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PROMOTING SHORT TERM LOAD FORECASTING BY USING ARTIFICIAL INTELLIGENCE

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Abstract- **Load forecasting has always been the essential part of an efficient power system planning and operation. Several electric power companies are now forecasting power demand (load) based on conventional methods and some on the behalf of artificial intelligence. On the behalf of that review, this paper presents the short term load forecasting on the basis of MAPE and MAE accuracy criteria by using time series as an input pattern selection for neural networks. The input data is trained by FFNN and in an another model to overcome the drawback of Gradient descent algorithm problem of local minima another global search algorithms GA is used for initialization of input parameters of neural network called GANN technique. The data used for the analysis is collected for the year 2012 from Ontario Electricity Market and prediction is done on time series frame work for first four weeks of December 2012.**

Key Words- **Electricity Market, Load Forecasting, Neural Network**

I. INTRODUCTION

Nowadays almost all the countries are adopting deregulated industry structure for better utilization of the resources and for providing choice and quality service to the consumers at economical prices resulting in transparent price discovery [1]. In the current deregulated scenario, the forecasting of electricity load, price and wind power has emerged as one of the major research fields in electrical engineering. A lot of researchers and academicians are engaged in the activity of developing tools and algorithms for load, price and wind power forecasting. However, the electricity demand forecasting has reached in advanced stage of development [2], [3].

Since, the relationship between load power and factors influencing load power is nonlinear; it is difficult to identify its nonlinearity by using conventional methods. Most of the research has been deal with all short term, medium & long term load forecasting or next day peak load forecasting. There are basically two types of forecasting techniques based on input data selection, first is physical model and seconds is time series. The first technique physical technique requires physical data or condition of site for which we want to forecast. But the second technique time series requires only time series data of electricity load and input time lag for neural networks training is selected on the basis of Autocorrelation Function and Partial Autocorrelation Function (PACF) [4-6].

In the available literature, several techniques to forecast electricity prices, load and wind power forecasting have been reported, namely hard and soft computing techniques. These approaches can be very accurate; but, they require lot of information & computation [7], [8]. Yun et.al [9] makes a model to forecast short term load is established by combining the radial basis function (RBF) neural network with the adaptive neural fuzzy inference system (ANFIS). Almeshaiei et.al [10] presents a pragmatic methodology that can be used as a guide to construct Electric Power Load Forecasting models. This methodology is mainly based on decomposition and segmentation of the load time series. Amjady et.al [1] predicts load on short-term basis in microgrids environment by a new bilevel prediction strategy. Bhaskar et.al [12] proposed a statistical-based wind power forecasting without using numerical weather prediction (NWP) inputs. The proposed approach utilized adaptive wavelet neural network (AWNN) and feed-forward neural network (FFNN) to predict wind speed and power up to 30 h ahead. Zhou et.al [13] proposes a new short-term forecasting algorithm for congestion, LMPs, and other power system variables based on the concept of system patterns combinations of status flags for generating units and transmission lines. Ping-Feng Pai et.al [14] decomposed a recurrent support vector machines with genetic algorithms (RSVMG) to forecast electricity load. In addition, genetic algorithms (GAs) are used to determine free parameters of support vector machines.

This paper presents the short term load forecasting results on the basis of MAPE and MAE accuracy criteria by using time series as an input pattern selection for neural networks. The input data is trained by FFNN and in an another model to overcome the drawback of Gradient descent algorithm problem of local minima another global search algorithms GA is used for initialization of input parameters of neural network called GANN technique. The data used for the analysis is collected for the year 2012 for Ontario Electricity Market and prediction is done on time series frame work for first four weeks of December 2012.

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II. TIME SERIES FORECASTING

Time series methods make forecasts based solely on historical patterns in the measurement data by using time as independent variable. In a time series, measurements are taken at successive points or over successive periods. The ANN trained with time-series data have the ability to model arbitrarily linear and non-linear functions. Being widely utilized in various different fields including transient detection, pattern recognition, function approximation, and time series forecast, ANN is a promising technology which may be utilized for electric load forecasting as well [15, 16].

A. Neural Networks

The human being and animals are much better and faster than the most advanced computers. Although computers outperform both biological and artificial neural systems for tasks based on precise and fast arithmetic operations, artificial neural systems represent the promising new generation of information processing networks. Advances have been made in applying such systems for problems found intractable or difficult for traditional computation. A neural network's ability to perform computations is based on the hope that we can reproduce some of the flexibility and power of the human brain by artificial means [5, 6].

