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Analysis of Long Term Load Forecasting using Ann Technology

KEYWORDS: Back-propagation, Feed-forward, Weighted input, Validation and Testing.

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ABSTRACT *Generation of power and load forecasting plays a vital role in the demand side management. The dissertation presents a new approach for long term electrical load forecasting using an artificial neural network for power systems. Throughout the world , electrification is an ongoing process. The reason for this phenomenon is the preference for the electrical energy. Increasing demand is due to several factors as population growth, growth of per-capita income , migration to cities and increasing energy using products.In recent years, load forecasting has become one of the major areas of research in electrical engineering and is an important problem in the operation and planning of electrical power generation. Most traditional forecasting models, artificial intelligence, regression analysis ,genetic algorithm tool technique and neural network techniques have been tried out this task. Artificial neural network (ANN) has lately received much attention, and a great number of people have repeated successful experiments and practical tests .The proposed work concentrates on analysis of long term datas of power generation , MATLAB ANN tool and ANN algorithm has been developed to predict the variation of the load forecasting for the further long term of more than 10-20 years*

I Introduction

Load forecasting is a technique of estimating or prediction of requirement of electricity by the urban , rural-residencies, companies and other institutions in the future. The general objective of this project is to develop a software product that can be used by electric utility operators to predict the long term load demand. In the recent days the demand for electrical load is increasing drastically so it has become essential to advance the generation. Load forecasting plays an important role in determining the future number of generation units in order to meet the ever increasing demand. ANN plays a vital role in determining the future role. Thus by predicting the load demand using ANN eliminates the future uncertainties. The results obtained using ANN has been found more accurate.

Neural networks have the ability to derive meaning from complicated or imprecise data, can extract patterns and detect trends that are too complex to be noticed by other computer techniques. ANN technology is required because of the current technology limitations, like Speed, Intelligence & Fault tolerance. The computational speed of ANN is very fast compared to other technologies due to its parallel-distributed nature of processing. It has power of intelligence because of adaptability. Since ANN is composed of large number of simple computational units operating in parallel, training algorithm can organize these existing computational units in such a way that the network acquires the potential to provide fault tolerance

II Methodology.

The survey has been made to collect the datas from north bank of KRS mini hydel power station which consists of two 6MW generators. The collected datas are in terms of MW(real power) from 1999 to 2013(monthly basis).The fifteen years future generation power is predicted using ANN technique in which fitting tool, time series tool, genetic algorithm code are used. The results are obtained from all the above methods and the deviation from the target is been noticed and the result with least deviation is preferred to determine the future load demand. The proposed algorithm consists of 3 sub-programs as mentioned below

1. Program to read the data from XL sheet and its normalization.
2. Program for power demand forecast for complete year from previous year record.
3. Program to forecast complete year.

An MLP is a powerful system, often capable of modeling complex, relationship between variables. It allows prediction of an output object for a given input object. The architecture of MPL is a layered feed forward neural network in which the nonlinear elements (neurons) are arranged in successive layers, and the information flow uni-directionally from input layer to output layer through hidden layer. Fig 1 shows a typical multi-layer perceptron network

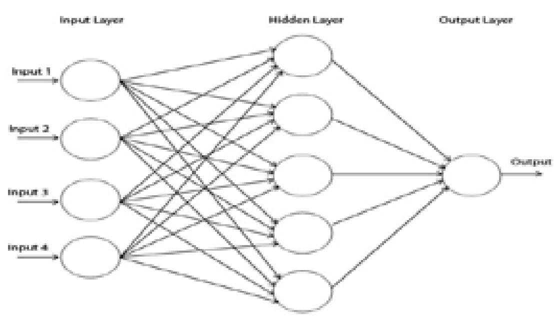

Fig 1. Typical multilayer perceptron network

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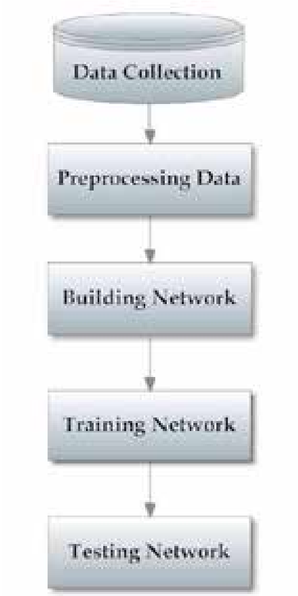

Fig 2.Process of load forecasting ANN technique

I. Data collection-Collecting and preparing sample data is the first step in designing ANN models.

II. Data pre-processing: After data collection, three data preprocessing procedures are conducted to train the ANNs more efficiently. These procedures are: (1) solve the problem of missing data, (2) normalize data and (3) randomize data.

