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Short Term Load Forecasting Using ANN Considering Weather Information and Price

Needhu Varghese, Reji P

Abstract— Short-term load forecast is an essential part of electric power system planning and operation. Forecasted values of system load affect the decisions made for unit commitment and security assessment, which have a direct impact on operational costs and system security. Conventional regression methods are used by most power companies for load forecasting. However, due to the nonlinear relationship between load and factors affecting it, conventional methods are not sufficient enough to provide accurate load forecast or to consider the seasonal variations of load. In recent years multilayered feed forward (MLFF) networks with back propagation learning algorithm have been extensively applied to short term load forecasting (STLF) in electric power systems with very good results. This paper presents an artificial neural network based approach for short-term load forecasting that uses temperature, humidity, wind speed and price as inputs. The results are compared by calculating mean Absolute percentage error (MAPE). The suitability of the proposed approach is illustrated through an application to the actual load data of the Kerala System for regulated system and Lanco Kondapilli for deregulated system.

Index Terms— Artificial neural network, back propagation algorithm, deregulated system and short term load forecasting.

I. INTRODUCTION

In the recent years, along with the power system privatized and deregulated, the issue of accurately electric load forecasting has received more attention in a regional or a national system. The error of electric load forecasting may increase the operating cost. Therefore, overestimation of future load results in excess supply, and it is also not welcome to the international energy network [1]. In the contrast, underestimation of load leads to a failure in providing enough reserve and implies high costs in peaking unit. Adequate electric production requires each member of the global cooperation being able to forecast its demands accurately [2]. However, it is complex to predict the electric load, because the influencing factors include climate factors, social activities, and seasonal factors. Climate factors depend on the temperature, wind speed and humidity; social factors imply human social activities including work, school and entertainment affecting the electric load; seasonal factors then include seasonal climate change and load growth year after year [3].

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Needhu Varghese, EEE, IES College of Engineering, Chittilappilly affiliated to Calicut University, India.

Dr. Reji P, EEE, Government Engineering College Thrissur, Thrissur affiliated to Calicut University, India.

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The second category is based on the artificial intelligence techniques which include Expert System [7], Neural Network [15, 16] and Fuzzy Theory [17, 18]. The trend in current research tends to combine these techniques to create a hybrid method making the most of the strengths of each technique. The most popular line of research using hybrid is to combine fuzzy theory and neural networks [19, 20, 21].

The models that have received a high share of efforts and focus are the artificial neural networks (ANN). The main advantage of ANNs is their outstanding performance in data classifications and detecting dependencies from historical data without the need to develop a specific regression model [15].

This paper mainly focuses on short term load forecasting which provide the load predictions for the basic generation scheduling functions, assessing the security of the power system at any time point and timely dispatcher information. The input variables like historical load, temperature, wind speed and humidity are considered for Kerala system. In this case price is not considered as it is a regulated system. The proposed method is artificial neural network. Each input variable is applied separately and then a combination of input variables is applied. Another case study taking historical load and price as inputs are conducted on Lanco Kondapilli which is a deregulated system. Sensitivity analysis is done to study the influence of input variable that greatly affects short term load forecasting.

II. LOAD FORECASTING

Load forecasting is vitally important for the electric industry in the deregulated economy. It has many applications including energy purchasing and generation, load switching, contract evaluation, and infrastructure development. A large variety of mathematical methods have been developed for load forecasting. Accurate models for electric power load forecasting are essential to the operation and planning of a utility company. Application of load forecasting depends upon the type of load forecasting and also the factors affecting it.

A. Short Term Load Forecasting

The basic quantity of interest in STLF is, typically, the hourly integrated total system load. In addition to the prediction of the hourly integrated total system load, an STLF is also concerned with the forecasting of the daily peak system load, the values of system load at certain times of the day, the hourly or half-hourly values of system energy, the daily and weekly system energy.

