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Short Term Load Forecasting of a Region of India using Generalized Regression Neural Network

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Short Term Load Forecasting of a Region of India using Generalized Regression Neural Network

Ram Dayal Rathor [α] & Dr. Annapurna Bharagava [σ]

Abstract- In this paper the Generalized Regression Neural Network is used for short term load forecasting (STLF) of Rajasthan region, India. It is a power ful technique to schedule plant maintenance, power system control and load flow. Rajasthan state has rich cultural and geographical diversities. It is the biggest state of India and its land area is 342,239 km². The actual data of load and temperature have been collected from Load Dispatch Center, Rajasthan and Meteorological Center Jaipur, Rajasthan, for the duration from January 2008 to December 2008. Load is forecasted with help of Artificial Neural Network and Generalized Regression Neural Network (GRNN) based models for summer, monsoon and winter seasons. Last 24 hours load, maximum and minimum temperature, season code, day type and effect of social celebrations are used as input of the networks. Results have been obtained for different patterns of load. Results show that both models have good performance and reasonable prediction accuracy. Their comparison demonstrates that GRNN model is much faster, more reliable and accurate for effective STLF of Rajasthan region, India.

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I. Introduction

Electrical load forecasting is important for the power industries in the deregulated economy. Operative forecasting is essential for generation control and power dispatch [1]. Operational decisions in power systems, such as unit commitment, economic dispatch, automatic generation control, security assessment, maintenance planning, and energy trading depend on the forthcoming trends of loads [2]. Accurate short term forecasting results in better economic and trouble free operations. The improved efficiency and accurate load scheduling, decreases power system reserves [3]. Short-term load forecasting plays an important role in reliability of power grid, prevent overloading and reduce the occurrence of blackouts [4]. Load forecasting have many applications such as energy trading, power generation, load flow and infrastructure development [5]. It plays an important role to take decisions relating to electrical network. STLF is required for power system control, unit commitment, security assessment, planning spinning reserve, energy exchange, inputs to load flow studies and contingency analysis resulting in predictive assessment of the security of the power system in which effect of loss of each generator on each transmission circuit is evaluated. The accuracy and reliability of load forecast have considerable effect on economics of power system operation [6, 7, 8]. Load forecasting can be categorize in very short term forecasting, short term forecasting, medium forecasting and long term forecasting [9]. Economic load dispatching requires the minute to minute load allocation to the generating units, to meet the varying demand at minimum cost and appropriate degree of system security. It is essential to minimize the cost function, subjected to a large number of operating units, plant characteristics and transmission system limits. There are a number of factors which effects STLF such as temperature variations, climatic conditions, social celebrations, agricultural load demand and tariff structure. Load forecasting remains a difficult task because the system loads generally display periodicity and seasonality at multiple time scales and beside this there are many outside variables, such as weather conditions. Therefore it is concluded that there is not a single forecasting model which can give accurate results for all power systems [10].

Out of many of STLF techniques, in recent years, ANN based techniques are being used due to their good characteristics for high-speed computation, potential methodology for modeling hourly and daily energy consumption, their ability to perform better during rapidly changing weather conditions and the short time requirement for their development. ANN based methods uses a functional relationship between load and affecting factors, and estimate the functional coefficients by using historical data [11]. Neural network based models have mainly the drawback of using simple neuron having summation and sigmoid as transfer functions. These requires large numbers of neurons and hidden layers for complex function approximations and takes large training time and have problem of convergence. Use of the sigmoidal transfer function and ordinary summation or product as aggregation functions in the simple ANN based models fail to cope with the nonlinearities involved in real life

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problems [12, 13].In this research the Generalized Regression Neural Network (GRNN) based model is used for short term load forecasting of Rajasthan state in India. GRNN is related to radial basis function of network and is based on standard statistical technique called Karnel regression. It is a powerful method to solve problems like forecasting, control, plant operation and fault identification and it does not provide negative estimation and approximates the training data with less error [14-16]. Rajasthan region has large variations in climatic, social and geographical conditions. A big part of region is desert which has very low rainfall in comparison of south east part of province. Most of the load is agricultural and domestic and therefore load profile is dependent on temperature variations, rain fall, social celebrations, type of crop and crop cycle.