III. Building the network: At this stage, the designer specifies the number of hidden layers, neurons in each layer, transfer function in each layer, training function, weight/bias learning function, and performance function. In this work, multilayer perceptron (MLP) and radial basis function (RBF) networks are used.

IV. Training the network: During the training process, the weights are adjusted in order to make the actual outputs (predicated) close to the target (measured) outputs of the network and different types of training algorithms are investigated for developing the MLP network.

V. Testing the network: The next step is to test the performance of the developed model. At this stage unseen data are exposed to the model. Sigmoid is selected as it has biological basis, since the firing frequency of biological neurons as a function of excitation follows a sigmoid characteristic. In simple it represents the mathematical model of biological neuron activity. Unlike the Step and the Ramp function, Sigmoid has smooth threshold for bounding the output response and exhibits a graceful balance between the linear and non-linear characteristics

II.Results and discussion

Data analysis: The datas of 15 years from april to march has been collected to predict the future power demand for the rest of 10-15 years. The MATLAB fitting function too has been used to predict the future power demand for the year 2014 and 2015 based on the previous year data collected. Table 1 shows the input power generated of two generating stations of capacity of 12MW for the year 2013, and the target output for the year 2014 has been calculated from the derived equation target output= 0.98* input+0.1 based on the 15 years data, with the input and target data using ANN MATLAB fitting tool, the accurate output is predicted for 6 iterations.

Table 1 input, target and predicted using ANN MATLAB fitting tool for the year 2014.

MONTH	Input in MW	FITTING TOOL PREDICTED	target output in MW
	G1+G2	G1+G2	G1+G2
APRIL	0	0	0
MAY	0	0	0
JUNE	0		0
JULY	0	0	0
AUG	7.67	7.64	7.62
SEPT	19.64	19.73	19.83
OCT	27.49	27.66	27.84
NOVE	39.25	39.34	39.84
DEC	49.313	49.74	50.11
JAN	53.63	54.07	54.52
FEB	59.03	59.52	60.03
MARCH	0	0	0

Table 1 input, target and predicted using ANN MATLAB fitting tool for the year 2015.

MONTH	Input in MW	FITTING TOOL OUTPUT	Target in MW
	G1+G2	G1+G2	G1+G2
APRIL	0	0	0
MAY	0	0	0
JUNE	0	0	0
JULY	0	0	0
AUG	7.64	7.73	7.67
SEPT	19.73	19.79	19.64
OCT	27.66	27.99	27.49
NOVE	39.34	40.09	39.25
DEC	49.74	50.06	49.313
JAN	54.07	55.92	53.6
FEB	59.52	60.6	60.03
MARCH	0	0	0

Graphical analysis: From the collected and predicted data the comparitive graphical analysis has been made for the year 2014 and 2015. The predicted output has the range of 0.2 to 0.6 comparitively with the input and target output. The fig.2 and fig.3 shows the comparitive graph of input, target and predicted output.

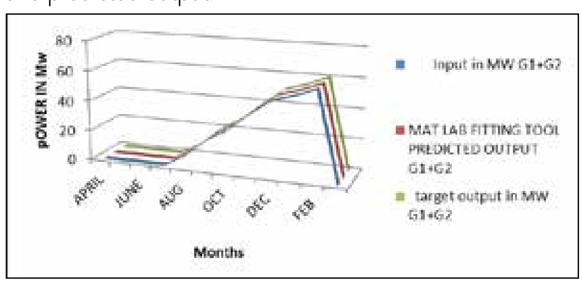

Fig3. Comparitive graph of input, target and predicted output 2014.