Genetic algorithms are a part of growing set of evolutionary algorithm that applies the search principles of natural evolution for parameters optimisation. In this work, neural network parameters namely weights are biases are optimized using genetic algorithm. Also it may be noted that BPNN determine its weight based on gradient search technique hence it may encounter a local minima problem and sensitivity to initial values persist. So to resolve above said problem GA is used to initialize the weights and biases. In this weight & biases are defined as a string in GA population and fitness of each individual is calculated & based on fitness weights are extracted from each chromosome [15]. The GA process is shown in Figure 1.

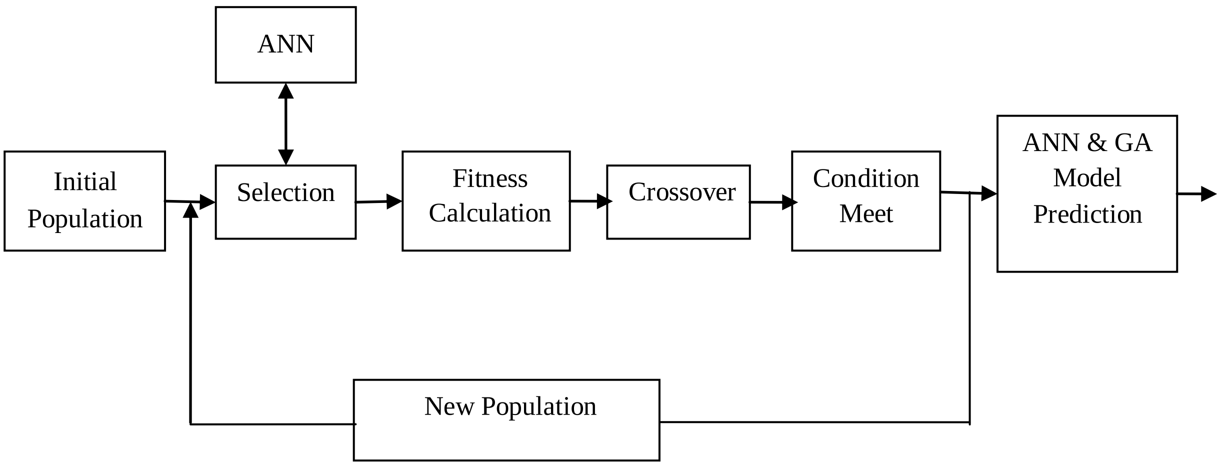

Figure 1: GA processing for estimation of the input parameters of FFNN

B. Electricity Load Data Inputs and Parameters Selection

In this paper, in order to investigate the performance consistency of different forecasting models, electric power generation data from Ontario Electricity market [17] has been considered as the test case system.

The real data of hourly electric load is collected from Ontario Electricity market for the year 2009-12 from January 2009 to December 2012. In order to avoid the overtraining during the learning process and to get more accuracy a very large amount of data is not used. Since, electric load generation is dependent on weather conditions, temperature and even the season. From month to month, wind capacity (the amount of energy actually produced compared to the amount the turbines are capable of producing given perfect conditions) can vary. It can be observed that there is significant variation in electric load generation.

Training Set: To build the forecasting model for electric load forecasting, the training data from January 01, 2009 to November 30, 2012 has been considered.

Test Set: For the testing of FFNN and GANN models prediction has been done for the period from December 1, 2012 to December 28, 2012 (28 days x 24 hours).

One of the most important tasks in developing a successful time series forecasting model is the selection of the input variables, which determines the architecture of the model. Although for the AI based models, there is no systematic approach, which can be followed, some statistical methods can be used to find relevant inputs. The auto-correlation function (ACF) of a sample electric load series over the lag hours is shown in Figure 2. The ACF series used for the prediction in time series is (t-1), (t-2), (t-3), (t-4), (t-23), (t-24), (t-25), (t-47), (t-48) and (t-49). The other series with higher values can also used but to reduce the possibilities of overtraining and over-fitting these values has not been used. The lower values of ACF are not utilized in preprocessing of input data because lower values means weak correlation of present data with past data series. It shows that correlation between successive lags is very strong and it drops off very quickly over large time lags. The load forecast problem aims to find an estimate *f(t+k)* of the load series vector y*(t+k)* based on the previous n measurements $y(t)$, $y(t+1)$, . . . , $y(t-m+1)$. In order to have accurate load forecast, k is chosen to be small and this is called short-term load forecasting.