II. Basic Structure of Artificial Neural Network Based Model

The neural network derives its computing power through its massively distributed structure and has ability to learn and therefore generalization. The flexibility of the generalized neuron can be improved by using more number of activation functions like Sigmoid, Gaussian and straight line. This reduces the size of network. The working of ANN model is explained with the help of Fig. 1

The output of ANN,

$$\text{Output} = f(W_i x_i + b)$$

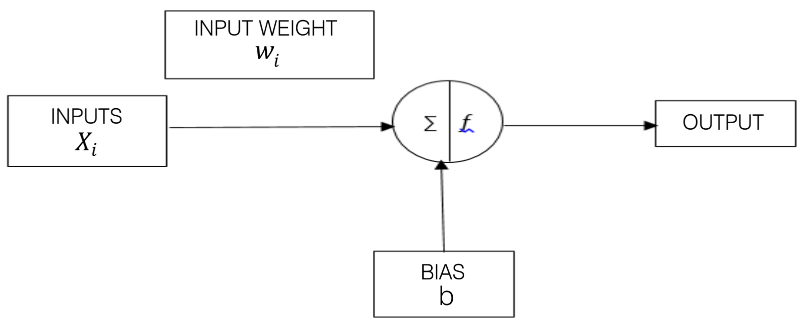

Fig. 1: Block diagram of ANN

In Fig.1,*f*is the transfer function (activation function) and *b* is thresh hold value(bias).

III. Generalized Regression Neural Network Based Model

The working of GRNN model is shown in Fig. 2.

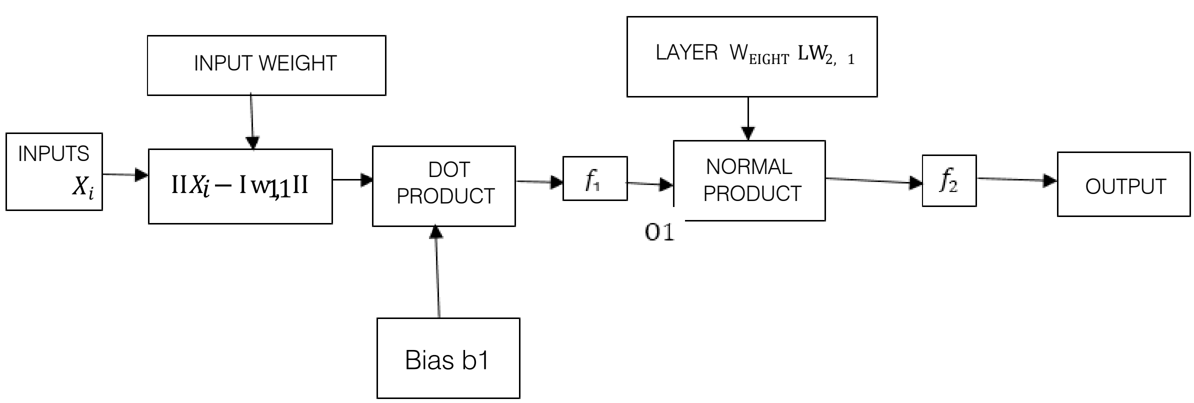

Fig. 2: Block diagram of GRNN

In Fig.2

$LW_{2,1}$ = Weight of signal between layer 1 and 2.

O1 = Output of the first layer

Output= Output of GRNN,

IV. Design of Implementation

a) Data Collection

The real data are collected from January 2008 to December 2008. For ensuring selection of most relevant data and assurance of error free data used for forecasting of electrical load of Rajasthan state, electrical load data and meteorological data are collected from concerned government agencies Rajasthan RajyaVidyutPrasaran Nigam Ltd (RRVPNL), State Load Dispatch Centre (SLDC), Jaipur and India Meteorological department, MausamBhawan, Jaipur respectively. These data are provided by these departments on concession rates applicable to research students. Two types of data have been collected for short term load forecasting of Rajasthan state:

- Every fifteen minute interval data of electrical energy consumption of year 2008
- Maximum and Minimum temperature of the days of year 2008

The load of all four season's spring, summer, monsoon, winter is collected. As Rajasthan is a big state maximum and minimum temperature of zonal head quarter Jaipur, Bikaner and Kota are taken as temperature input.

b) Data Preparation

The use of original data as input to neural network may cause convergence problem. To improve (and sometimes ensure) convergence, the data must be scaled or normalize such that to unify the very different ranges of the data originally collected. Neural network training can be made more efficient if certain preprocessing steps are performed on the network inputs and targets. Before training, the inputs and targets are normalized so that they always fall within a specified range. There is a strong correlation between the behavior of power consumption and weather variables. Here temperature (maximum and minimum) of three stations are considered as weather variables because other factors have weak effect on electric power consumption. In this model three types of variables are used as inputs to the neural network for training: (a) day indicator i.e. date, month and day code, (b) weather related inputs i.e. maximum and minimum temperature of the day, and (c) load of previous 24 hrs.