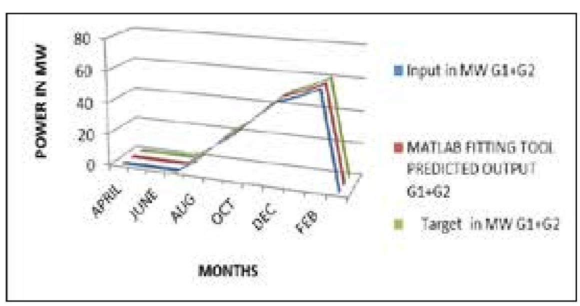

Fig 4. Comparitive graph of input, target and predicted output 2015.

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Fig5. 1-10-1 MLP(Multilayer Perceptron Network) of 2014

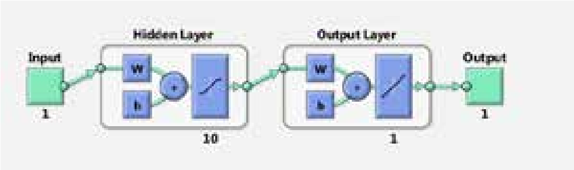

Fig.5 shows 1-10-1 multilayer perceptron of 2014 in which power is inputted in MW of 12 months in which the validation is set to 15% , testing is set to 15% and training is set to 70% and the number of hidden layers is 10.

Fig6. 1-15-1 MLP(Multilayer Perceptron Network) of 2015

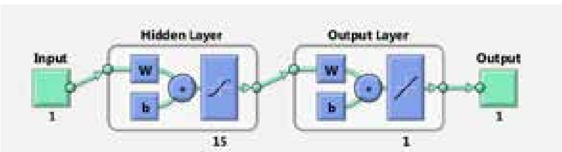

Fig.6 shows 1-15-1 multilayer perceptron of 2015 in which power is inputted in MW of 12 months in which the validation is set to 15% , testing is set to 15% and training is set to 70% and the number of hidden layers is 15.

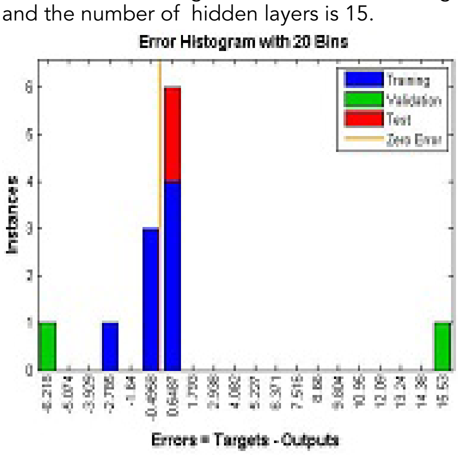

Fig7. Simulated result of error histogram of 2014

Fig 7 shows the error histogram of 2014 in which testing , validation and training is represented. The point at which the zero error lies is the minimum error possibility.

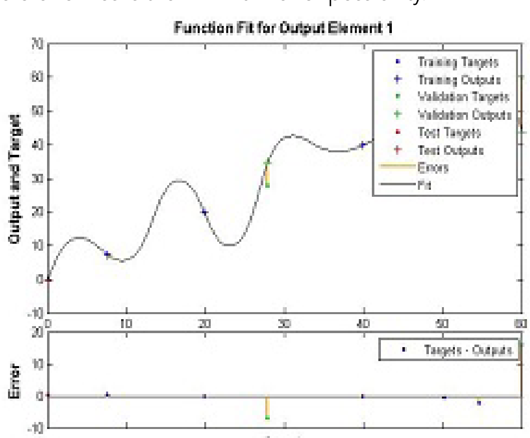

Fig.8 Simulated result of function fit of 2014

Fig 8 shows the variation in targets and outputs of testing validation and training.

Fig.9 Simulated result of function fit of 2014

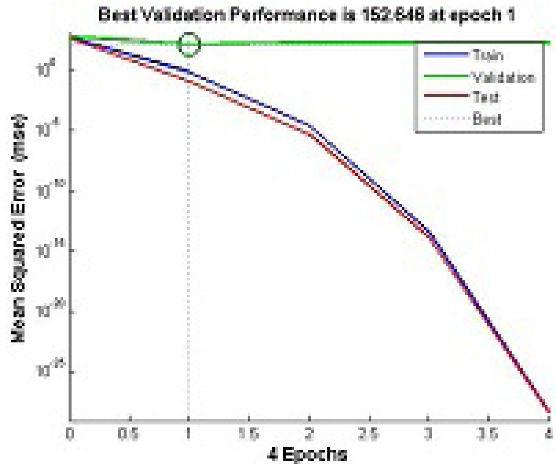

Fig.9 shows the deviation of testing validation and training data at each epochs.