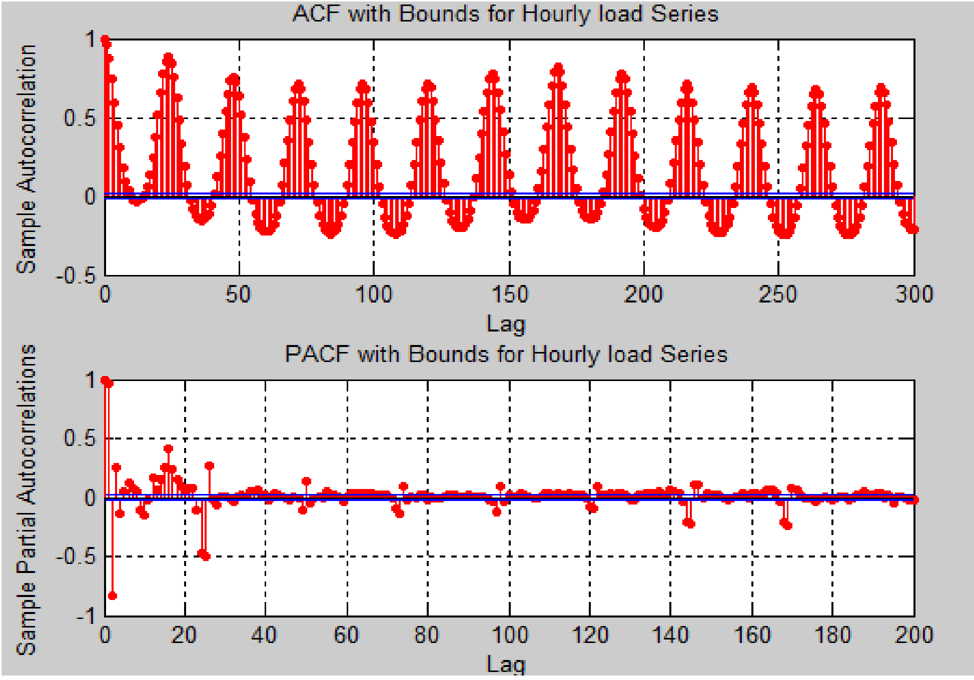

Figure 2: Autocorrelation and Partial Autocorrelation Function plot

Training an ANN model by using time series implies necessarily to know the relation that exists between the series and their lags. These methods come from the development of linear models, but, since neural networks are non-linear approaches, then their calculation gives an indication rather than a standard tool for finding useful variables and lags. The ACF was used as a first step for the selection of useful variables [2-4]. The number of hidden neurons used is twelve with the Levenberg Marquardt learning algorithm, five, eight and eleven input time lag and one output neuron is used in neural network structure. The Figure 2 shows Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plot of electric load generation in Ontario for year 2012. The input time lag selection as depend only on the values of ACF & PACF.

III. Results & Discussion

The methodology described above has been applied to predict the electric load for Ontario Electricity market. The performance of the load forecasting by FFNN and GANN techniques has been compared. The software used for training and testing of neural network is MatLab version R2010a. The MAPE & MAE results for one step ahead forecasting for year 2012 load forecast are shown in Table 1. The training period of 1 year has been considered. Overall performance of GANN is better as compared to FFNN. From Figure 3 to Figure 6 shows the weekly results for both models using time series with 8 input time lags (t-1), (t-2), (t-3), (t-23), (t-24), (t-25), (t-47), (t-48). In all figures, the 168 hours prediction for the first week of December 2012 results has been presented.

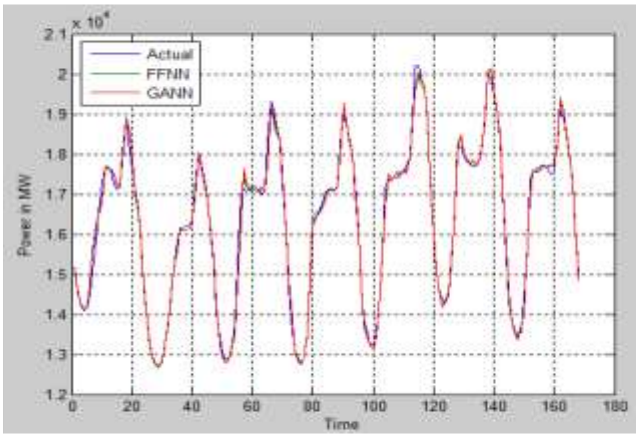

Figure 3: The prediction result for first week with 8 input lag by both ANN & GANN