Total 105 data are given as input to the network, in which first 3 are used to recognize season and day code. Next 6 data are maximum and minimum temperature data and remaining 96 data are loads of every 15 minute in 24 hour of the day, starting from 0.15 AM midnight. During training of ANN and GRNN models, previous day's data are taken as input and same day data are taken as target. After training of models, data of day before forecasting day are taken as input and data of forecasting day are taken as target.

c) Simulation of ANN Model

ANN model has three layers, in which Gaussian, Log Sigmoid and Straight line are used as activation functions. Fig. 1 shows the structure of ANN model. This figure is directly taken from MATLAB during training to show the training parameters.

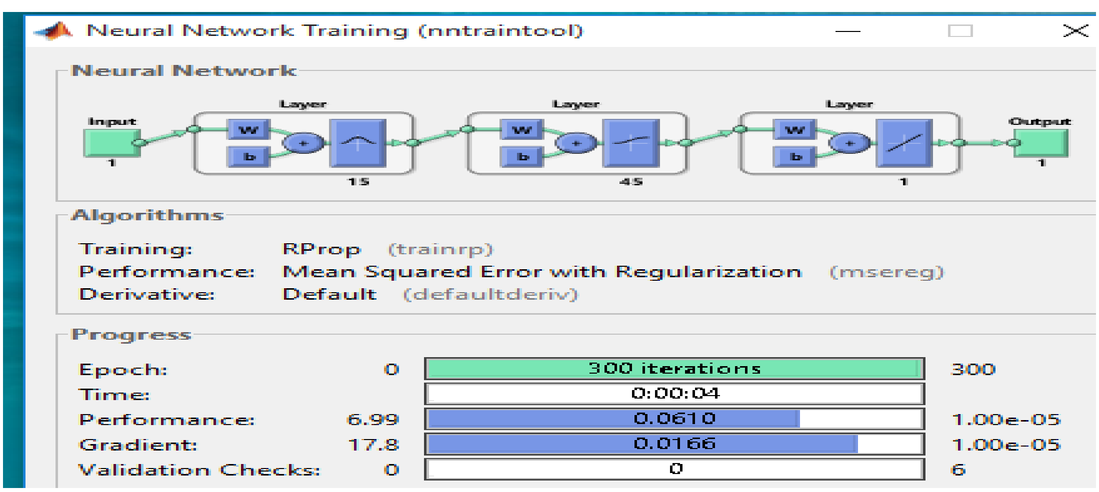

Fig. 3: ANN Model

The parameters of three layer feed forward neural network for network training are as given below:

- Number of layers: 3 (Input, Hidden, Output layer)
- Number of neurons in input layer: 15
- Number of neurons in hidden layer: 45
- Number of neurons in output layer: 1
- Activation function of input layer: *radbas*
- Activation function of hidden layer: *logsigmoid*
- Activation function of output layer: *purelin*
- Training algorithm: *trainrp*
- Number of input variables: 105 (96 + 9)
- Number of output variable: 105

- Number of data sets in each Epoch: 100
- Number of Epochs for training: 300

d) Simulation of GRNN Model

A generalized regression neural network (GRNN) is often used for function approximation. As shown in architecture, it has a radial basis layer and a special linear layer. Fig. 2 shows the structure of GRNN Model. This figure is taken from MATLAB during simulation.

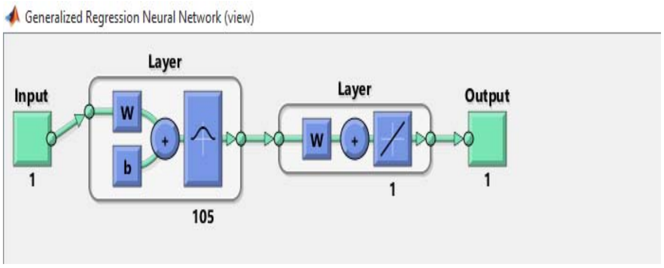

Fig. 4: GRNN Model

The parameters of GRNN for day ahead load forecasting are as given below:

- Number of layers: 2 (Input layer, Output layer)
- Number of neurons in input layer: 105
- Number of neurons in output layer: 1
- Activation function of input layer: radbas
- Activation function of output layer: purelin
- Number of input variables: 105 (96 + 9)
- Number of output variable: 105
- Spread: 0.009

V. Performance Matrices

The accuracy of the forecasting is measured the following Performance Matrices

1. Mean Absolute Error (MAE)

$$\text{MAE} = \frac{1}{M}\sum_{i=1}^{M}\left|actual(i) - forecast(i)\right|$$ Where

M is the total number of data points, $actual(i)$ is the ith actual value, and $forecast(i)$ is the ith forecast.

