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Short Term Load Forecasting Using Artificial Intelligence Technique In Power System

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ABSTRACT*: Load forecasting is the prediction of future loads of a power system. It is an important component for power system energy management. Precise load forecasting helps to make unit commitment decisions, reduce spinning reserve capacity and schedule device maintenance plan properly. Besides playing a key role in reducing the generation cost, it is also essential to the reliability of power systems. By forecasting, experts can have an idea of the loads in the future and accordingly can make vital decisions for the system. This work presents a study of short term hourly load forecasting using different types of Artificial Neural Networks. Artificial Neural Network (ANN) based solutions of Short Term Load Forecasting (STLF) have gained great popularity in time-series prediction and classification tasks because of their simplicity and robustness. However, the approach of using ANN methodology alone is limited which has generated interest to explore hybrid solutions for a better alternative. This paper presents a brief review of the recent work focusing on the STLF solution based on combining ANN approach with other techniques .*

Keywords: *Short Term Load Forecasting, Artificial Neural Network,Gentic Algorithm, Evolutionary Algorithm***,** *Artificial Immune System, Particle Swarm Optimization, Ant Colony Optimization.*

I. INTRODUCTION

Electricity demand forecasting is of great importance for the management of power system. Load forecasting is an important component for power energy management system. Precise load forecasting helps the electric utility to make unit commitment decision, reduce spinning reserve capacity and schedule device maintenance plan properly. The total amount of electric power in MW consumed in an electrical power system must be balanced with an equal amount of generated power. This is managed by power system forecasting.

Power system forecasting divided into load forecasting and electrical consumption predicting according to forecasting matter. In terms of lead time, load forecasting is divided into long-term load forecasting, mid-term forecasting, short-term forecasting and ultra short-term/very short-term forecasting. Long-term forecasting with lead time more than one year.Mid-term forecasting with the lead time one week tone year. Short-term load forecasting with lead time of 1 to 168 hours. Very Short-term load forecasting with lead time shorter than one day. Long-term forecast of the peak electricity demand are needed for capacity planning and maintenance [1]. Medium-term demand forecasts are required for power system operation and planning [2]. Short-term load forecasts are required for the control and scheduling of power system .How to improve the accuracy of power load forecasting is valuable research. Generally speaking, long-term accuracy of the forecast will be lower while short-term will be higher.

II. FACTORS EFFECTING SYSTEM LOAD

The four major categories of factor that influencing system load are

Economic Factor

Economic factors will not influencing the STLF as this factor typically change usage over a longer time than 24 hours [4].However, economic factor can be the inspiration for studying system load pattern and implementing load reduction initiatives. Economic factor uses for long and medium-term forecasting models and not need for STLF.

A. Time Factor

The load is affected by time factor in the point of seasonal effects, weekly-daily cycle and holidays. Seasonal effects determine utilities peaking (summer/winter) and also bring out structural modification in electricity consumption pattern. The weekly-daily cycle of the load is consequence of the work-rest pattern of service is population. The load decreases considerably on holidays the tendency of the people to have extended weekends could also affect the loads on the preceding and following holidays.

B. Weather Factor

Weather factor having a significant effect on the short-term load profile of a power system [3],[4],[5].Weather factor includes temperature, humidity, precipitation, wind speed, cloud cover, light intensity & etc.

C. Random Effects

Random factor that influence the electrical load profile consists of the other entire random disturbance in the load pattern that can't be explained by the previous three factor [4].It includes load such as steel mills, wind tunnels whose operation can cause large variation in electricity usage.

III. LOAD FORECASTING METHODS

There are ten types of Load Forecasting Methods

A. Regression Method

The Multiple Linear Regression (MLR) method calculates the electric load at a specific time t using explanatory weather and non-weather variables that are known to have some influence on the electric load [6],[7],[8].

The MLR electric load mode has the following form

$$y(t) = a_0 + a_1x_1(t) + \ldots + a_nx_n(t) + a(t) \qquad (1)$$

Where,

$y(t)$ = electrical load

$x_1(t)\ldots x_n(t)$ = explanatory variables correlated with $y(t)$

$a(t)$ = a random variables with zero mean and constant variance

B. Time Series

Time series methods are based on the assumption that the data have an internal structure such as auto correlation, trend or seasonal variation. Classical time series method is often used in ARMA (Autoregressive Moving Average), ARIMA (Autoregressive Integrated Moving Average), and ARIMAX (Autoregressive Integrated Moving Average with Exogenous Variables).