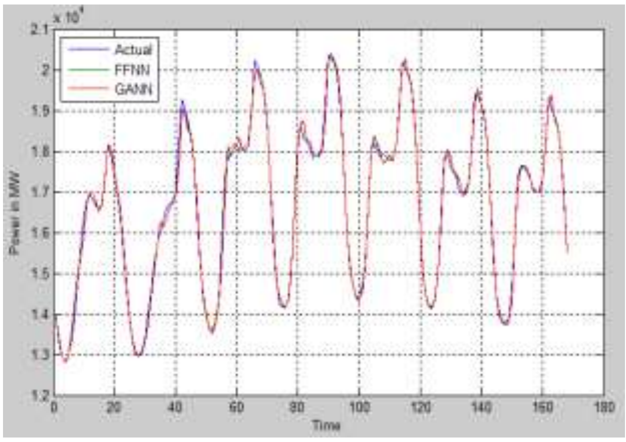

Figure 4: The prediction result for second week with 8 input lag by both ANN & GANN

Table 1: MAPE & MAE results by ANN & GANN with different input Lags

	Input Lag 8'		Input Lag 5'		Input Lag 11'	
	ANN	GANN	ANN	GANN	ANN	GANN
MAPE	0.7 %	0.72 %	1.14 %	1.17%	0.8%	0.76%
MAE	114.16 MWh	118.27 MWh	192.59 MWh	197.42 MWh	132.10 MWh	125.67 MWh
Daily Peak MAPE	0.7 %	0.69 %	1.01 %	1.31%	0.65%	0.79%

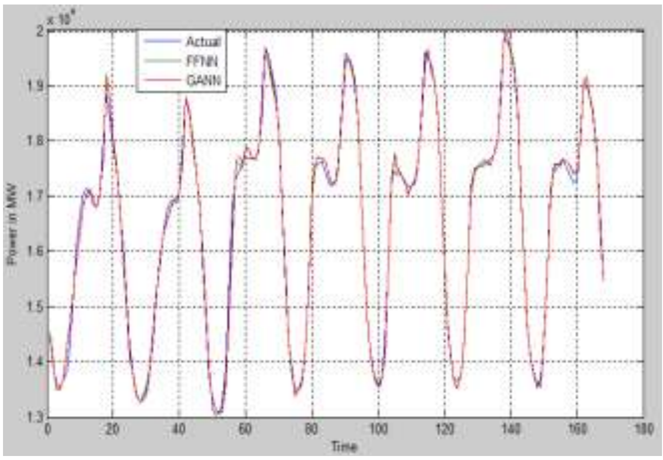

Figure 5: The prediction result for third week with 8 input lag by both ANN & GANN

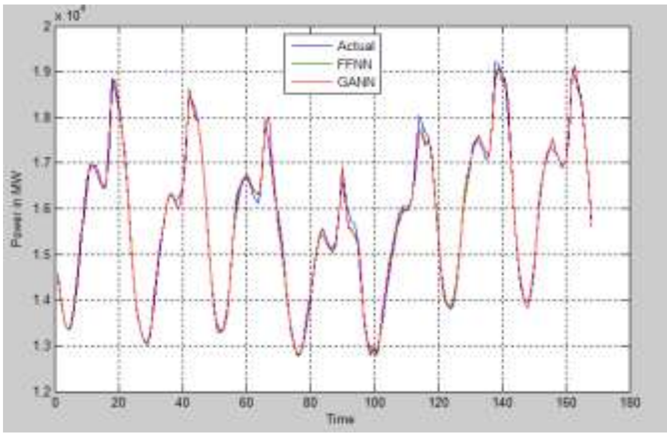

Figure 6: Prediction result for fourth week with 8 input lag by both ANN & GANN

Three different cases have been considered. In the case study 1, 5 input time lags and in case study 2, 8 input time lags have been considered. In case study 1 the value of MAPE for FFNN is found to be 1.14 and for GANN is found to be 1.17%. The value of MAE for the case study 1 is 192.59 MWh for FFNN and 197.42 for GANN. In case study 2 the value of MAPE is good as compare to case study 1 the value of MAPE for FFNN model is 0.7% as given in Table 1 and MAPE for GANN is found to be 0.72%. The value of MAE for the case study 2 is 114.16 MWh for FFNN and 118.27 for GANN.

In the case study 3 the time lag used is 11 and the time lag series is (t-1), (t-2), (t-3), (t-23), (t-24), (t-25), (t-47), (t-48), (t-49), (t-71), (t-72). The value of MAPE is good as compare to case study 1 but not good as compared to case study 2 the value of MAPE for FFNN model is 0.8% as given in Table 1.1 and MAPE for GANN is found to be 0.76% slightly better than FFNN. The value of MAE for the case study 3 is 132.10 MWh for FFNN and 125.67 MWh for GANN.