Fig.10 Simulated result of regression of 2014

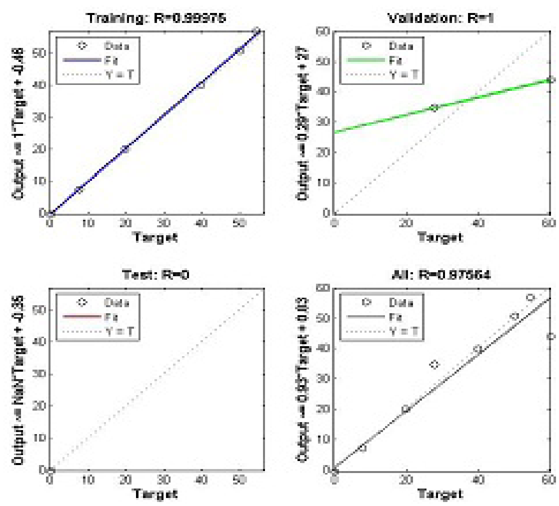

Fig 10 shows the variation of output with respect to the target.

Fig.11 Simulated result of training graph of 2014

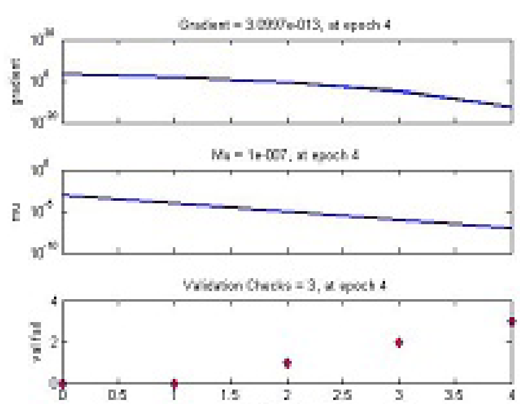

Fig.11 shows the gradient initial input weight and validation

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fail at each epochs.

Fig.12 Simulated result of error histogram of 2015

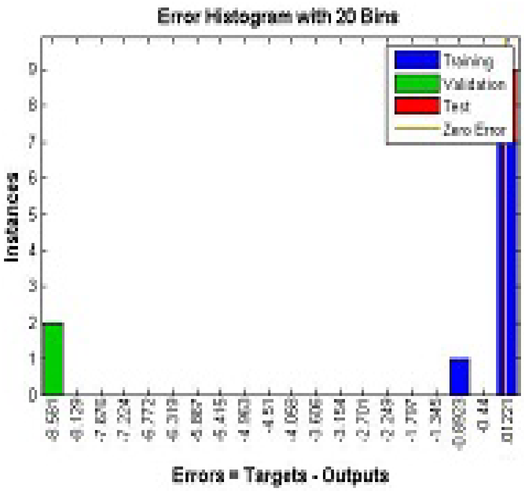


Fig 12 shows the error histogram of 2015 in which testing , validation and training is represented. The point at which the zero error lies is the minimum error possibility.

Fig.13 Simulated result of function fit of 2015

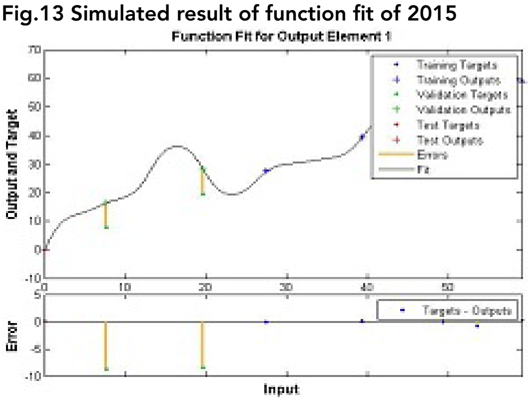


Fig 13 shows the variation in targets and outputs of testing validation and training