STLF plays a key role in the formulation of economic, reliable, and secure operating strategies for the power system. The principal objective of the STLF function is to provide the load predictions for

1. the basic generation scheduling functions
2. assessing the security of the power system at any time point
3. Timely dispatcher information**.**

The primary application of the STLF function is to drive the scheduling functions that determine the most economic commitment of generation sources consistent with reliability requirements, operational constraints and policies, and physical, environmental, and equipment limitations. A closely associated scheduling task is the scheduling and contracting of interchange transactions by the interchange evaluation function. For this function, the short-term load forecasts are also used to determine the economic levels of interchange with other utilities.

A second application of STLF is for predictive assessment of the power system security. The system load forecast is an essential data requirement of the off-line network analysis function for the detection of future conditions under which the power system may be vulnerable. This information permits the dispatchers to prepare the necessary corrective actions (e.g., bringing peaking units online, load shedding, power purchases, switching operations) to operate the power systems securely.

The third application of STLF is to provide system dispatchers with timely information, i.e., the most recent load forecast, with the latest weather prediction and random behavior taken into account. The dispatchers need this information to operate the system economically and reliably [22]

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III. ANN STRUCTURE

The three-layer fully connected feed-forward neural network is used here; it includes an input layer, one hidden layer and an output layer [23]. Signal propagation is allowed only from the input layer to the hidden layer and from the hidden layer to the output layer. Input variables come from historical data corresponding to the factors that affect the load. The number of inputs, the number of hidden nodes, transfer functions, scaling schemes, and training methods affect the forecasting performance and hence need to be chosen carefully [24].

The STLF procedure for the chosen ANN model is shown in Fig.1

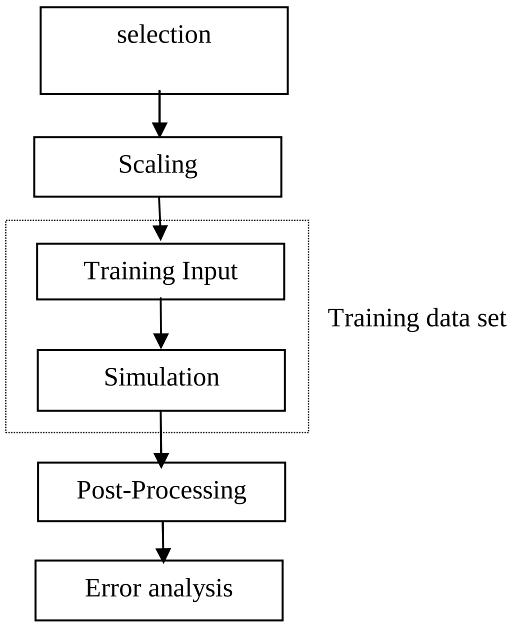

Fig. 1 ANN-based load forecasting procedure

1. Input Variable Selection: Input variables such as load, temperature, humidity, wind speed and spot prices of the previous day and of the forecasting day are initially chosen.
2. Scaling: Since the variables have very different ranges, the direct use of network data may cause convergence problems. All input Xi and output Oi variables are scaled to be in the [0, 1] range; hence, the input and output variables are scaled as follows:

$$X_i^{'(k)} = X_i^{(k)} / \max\left(X_i^{(k)}\right)$$
$$O_i^{'(k)} = O_i^{(k)} / \max\left(O_i^{(k)}\right) \qquad (1)$$

where k is the index of input and output vectors/patterns.

3. Training: Each layer's weights and biases are initialized when the neural network is set up. The network adjusts the connection strength among the internal network nodes until the proper transformation that links past inputs and outputs from the training cases is learned. Data windows are used for training and moved one day ahead.
4. Simulation: Using the trained neural network, the forecasting output is simulated using the input patterns.
5. Post-Processing: The neural network output need de-scaling to generate the desired forecasted loads. If necessary, special events can be considered at this stage.
6. Error Analysis: As characteristics of load vary, error observations are important for the forecasting process. Hence, the following Mean Absolute Percentage Error (MAPE) is used here for after-the-fact error analysis:

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\frac{\left|X_t - X_f\right|}{X_t} * 100 \qquad (2)$$

X_t is the actual load and X_f is the forecasted load

For practical reasons, ANNs implementing the back propagation algorithm do not have too many layers, since the time for training the networks grows exponentially. Also, there are refinements to the back propagation algorithm which allow a faster learning.