IV. CONCLUSION

The growth of power demand is increasing at a very fast rate because of social and economical growth therefore utilities are moving towards deregulated structure. So, to adapt this structure, it is necessary to have an accurate electric load forecasting model. In the proposed prediction method, the forecasted load is obtained by using time series as an input pattern section technique for training of neural networks on short term basis. In this thesis a single step ahead electric load forecasting comparison of FFNN and GANN models has been presented in a time-series framework. The real electricity load data from Ontario Electricity Market for the year 2012 has been used for the prediction. The FFNN has been trained by Levenberg-Marquardt (LM) training algorithm and the weights and biases of GA based Neural Networks have been initialized by using Genetic Algorithms. The performance accuracy of both the models has been compared on MAE and MAPE performance metrics. It is found that the result obtained by Genetic Algorithms based neural networks is almost similar to FFNN.

V. REFERENCES

[1] Sumit Saroha and Rohit Verma, “Cross-border power trading model for South Asian Regional Power Pool,” Electrical Power and Energy Systems, vol. 44, pp.146-152, 2013.

[2] S. K. Aggarwal, L. M. Saini and Ashwani Kumar, “Electricity price forecasting in deregulated markets: A review and evaluation”, Electrical Power and Energy Systems, vol. 31, pp. 13-22, 2009.

[3] Sumit Saroha and S.K. Aggarwal, “A Review and Evaluation of Current Wind Power Prediction Technologies,” WSEAS Transaction on Power System, vol. no. 10, pp. 1-12, 2015.

[4] S.K. Aggarwal and Sumit Saroha, “Electrical Energy Forecasting in Present Day Power System”, Electrical India Magazine, vol. 55, no. 4, pp. 78-83, April 2015.

[5] Sumit Saroha and S.K. Aggarwal, “Hybrid WT-PSO Based Neural Networks for Wind Power Prediction of Ontario Electricity Market”, International Journal on Electrical Engineering and Informatics, vol. 7, no. 2, pp. 237-249, 2015.

[6] Sumit Saroha and S.K. Aggarwal, "Multi Step Ahead Forecasting of Wind Power by Different Class of Neural Networks", IEEE International Conference, RAECS 2014 at UIET, Chandigarh, 06 - 08 March, 2014.

[7] J. P. S. Catalão, H. M. I. Pousinho and V. M. F. Mendes, "Hybrid wavelet-PSO-ANFIS approach for short-term wind power forecasting in Portugal," IEEE Transactions on Sustainable Energy, vol. 2, no. 1, pp. 50-59, January 2011.

[8] J. P. S. Catalão, H. M. I. Pousinho, and V. M. F. Mendes, "Hybrid wavelet PSO ANFIS approach for short-term electricity forecasting," IEEE Transactions on Power Systems, vol. 26, no. 1, pp. 137-144, February 2011.

[9] Zhang Yun, Zhou Quan, Sun Caixin, Lei Shaolan, Liu Yuming, and Song Yang, "RBF neural network and ANFIS-based short-term load forecasting approach in real-time price environment," IEEE Transactions on Power Systems vol. 23, no. 3, pp. 853-858, August 2008.

[10] Eisa Almeshaiei and Hassan Soltan, "A methodology for electric power load forecasting," Alexandria Engineering Journal, vol. 50, pp. 137-144, 2011.

[11] Nima Amjady, Farshid Keynia, and Hamidreza Zareipour, "Short-term load forecast of microgrids by a new bilevel prediction strategy," IEEE Transactions on Smart Grid, vol. 1, no. 3, pp. 286-294, December 2010.

[12] Kanna Bhaskar and S. N. Singh, "AWNN assisted wind power forecasting using feed forward neural network," IEEE Transactions on Sustainable Energy, vol. 3, no. 2, pp. 306-315, April 2012.

[13] Qun Zhou, Leigh Tesfatsion, and Chen Ching Lin, "Short-Term Congestion Forecasting in Wholesale Power Markets," IEEE Transactions on Power Systems, vol. 26, no. 4, pp. 2185-2196, November 2011.

[14] Ping-Feng Pai and Wei-Chiang Hong, "Forecasting regional electricity load based on recurrent support vector machines with genetic algorithms," Electric Power Systems Research 74, 417-425, 2005.

[15] Sumit Saroha and S.K. Aggarwal, "Multi Step Ahead Forecasting of Wind Power by Genetic Algorithm based Neural Networks", IEEE International Conference, PIICON 2014 at Delhi Technological University, Delhi, 05-07 December, 2014.

[16] Kanna Bhaskar, and S. N. Singh, "AWNN-assisted electric load forecasting using feed-forward neural network," IEEE Transactions on Sustainable Energy, vol. 3, no. 2, pp. 306-315, April 2012.

[17] Ontario Electricity Market, ISO.