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Short Term Load Prediction of a Distribution Network based on an Artificial Intelligent Method

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***Abstract*: -Accurate load forecasting plays a key role in economical use of energy and real time security analysis of system. Artificial Neural Network (ANN) model have been extensively implemented to produce accurate results for short-term load forecasting with time lead ranging from an hour to a week. In this paper a practical case of the small load area of a town getting supplied by 19 distribution feeders is considered with dominant residential-type of load. Historical load and temperature data is collected from January-2010 to December- 2010.Four weather seasons are defined by the Meteorological Department, India. Each season includes the group of month .Representative months are selected from each season by observing the variation in load behavior patterns. An input vector composed of load and temperature values at previous instants, is employed to train ANN designed for each selected month by using Back-Propagation algorithm with Momentum learning rule. ANN testing is carried out and their performance is evaluated using mean absolute percentage error (MAPE) criterion. Finally, error values are compared for each month and hence the deviation in forecasting ability of ANN is observed for each month and season.**

***Key words*:Artificial Neural Network,Back-Propagation algorithm,mean absolute percentage error.**

I. INTRODUCTION

Electric load forecasting is the process used to forecast future electric load, given historical load, weather information along with current and forecasted weather information. There is a growing tendency towards unbundling the electricity system. This is continually confronting the different sectors of the industry (generation, transmission, and distribution) with increasing demand on planning management and operations of the network. Load forecasting plays a key role in helping an electric utility to make important decisions on power cut, load switching, voltage control, network re-configuration, infrastructure development, purchasing and generating electric power. Load forecast are extremely important for energy suppliers, ISOs, financial institutions, and other participants in power energy generation, transmission, distribution, and markets [1].]Load forecasting is however a difficult task as the load series is a complex pattern and exhibits several levels of system seasonality [2].Several conventional techniques had been used for the load forecasting [3],[4],[5]. However, the disadvantages of these techniques have led to the use of the artificial intelligence technique. Artificial Neural Network (ANN) is the most proved for forecasting application [6], [7], [8]. The reason is, ANN methodology solves the complex relationships between the independent and dependent variables by a mathematical mapping algorithm without detailed mathematical modeling [9].Short-term load forecasting (one hour to one week ahead) plays a key role in power system operations .Next hour load forecasting displays a great ability for economic and secure operationof power system. In rapidly growing power market likeIndia with complex distribution structure, it is difficult todetermine the exact variables on which the load structuredepends. Also the study of the monthly load pattern isimportant to understand the nature of power-system. Inthis paper the duration from January-20l O to December-2010 is selected for analysis and forecasting. Each seasonof a year exhibits difference in their load characteristicswhich is significant in case of small load areas ascompared to the large system. These variations affect theforecasting ability of ANN. Thus, aim of this paper is tostudy the change in the seasonal load behavior patternand to observe the variation of the functionapproximating ability and forecasting accuracy of ANNfor selected representative months of each season.

Thepaper is organized as follows: Section II gives briefintroduction to the Artificial Neural Network, Multi-layerNetwork, Back-Propagation algorithm and Momentumlearning rule. Section III describes the month selectionand data analysis process. Section IV discusses the inputvector design, network topology and training -phase. InSection V the results for the testing phases and monthlyerror variation is discussed. Section VI describes theconclusion of the work.

II. ARTIFICIAL NEURAL NETWORK

ANN is originally developed to mimic basic biologicalneural systems. An Artificial Neural Network (ANN) isan information processing paradigm that is inspiredbythe way biological nervous systems, such as the brain,process information. The key element of this paradigm isthe novel structure of the information processing system.It is composed of a large number of highly interconnectedprocessing elements (neurons) working in unison to solvespecific problems. ANNs,like people, learn by example.Neural networks are essentially nonlinear circuits thathave the demonstrated capability to do non-linear curvefitting. The basic elements of the neuron model are: l. Aset of weights, each of which is characterized by astrength of its own. A signal Xj connected to neuron 'k' is multiplied by the weight Wkj'. The weight of an artificial neuron may lie in a range that includes negative as well as positive values. 2. An adder for summing the input signals, weighted by the respective weights of the neuron. 3. An activation function for limiting the amplitude of the output of a neuron. Fig. 1 represents the connection between these elements in a neuron structure [10].

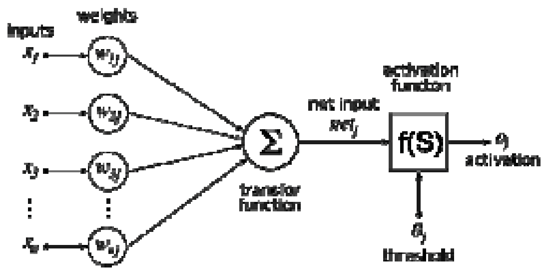

Fig.1. Neuron Structure.