IV. SHORT TERM LOAD FORECASTING USING ANN

Training sets are historical load, temperature, humidity and wind speed from 18th April 2010 to 29th April 2010. In this case price is not considered as Kerala is a regulated system. The input variables for each case were obtained using trial and error method.

A program was developed in MATLAB 7.6 version. By trial and error method to reduce error, the following optimized parameters for the program were obtained. The no. of hidden layers depends upon the no. of input variables. It is also determined by trial and error method.

Table 1 ANN Parameters

Parameters	Optimized value
Learning algorithm	Back propagation algorithm
No. of training sets used	12
Learning rate	0.25
Momentum factor	8
No. of iterations	~30000
No. of hidden layers	7
No. of inputs	7
Transfer Functions	Linear (input layer) Transig (Hidden layer) Transig(Output layer)

V. APPLICATIONS AND RESULTS

After training, the trained network is validated. Validation is the process of testing the trained network by applying some other input set. Validation is done using the data corresponding to 30th April 2010.

Following are the inputs and outputs while temperature is considered. The output of ANN is P(d,t), which is the load at a given hour. There are 7 input variables and they are :

- P(d-1,t): the load value of the day preceding the forecasted day at same hour
- Tmin(d), Tmax(d), Tavg(d): minimum, maximum and average temperature of the forecasted day
- Tmin(d-1), Tmax(d-1,t-1), Tavg(d-1): minimum, maximum and average temperature of the day preceding the forecasted day

Following are the inputs and outputs while relative humidity is considered. The output of ANN is P(d,t), which is the load at a given hour.

- P(d-1,t): the load value of the day preceding the forecasted day at same hour
- RH(d,min), RH (d,max), RHavg(d): minimum and maximum relative humidity and average relative humidity of the forecasted day
- RH(d-1,min), RH (d-1,max), RHavg(d-1): minimum and maximum relative humidity and average relative humidity of the day preceding the forecasted day

There are 7 input variables when wind speed is considered. The output of ANN is P(d,t), which is the load at a given hour :

- P(d-1,t): the load value of the day preceding the forecasted day at same hour
- WS(d,min), WS(d,max), WSavg(d): minimum, maximum and average wind speed of the forecasted day
- WS(d-1,min), WS(d-1,max), WSavg(d-1): minimum, maximum and average wind speed of the day preceding the forecasted day

When all the input variables are considered, i.e., historical load, temperature, relative humidity and wind speed, 9 inputs have to be considered. They are P(d,t-1), P(d,t-2), P(d-1,t), Tavg(d), Tavg(d-1), RHavg(d), RHavg(d-1), WSavg(d) and WSavg(d-1). The output of ANN is P(d,t), which is the load at a given hour. Table 2 shows the comparison of forecasted load for various inputs.

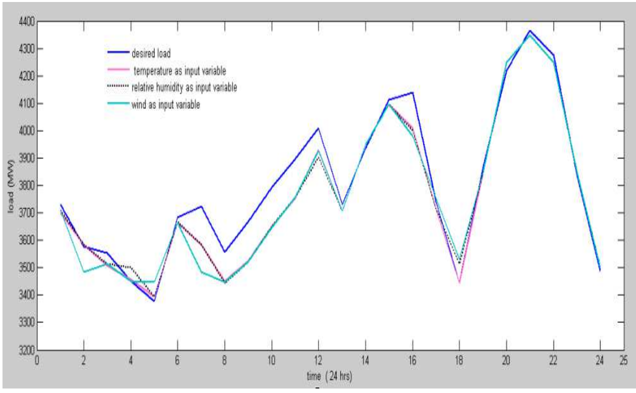

Fig 2 Comparison of results using ANN giving temperature, relative humidity and wind speed as inputs

When price is considered, case study is done on Lanco Kondappilli which is a deregulated system. There the inputs considered are P(d-1, t), MP(d,t-1), MP(d-1,t) and MP(d-1,t-1). The output of ANN is P (d, t), which is the load at a given time. MP(d,t-1) is the market clearing price on the same day one hour preceding the forecasted hour. Table 3 shows the comparison of forecasted load and desired load when price is given as input for deregulated system.