The Autoregressive (AR) process defines the forecast electric load y(t) in terms of the previous load and random noise signal a(t) [6].

$$y(t) = \Phi_1y(t-1) + \Phi_2y(t-2) + \ldots + \Phi_py(t-p) + a(t) \qquad (2)$$

The Moving-Average (MA) process defines the forecasted electric load in term of the current and previous random noise signal. The noise series is constructed from the previous forecast errors [6].

$$y(t) = a(t) - \theta_1a(t-1) - \theta_2a(t-2) \ldots\ldots \theta_{q1}a(t-q) \qquad (3)$$

The Autoregressive Moving-Average (ARMA) process defines the forecasted load using a combination of AR and MA process [6].

$$y(t) = \Phi_1y(t-1) + \Phi_2y(t-2) + \ldots\ldots + \Phi_py(t-p) + a(t) - \theta_1a(t-1) -$$

$$\theta_1a(t-1) - \theta_2a(t-2) - \ldots\ldots - \theta q_1a(t-q) \qquad (4)$$

C. General Exponential Smoothing (GES)

The General Exponential Smoothing load forecasting method models the observed load as [6],[10].

$$y(t) = \beta(t)^Tf(t) + \varepsilon(t) \qquad (5)$$

Where,

$f(t)$ = vector of linearly independent and stationary fitting function.

$\beta(t)$ = coefficient vector that is locally constant

$\varepsilon(t)$ = white noise

T = transpose operator

D. State Space (SS)

The state space load forecasting method has many variation but they all model the load as a state variable using a state space formulation. Often, this state formulation consists of two equations [6]:

State Space Equation:

$$X(k+1) = \Phi(k)X(k) + W(k) \qquad (6)$$

Measurement Equation:

$$Z(k) = H(k)X(k) + V(k) \qquad (7)$$

Where,

$X(k)$ = $(n\times1)$ process vector at time t_k

$\Phi(k)$ = $(n\times n)$ state transition matrix relating $X(k)$ to $X(k+1)$ when no forcing function exists

$W(k)$ = $(n\times1)$ white noise with a known covariance $Q(k)$

$Z(k)$ = $(m\times1)$ vector of load measurement at time t_k

$H(k)$ = $(m\times n)$ matrix relating $X(k)$ to $Z(k)$ without noise

$V(k)$ = $(m\times1)$ load measurement error which is a white noise with a known covariance $R(k)$

E. Knowledge-Based Expert System (KBES)

Knowledge-Based Expert Systems (KBES) attempt to emulate the decision making abilities of power system operator when forecasting future system load. The KBES is a computer program, but it is not described as algorithm. It extracts the intuitive relation between load and weather, time, date, and season from the system operator or expert to construct the knowledge base.

F. Fuzzy Logic

Fuzzy Logic is a generalization of Boolean logic which is used for design of digital circuit. An input under Boolean logic takes on a value of “True” or “False”. After the logical process of fuzzy input, a “defuzzification” can be used to produce such precise outputs [11],[12],[13] describe application of fuzzy logic to load forecasting.

G. Datamining

It is the process that explores information data in a large database to discover rules, knowledge etc [14],[15].This method is based on a hybrid technique of optimal regression tree and an artificial neural network.

H. Wavelets

A STLF model of wavelet based network is proposed [16] to model the highly nonlinear dynamic behavior of the system load and to improve the performance of traditional ANN.

I. Evolutionary Algorithm (EA)

Evolutionary Algorithm (EA) like genetic algorithm (GA) [14-23], particle swarm optimization (PSO) [24-26], and artificial immune system (AIS) [27], ant colony optimization (ACO) [28] have been used for training neural network in short term load forecasting applications. These algorithms are better than back-propagation in convergence and search space capability.

J. Neural Networks (NN)

The use of artificial neural networks (ANN) has been widely studied load forecasting technique since 1990 [29]. Neural networks are essentially non linear circuit that have the demonstrate capability to do non linear curve fitting.

IV. NECESSITY OF STLF PROCESS

A. ACCURACY

Good accuracy is the basis of economic dispatch, system reliability and electricity markets.

B. Fast Speed

Speed of the forecasting is a basic requirement of the forecasting program. Programs with two long training time should be abandoned and new techniques shortening the training time should be employed. Normally the basic requirement of 24 hour forecasting should be less than 20 minutes.

C. Automatic Bad Data Detection

In the modern power system, the measurement devices are located over the system and the measured data are transferred to the control centre by communication lines. The new trend is to let the system itself do this instead of the operator to decrease their work burden and to increase detection rate.

D. Friendly Interface

The user can easily define what they want to forecast, whether through graphics or tables. The interface of the load forecasting should be easy, convenient and practical.

E. Automatic Data Access

The historical load, weather and other load relevant data are stored in the database. The STLF system should be able to access it automatically and get the needed data.