Fig.14 Simulated result of function fit of 2015

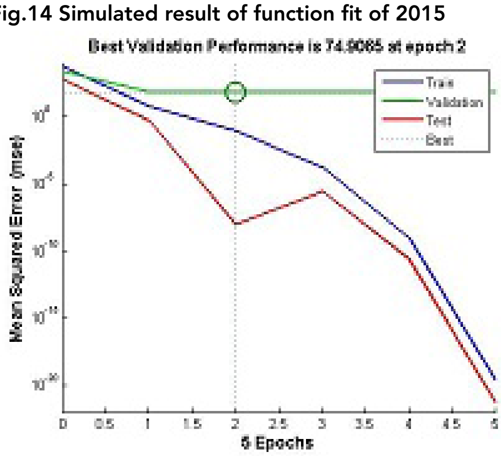


Fig.14 shows the deviation of testing validation and training data at each epochs.

Fig.15 Simulated result of regression of 2015

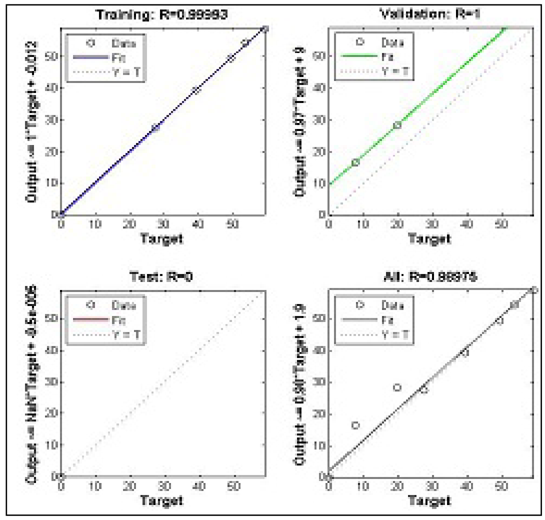
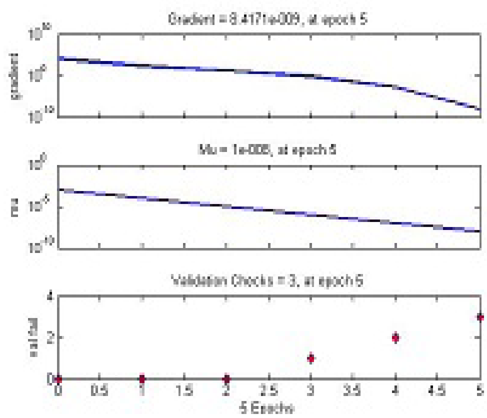


Fig 15 shows the variation of output with respect to the target.

Fig.16 Simulated result of training graph of 2014



IV Conclusion

The datas from 1999-2013 are inputted with the available target outputs and the error have been calculated by all the three methods i.e, fitting tool, time series tool and genetic algorithm code. The results obtained from each method are compared .

Comparatively, the predicted results are found to be more accurate in the fitting tool with the error percentage not exceeding 5%.

Accordingly the load is predicted for the next two years from fitting tool.

The forecasted load results found from ANN analysis technique has been submitted to the north bank of Krishna Raja Sagar (KRS) mini hydel power station so as to incorporate the predicted datas in order to expand the future power generation to meet the ever increasing demand.

REFERENCE

1.Dr. B J Ranganath and Mr Amruth R T (july 2013), " Design of DC-DC buck boost converter charge controller for solar power applications" international global research multi-subject journel ,ISSN: 22777-8160,vol.2,issue no.7, pp.63-65. | 2.Ahmed, M., Ahmad, F. & Wasim Akhtar, M. (2009). Estimation of global and diffuse solarradiation for Hyderabad, Sindh, Pakistan, Journal of Basic and Applied Sciences, Vol.5, No. 2, pp. 73-77. | 3.Alam, S., Kaushik, S. & Garg, N. (2009).Assessment of Diffuse Solar Energy under General | Sky Condition using Artificial Neural Network, Applied Energy, Vol. 86, pp. 554-564. | | 4.Al-Alawi, S. & Al-Hinai, A. (1998). An ANN-based Approach for Predicting Global Solar | Radiation in Locations with no Measurements, Renewable Energy, Vol. 14, No, 1–4, | pp. 199-204. |