Table 2. Comparison of forecasted load using ANN giving temperature, wind speed and relative humidity as inputs

Time	Desired load (MW)	Forecasted load (MW) giving temperature as input variable	Forecasted load (MW) giving relative humidity as input variable	Forecasted load (MW) giving wind speed as input variable	Forecasted load (MW) giving temperature, relative humidity and wind speed as input variables
1 am	3730	3699.8	3710.6	3708.8	3716.1
2 am	3577	3585.4	3585.5	3484.3	3598.2
3 am	3553	3507.7	3514.1	3512.7	3487.2
4 am	3450	3457.4	3499.9	3449.7	3406.8
5 am	3379	3395.5	3394.9	3446.6	3336.3
6 am	3684	3665.2	3666.1	3664.6	3452.7
7 am	3722	3584.3	3585.5	3484.1	3547.5
8 am	3557	3451.3	3443.6	3447.2	3429.5
9 am	3668	3525.2	3522	3520.3	3489.6
10 am	3793	3651.1	3649.6	3648.5	3645.7
11 am	3895	3752.8	3756.3	3755.5	3769.8
12 noon	4009	3930.9	3902.2	3925.6	4020
1 pm	3730	3706	3707.1	3705.5	3655.3
2 pm	3935	3949.9	3950	3949.9	3949.9
3 pm	4112	4096	4096.9	4095.5	4031.6
4 pm	4140	4010.2	3999.2	3980.1	4150.3
5 pm	3740	3713.8	3713.8	3752.2	4059.9
6 pm	3444	3444	3514.1	3532.2	3700.6
7 pm	3868	3850	3850	3850	3850
8 pm	4218	4250	4250	4250	4250
9 pm	4364	4350	4350	4350	4350
10 pm	4274	4250	4250	4250	4250
11 pm	3841	3850	3850	3850	3845
12 midnight	3488	3500	3500	3500	3500

Table 3 Comparison of forecasted load and desired load giving market clearing price as input

Time	Desired load (MW)	Forecasted load (MW) giving price as input variable
1 am	3730	3699.8
2 am	3577	3585.4
3 am	3553	3507.7
4 am	3450	3457.4
5 am	3379	3395.5
6 am	3684	3665.2
7 am	3722	3584.3
8 am	3557	3451.3
9 am	3668	3525.2
10 am	3793	3651.1
11 am	3895	3752.8
12 noon	4009	3930.9
1 pm	3730	3706
2 pm	3935	3949.9
3 pm	4112	4096
4 pm	4140	4010.2
5 pm	3740	3713.8
6 pm	3444	3444
7 pm	3868	3850
8 pm	4218	4250
9 pm	4364	4350
10 pm	4274	4250
11 pm	3841	3850
12 midnight	3488	3500

An average of the absolute error for one day may be used for an overall evaluation and comparison of the two techniques

Table 4. Comparison of results giving historical load, temperature, wind speed, humidity and price as inputs

Inputs used	MAPE (%)
Historical load only	2.14
Temperature	1.32
Relative humidity	1.40
Wind speed	1.49
Market clearing price	1.24
Considering all inputs except price	2.29

A. *Sensitivity Analysis*

Sensitivity analysis is done to study the influence of input variables on load forecasting. Here temperature, wind speed and relative humidity are the input variables considered in load forecasting

The temperature is taken in the range between 26°c to 32°c. The variation of forecasted load with temperature is shown in Fig.3. The forecasted load varies from 3708 to 3708.4 MW in this temperature range.

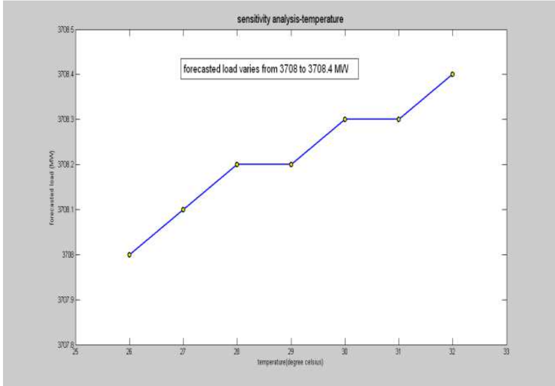

Fig. 3 Sensitivity analysis with respect to temperature

The relative humidity varies in the range between 65% to 95%. The variation of forecasted load with relative humidity is shown in Fig.4. The forecasted load varies between 3707.1 and 3707.2 MW.