A. Multi-layer ANN

ANN structure can be classified into two categories as single and multi layer network. Network with only input and output layer connected by the synaptic weights are termed as single layer network .Network having neuron layers between input and output layers are known as the multi-layer neural network. Fig 2 represents the multilayer ANN structure with three layers. The layer between input and output layer is referred as the hidden layer. Multi-layer neural network have greater computational abilities as compared to the single-layer network. These MLP networks have the ability to learn the complex relationship between the input and output patterns which are not possible in case of single layer networks [11].

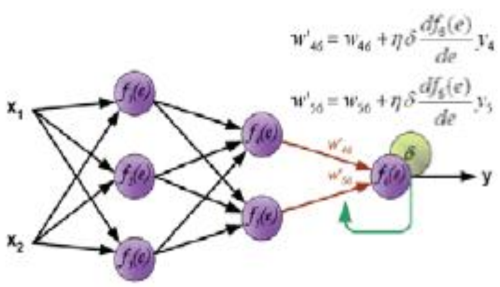

Fig 2.Multi Layer Neural Network

B. Back-Propagation algorithm

In 1986 G.E. Hinton, Rumelhart and R. 0 .Williams first introduced Back-Propagation algorithm. The Back-Propagation (BP) neural network model consists of an input layer, one or several hidden layers and an output layer. The links between these layers have the unique weight value. The input pattern is received by the input layer. The flow of information is in the forward direction. The nodes in the BP neural network receive input information from external sources, and then pass to hidden layer which is an information processing layer and is responsible for the information conversion; further nodes in the output layer provide the desired output information. After that, the anti-propagation of error is carried out by contrasting the actual with desired output. Each weight is revised and back propagated layer by layer from output layer to hidden layer and input layer. This process will be continued until the output error of network is reduced to an acceptable level or the predetermined time of learning is achieved. The processing results of information are exported by output layers as the outside.

C. Momentum learning rule (MLR):

Momentum learning is an improvement to the straight gradient-descent search in the sense that a memory term(the past increment to the weight) is used to speed up and stabilize convergence. Let wij represent the weight joining neuron 'i' and 'j'. While training the network with the back-propagation the error between the output and desired is calculated by equation (1);

$$E_p = \frac{1}{2}\sum_{j=1}^{n}\left(t_{pj} - \widehat{t_{pj}}\right)^2 \qquad (1)$$

Where; j i, the output node, tpj is network output at output node j, tpl is the desired output at output node j. By using this error function as the cost function to be optimized and following the Steepest Descent algorithm the weights are renewed between each layer of the network structure by the momentum learning algorithm.

III. MONTH SELECTION AND DATA ANALYSIS

Hourly load data for 19 distribution feeders supplying a part of a city of MeshkinShahr is obtained from Ardebil Province Electricity Distribution Company.

A. Customer Classification:

As represented in Fig. 3 nearly 90% of the end-user customers is of residential type, 6% includes the commercial type of end users such as shops, official end-users which includes schools, colleges and various departmental offices, whereas rest 4% includes the three-phase customers such as the flour -mills, stone-crushers the agriculture pumps etc . Thus, the dominant load for this area is of the residential type.

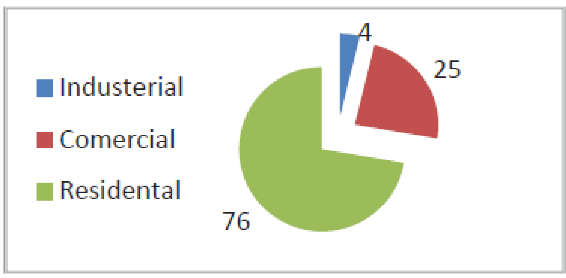

Fig3 Customer classification of the city

B. Representative month selection:

As the load consumption profile is influenced by theseasonal changes representative month are selected foreach season to study the load variation pattern andfunction mapping ability of ANN. Months exhibiting thevariation in their daily and weekly load pattern behaviorare selected. The selected months are:

- Winter Season(SI)- February(Feb.)
- Pre Monsoon Season(S2)- March , May

• Southwest Monsoon Season(S3) June,September(Sept.) and

• Post Monsoon Season(S4) October(Oct.)December(Dec.)

The area under Town-l exhibits the summer-peak typesystem. Within a year, due to seasonal variation, thepower consumption profile changes in different seasons.Also other activities like the festive season, socialgatherings affect the load behavior pattern for a smallload area with dominant residential-type load.