2. Mean Absolute Percentage Error (MAPE)

$$\text{MAPE} = \frac{1}{M}\sum_{i=1}^{M}\frac{\left|actual(i) - forcast(i)\right|}{actual(i)} \times 100\ \%$$

The MAE criterion penalizes all errors equally, whereas MAPE criterion is accepted industry standard for measuring load forecast quality.

VI. Results and Discussion

The load profile is dynamic in nature with temporal, seasonal and annual variations. The load pattern is divided into four categories: week days, weekend days, holidays and social celebration days. Forecasting results of all four seasons of week days have been shown in graphical form. Actual load, forecasted load and percentage forecast error for ANN and GRNN are also shown in tabular form.

Percentage forecasting error is calculated by the relation:

% error = [(Actual load-Forecasted load) /Actual load] * 100

ANN and GRNN models have been tested on data of Rajasthan region of India.

a) Results of Summer Season

In this category load curve of week day (5 June 2008, Thursday) in summer season is selected for forecasting. Fig.3. shows load curve of actual load, load forecasted by ANN and load forecasted by GRNN against day hours (every 15 minute interval). Comparison of forecasting error by ANN and GRNN is also shown in Fig.4.

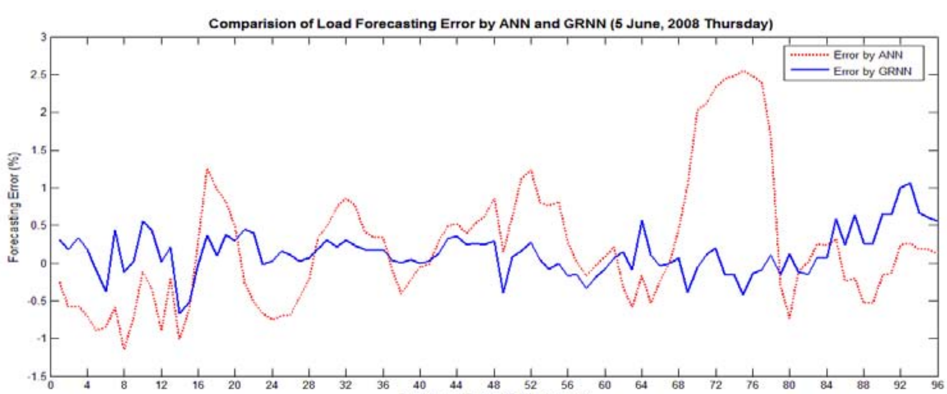

Fig. 5: Comparison of Forecasting Error by ANN and GRNN

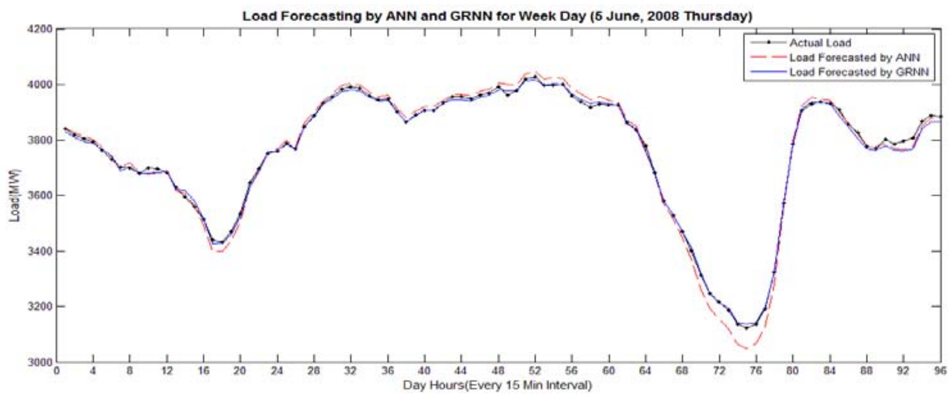

Fig. 6: Comparison of Load Forecasting by ANN and GRNN in summer

b) Results of Monsoon Season

In this category load curve of week day (11 August 2008, Monday) in monsoon season is selected for forecasting. Fig.5 shows load curve of actual load, load forecasted by ANN and load forecasted by GRNN against day hours (every 15 minute interval). Comparison of forecasting error by ANN and GRNN is also shown in Fig. 6