F. Automatic Forecasting Result Generation

To be more convenient, The system should generate the final forecasting result according to the forecasting behavior of the historical days.

G. Probability

Different power systems have different properties of load profiles. Therefore a normal STLF software application is only suitable for the area for which it has been developed. This is a very high level requirement for the load forecasting which has not been well realize up until to today.

V. PROBLEMS IN STLF

A. Precise Hypothesis Of The Input-output Relationship

Most of the STLF method hypothesize a regression function to represent the relationship between the input and output variables. How to hypothesize the regression form or the network structure is a major difficulty because it needs detailed a prior knowledge of the problem.

B. Generalization Of Expert's System

It is very natural to use expert systems & fuzzy interface for load forecasting. But transforming the expert's to a rule database is a difficult task, since the expert's forecasting is often intuitive.

C.The Forecasting Of Anomalous Days

Load of anomalous days are also not easy to predict precisely, due to the dissimilar load behavior compared with those of ordinary days during the year as well as the lack of sufficient samples.

D. Inaccurate Or Incomplete Forecasted Weather Data

The inaccurate weather report data employed in the STLF would cause large error. Another problem is sometimes the detailed forecasted weather data cannot be provided.

E. Less Generalization Ability Caused By Over fitting

Over fitting is a technical problem that needs to be solved for load forecasting. A significant disadvantage of neural network is over fitting. It shows perfect performance for training data prediction but much poorer performance for the future data prediction. Since the goal of STLF is to predict the future unknown data, technical solution should be applied to avoid over fitting.

VI. DESCRIPTION OF ANN

A. ANN

ANN or Artificial Neural network is a method to obtain an approximate solution through Artificial Intelligence techniques, which is based on the imitation of the function of brain. The ANN is hence capable of producing result similar to brain which is not possible on the part of conventional algorithm. The ANN network consist of input layer, which is consist of all inputs to the network, an immediate layer known as a hidden layer, for further processing of inputs and finally the output layer, which gives the specified problem the output of the load. The purposed formulation for the ANN network for the purpose of load forecasting is shown in fig.1

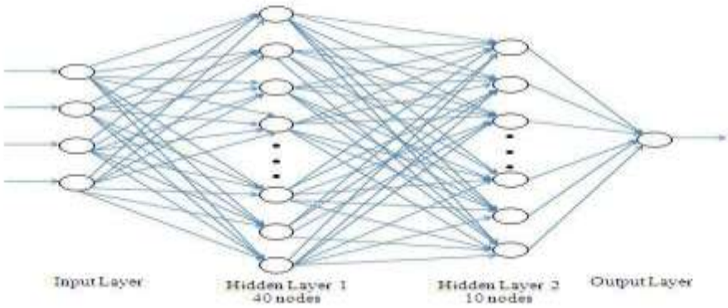


Fig.1. Propsed ANN network for Forecasting

B.Advantages

1) They are extremely powerful computational devices.
2) Massive parallelism makes them very efficient.
3) They can learn and generalize from training data. So there is no need for enormous feats of programming.
4) They are particularly fault tolerant. This is equivalent to the "graceful degradation" found in biological systems.
5) They are very noise tolerant. They can cope with situation where normal symbolic system would have ifficulty
6) In principle, they can do anything a symbolic/logic system can do or more.

C.Working Of Brain Replica Of An Artificial Neural Network

ANN is relatively crude electronic model based on the neural structure of the human brain which basically learns from experience. Learning in biological systems involves adjustment to the synaptic connection that exists between the neurons. The basic building block of all biological brains is a nerve cell or a neuron. A basic component of a neuron shows the various inputs to the network. It is represented by the mathematical symbol x (n). Each of the input is multiplied by a connection weight. The weights are represented by w (n).

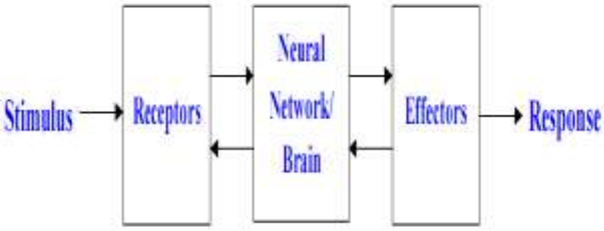


Fig.2. Block diagram of Human Nervous system

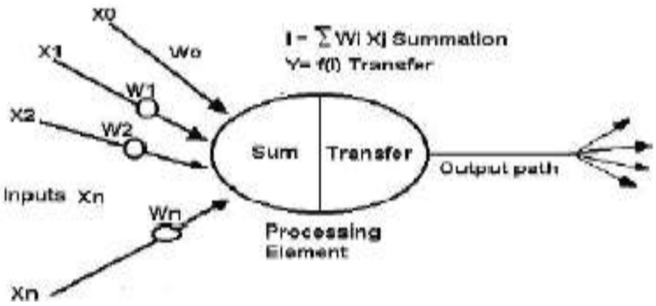


Fig.3. Working principle of ANN system

Above two figures shows similarity in the working principle of brain and ANN system.