As the dominant load is of residential-type, the loadswitching effect due to weather changes are quitefrequent especially in low temperature months. It is clearthat the load variation pattern changes for each seasonand even within a season there is a variation in loadconsumption profile for each month. For a small loadarea, the load variation pattern has the significant impacton load forecasting as compared to the large system(having load profile of hundreds and thousands ofMegawatt).

IV. SIMULATION

A. Input Vector:

The members of Input Vector is selected from vectormentioned in [12], with some changes as per the availabledata and conditions. In this vector the load at any futureinstant, along with the past load values, is considered as afunction of the minimum and maximum temperature aswell as the corresponding day of the week.

Each day is coded separately so that the designedANNscan distinguish the variation characteristics between theload profiles of days within a week which is significantfor the small load area. Training and testing of ANNmodels for each month is performed using the abovementioned input vector.

B. Network Topology:

In ANN, multi-layer networks are most commonly usedfor the forecasting application. In this work 3-layerednetwork is used. The number of neurons in the input layeris equal to the vector elements of input vector. The outputlayer consists of one neuron giving the load output at aparticular hour. The number of neurons in the hiddenlayer of the network was taken to be 11. Tangenthyperbolic (tanh) activation function is used for thehidden layer and linear activation function is used in the output layer. The inputs of the network are normalized in the range (-1, 1) and the desired output i.e. hourly load data is normalized in range. [14], [IS], [16].

C. Training and Validation:

Data set for each selected month was divided into 3 classes. From the total hourly load data samples of each month,7S% of load data was affiliated to train designed network, S% for validation and 20% for testing phase. Samples for each of these phases were constructed with a fair representation of all data set classes.

Training and validation for each selected month is carried out using input vector mentioned in part A. Mean Squared Error (MSE) criteria as given in equation (3) is used for the analysis purpose in training and cross validation phase.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(L_a - L_f\right)^2 \qquad (3)$$

The variation of the MSE during training for different values of network parameters is observed. The parameters which give the minimum MSE are considered to be optimum for a network. Designed ANNs are trained for each month separately. It is clear that the trammg learning curve shows an overall decline in the MSE as the epoch progress for all months.

V. RESULTS AND DISCUSSION

A. Test-phase:

Trained ANN models are tested using selected sample data sets for each month, which includes all the pattern variation and was not the part of the training data set. Mean absolute percentage error (MAPE) criteria are used for comparison of test-phase results. MAPE is calculated using (4).

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{\left|L_{ai} - L_{fi}\right|}{L_a} * 100\% \qquad (4)$$

In MAPE, the absolute value of error is taken so that the effective sum is the addition of all the positive values of an error. [18]. F rom the simulation , it can be seen that the ANN trained for Dec. has the most inaccurate forecast whereas ANN trained for May has good accuracy of forecasting.This representation of variation in forecasting accuracy for all four season is shown in Fig. 4.

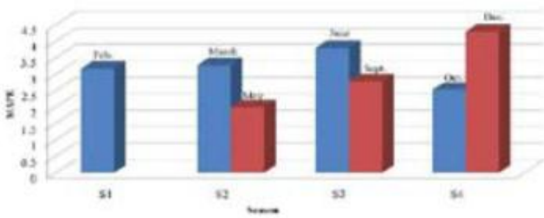

Fig 4. Seasonal forecasting error

From Fig. 4, it can be observed that within a season due to variation of load behavior pattern and its response to the factors included in vector considered in this paper, months of season S2, S3 and S4 shows deviation in intraseasonal forecasting accuracy. For improvement in forecasting accuracy, this necessitates detailed study of load curves of each month, load-temperature sensitivity analysis, study of load response to various factors and hence the formation of input vectors accordingly for each month of a year.

VI. CONCLUSION

Hourly load forecasting can be used as a tool fordemand side management and security analysis by distribution utilities in Iran. ANN has an ability to approximate the non-linear functions between the input and desired output variables. System considered in this paper, with residential-type of dominant load, exhibits changing load curve patterns in various months falling under different seasons. This change in load consumption profile throughout the year indicates the deviation in dependence of load on various exogenous factors. In this work the minimum and maximum temperature is taken as the exogenous variable. Along with temperature, load at past instants is also included in the input vector. However, after application of ANN for load forecasting of selected months, the error values varied in range of 4% in Dec. to l .98% in May. Thus, from this high deviation in accuracy range it can be inferred that the load in high error months (i.e. MAPE>3%) has its high dependence on factors other than that included in input vector and load components at some other instants. Months selected from Pre-Monsoon and Post-Monsoon season shows highvariation in intra-season forecasting accuracy as compared to winter and monsoon season. This again point towards the changing intra-seasonal load dependence factors which further affects the function mapping ability of ANN.

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