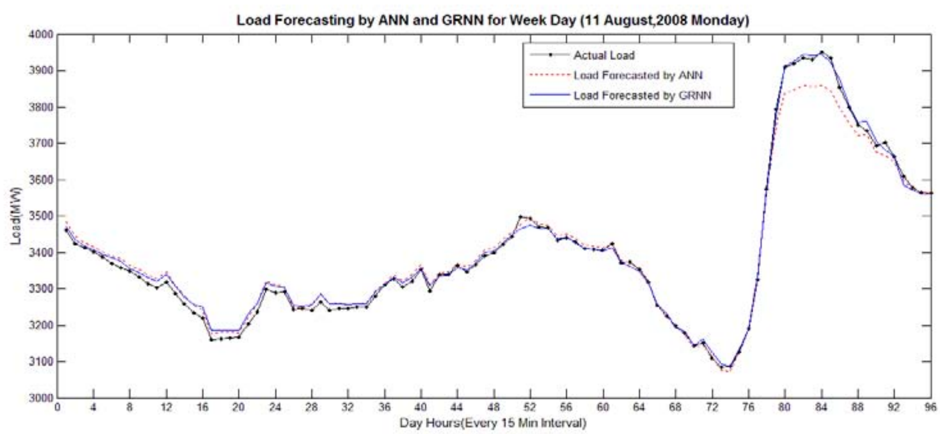

Fig. 7: Comparison of Load Forecasting by ANN and GRNN in monsoon

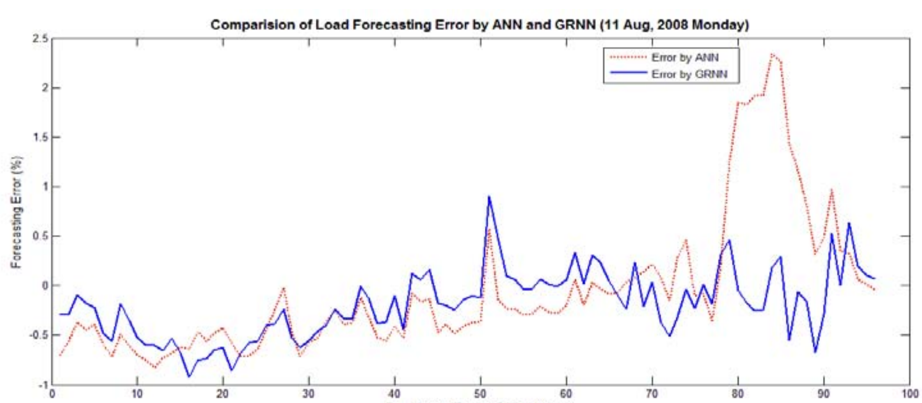

Fig. 8: Comparison of Forecasting Error by ANN and GRNN

c) Results of Winter Season

In this category load curve of week day (16 December 2008, Tuesday) in winter season is selected for forecasting. Fig.7. shows load curve of actual load, load forecasted by ANN and load forecasted by GRNN against day hours (every 15 minute interval). Comparison of forecasting error by ANN and GRNN is also shown in Fig.8.