D.Training

Training of an ANN consist of three steps during each iteration i.e.
1) Forward Propagation
The outputs are calculated for given input.

2) Backward Propagation

The error at output is propagated backward to the input layer with the partial derivative of the performance with respect to the weight and biases calculated in each layer.

3) Weight Adjustment

The error can minimize by the adjustment of weight which is determine from the multivariate nonlinear optimization algorithm.

E. Forecasting Procedure

Forecasting procedure of ANN is shown in fig.3.

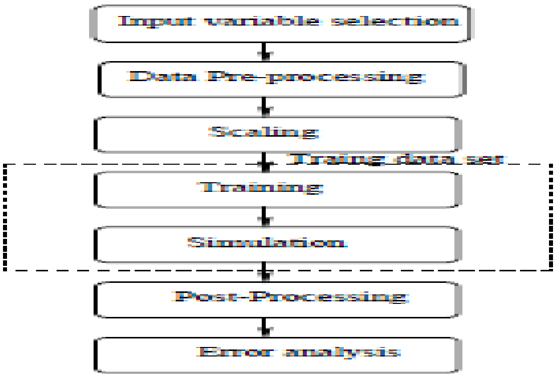


Fig.3. ANN based demand forecasting procedure

F. Performance

In this paper, the performance criteria taken is Mean Absolute Percentage Error (MAPE) which is defined as [30]

$$MAPE = \frac{|\text{Actual Load} - \text{Predicted Load}|}{\text{Actual Load}} \times 100\% \qquad (8)$$