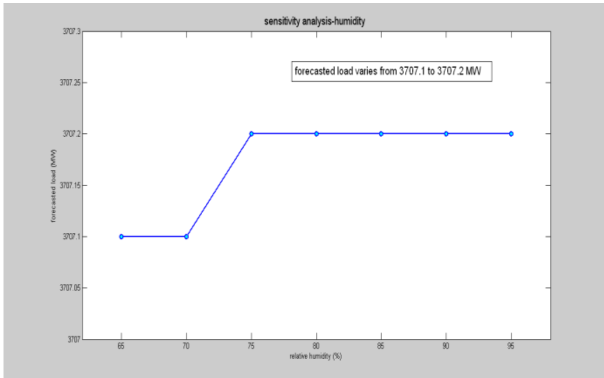

Fig. 4 Sensitivity analysis with respect to relative humidity

The wind speed varies from 0 to 12km/hr. The variation of forecasted load with relative humidity is shown in Fig 5. The forecasted load varies between 3716 to 3716.3 MW.

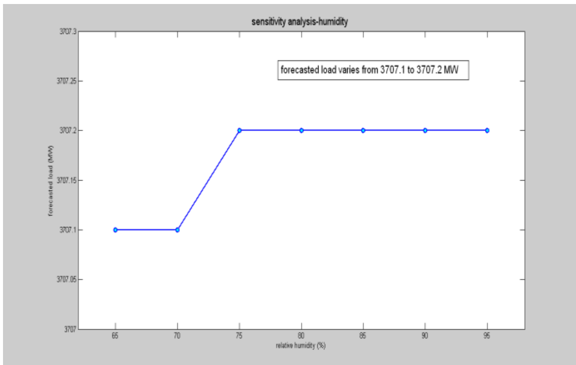

Fig. 5 Sensitivity analysis with respect to wind speed

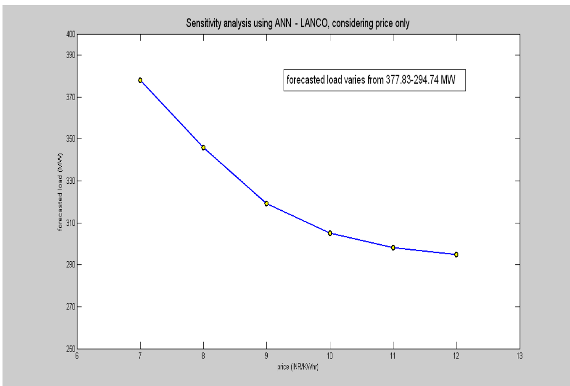

Fig. 6 Sensitivity analysis with respect to price

The price varies in the range between 7 to 12 INR/KWhr. The variation of forecasted load with price is shown in Fig. 6. The forecasted load varies between 377.83 and 294.74 MW within this range of price. When price increases load demand decreases.

While considering the validation results for regulated system MAPE is less when temperature alone is considered. But for deregulated system MAPE is very less when market clearing price alone is considered. From sensitivity analysis the forecasted load varies in wide range with variation in temperature. So temperature is the most influencing input variable.

VI. CONCLUSION

Load forecasting accuracy significantly impacts the cost of power utilities in operational planning of the energy supply. ANN based short-term load forecast is being widely used in utility industry. This paper describes an ANN based STLF with temperature, wind speed and relative humidity as inputs for regulated system and historical load and market clearing price as inputs for deregulated system . The proposed model is tested on the actual load data of Kerala system and Lanco Kondappilli. The performance of the proposed model shows low level of error and high degree of accuracy. The developed model results are then compared and sensitivity analysis is done to select most influencing input variable. The results are compared by calculating MAPE. From the results temperature is the most influencing input for regulated system and market clearing price for deregulated system.

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