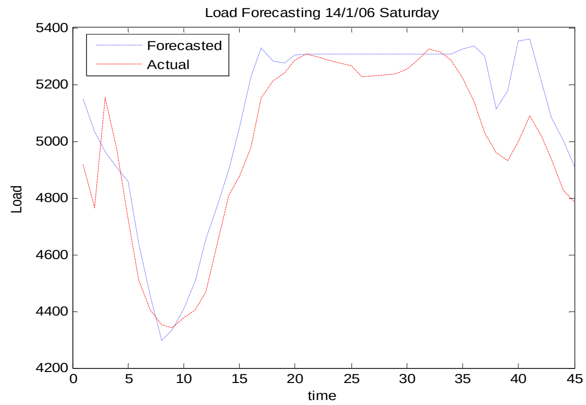

Fig. 4: Output (24 hours) compared to actual load

For more accurate evaluation of the ANN performance, the following absolute percentage error (e) is used and defined as

$$e = \frac{\text{actual load - forecasted load}}{\text{Actual Load}} \times 100 \qquad (1)$$

The maximum percentage error for January 14, 2006 is 6.6%. However, an average of this absolute error over a period of time may be used for an overall evaluation and comparison with other techniques. The mean absolute percentage error (MAPE) is defined as

$$\text{MAPE}(\%) = \frac{1}{N}\sum_{i=1}^{N}\frac{\left|L_F^i - L_A^i\right|}{L_A^i}\times 100 \qquad (2)$$

where L_A is the actual load, L_F is the forecasted load, N is the number of hours and i is the hour index.

The errors in forecasting on different week days are calculated and presented in Table 1. This shows that MAPE on different week days varies from 1.8% to 4.0%.

Table 1: Error in load forecasting on different week days

Day	Max. Error (%)	Min. Error (%)	MAPE (%)
Sunday	4.61	0.06	2.72
Monday	6.56	0.03	2.63
Tuesday	7.62	0.03	2.34
Wednesday	5.58	0.07	3.64
Thursday	6.63	0.16	4.00
Friday	4.68	0.02	1.80
Saturday	6.60	0.03	2.86

A study was also performed for prediction of 72 hours load as shown in Fig. 5. The maximum error was found to be 4.36%. The hourly error in the actual load (data2) and forecasted load is also plotted in Fig. 6.

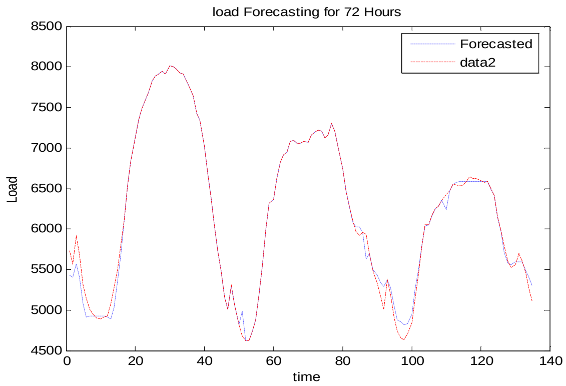

Fig. 5: Output (72 hours) compared to actual load

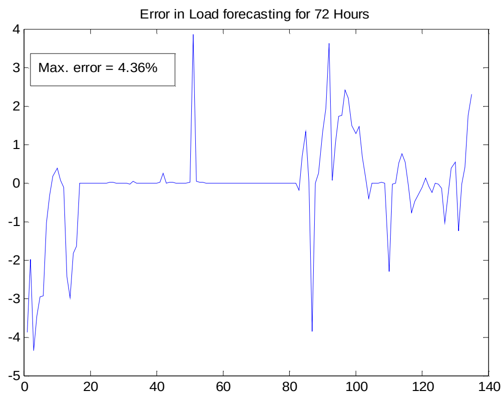

Fig. 6: Error in load forecasting for 72 hours

CONCLUSION

A reliable and robust system load forecasting model is an important decision support tool for operating the electric power system in secure, reliable and economical manners. Because of input-output mapping ability, artificial neural networks are well suited for this type of applications. In this work, a new radial basis function neural network (RBFN) known as generalized regression neural network (GRNN) for short term load forecasting has been proposed which demonstrated, through the test results, the better capabilities in the short-term load forecasting with the use of pricing signal as an input. In addition, day signal and temperature (from weather variables) are used. However, with some advance techniques such as wavelet transform along with the ANN may work better in the price volatility conditions. This approach is under investigation. Some more analysis is needed to obtain the suitable input feature selection.

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