VII. IMPLEMENTATION OF ANN USING MATLAB.1O

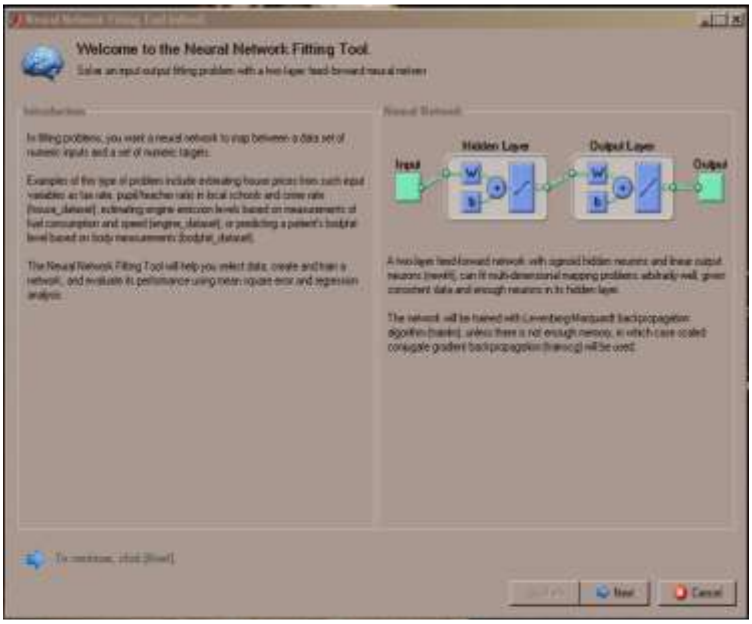


Fig.4. Open nftool in MATLAB.10

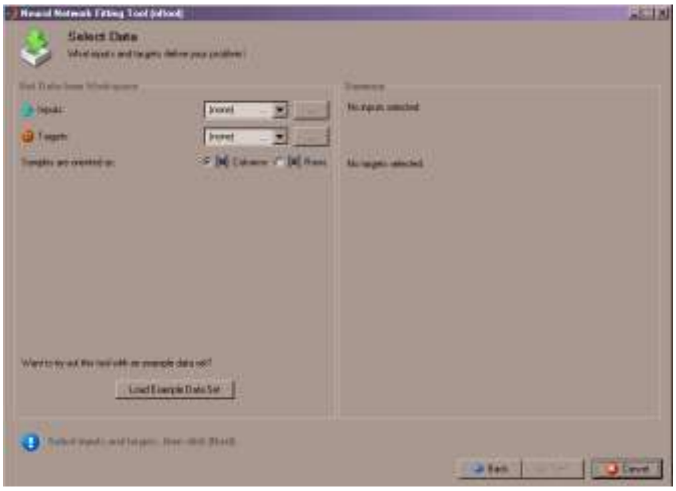


Fig.5.Import the input data and output data from workspace

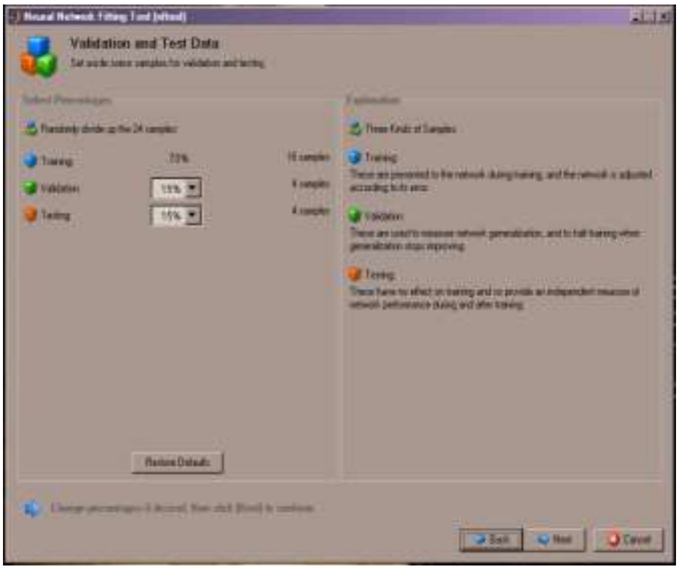


Fig.6. Set the percentage of Training, Validation and Testing according to need

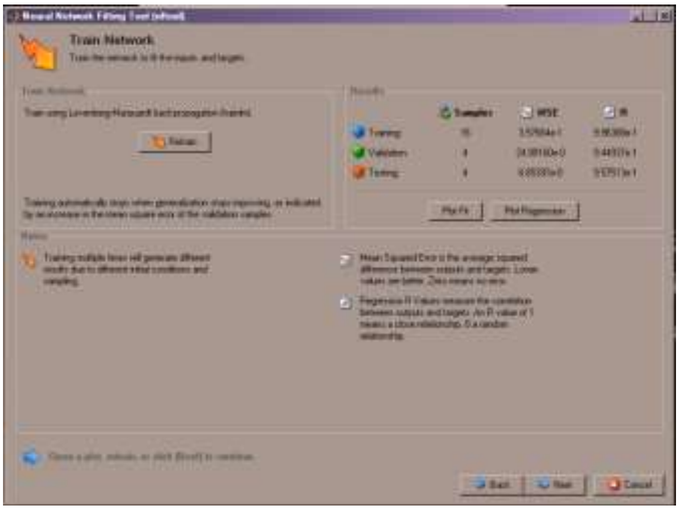
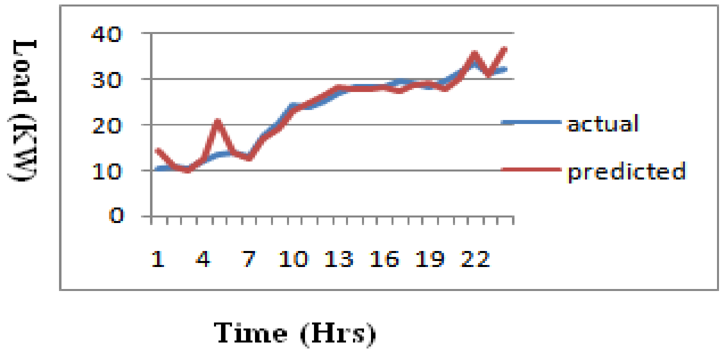


Fig.7. Error Retrain

VIII. COMPARISON OF ACTUAL LOAD AND PREDICTED LOAD [6][7]



IX. APPLICATION

The utility of Artificial Neural Network (ANN) models lies in the utility in the fact that they can be used to infer a function from observation. This is particularly useful in application where the complexity of the data or task makes the design of a function by hand impractical.

X. CONCLUSION

I have used MATLAB.10 for prediction of load. Its forecasting reliabilities were evaluated by computing the Mean Absolute Percentage Error (MAPE) between the actual load and predicted values. The result suggests that ANN model with the developed structure can perform good prediction with least error and finally this neural network could be an important tool for short term load forecasting.

XI. FUTURE SCOPE

Future studies on this work can incorporate additional information (such as customer class season of the year) into the network so as to obtain more representative forecast of future load. Network specialization (i.e. the use of one neural network for the peak periods of the day and another network for hours of the day) can also be experimented upon.

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