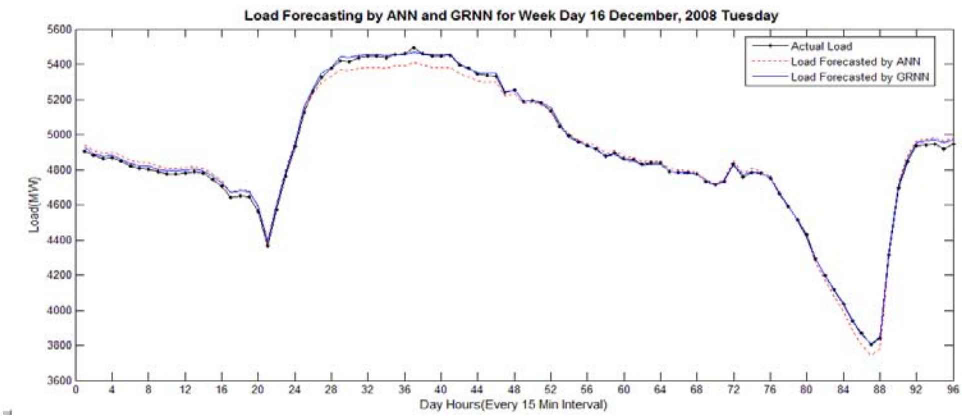

Fig. 9: Comparison of Load Forecasting by ANN and GRNN in winter

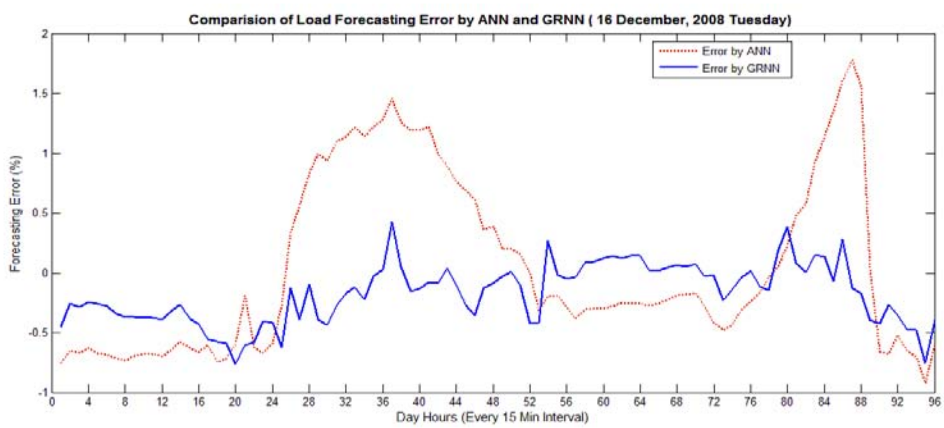

Fig. 10: Comparison of Forecasting Error by ANN and GRNN

The different performance matrices are summarized in tabular form in table no.1

Table 1: Error Comparison

Season	Model	Max. % Error	MAE	MAPE
Summer	ANN	0.0035	2.3852	23.003
	GRNN	**0.0021**	**1.0237**	**8.8046**
Monsoon	ANN	0.0073	2.3468	12.137
	GRNN	**0.0047**	**0.9272**	**10.712**
Winter	ANN	0.0009	1.7770	31.306
	GRNN	**0.0029**	**0.7645**	**11.316**

During result evaluation phase following points were noticed:

- Results demonstrate that optimal structure of both methods ANN and GRNN with minimum forecasting error achieved. The parameters of models were finalized after several trials and error efforts to give the optimum performance.
- In Rajasthan state load is mostly depending upon agriculture and crop cycle.
- GRNN model has less MAE and MAPE as compared to ANN model. This represents a high degree of accuracy in the ability of neural networks to forecast electric load.
- It is observed during case study that GRNN is very fast in comparison of ANN. GRNN does not require the optimization of numbers of neurons and layers in the network. GRNN based model is easy to design and implement.

VII. Conclusion

This work is an effort to examine the neural network based models for STLF. ANN based load forecasting models are very attractive alternative in energy management systems due to simplicity and accuracy. From the forecasting results it is found that GRNN based model produces better performance matrices. GRNN model is faster and easy to design and implementation in comparison of ANN based model.

References Références Referencias

1. Che Guan, Peter B.Luh, Laurent D. Michel, Yuting Wang, and Peter B. Friedland, "Very Short-Term Load Forecasting: Wavelet Neural Networks with

Data Pre-Filtering", IEEE trans. Power systems, vol. 28, no.1, pp. 30-41, Feb.2013.

2. Vitor Hugo Ferreira and Alexandre Pinto Alves da Silva, "Autonomous Kernel Based Models for Short-Term Load Forecasting," Journal of Energy and Power Engineering, pp.1984-1993, Dec.2012.
3. B.M. Hodge, D. Lew, and M. Milligan, "Short-Term Load Forecasting Error Distributions and Implications for Renewable Integration Studies", Proceedings of the IEEE Green Technologies Conference, Denver, Colorado, pp. 1-8, April 4–5, 2013.
4. John D. Hobby, Gabriel H. Tucci and Mustafa K. Do˘gru, "A Weather-Based Forecasting Method for Short-Term Aggregate Power Loads", IEEE trans. Power systems, pp.1-10, Nov. 2012.
5. Reza Afkhami, and F. Mosalman Yazdi, D.K. Chaturvedi, P.S. Satsangi, P.K. Kalra," Short-Term Load Forecasting using Generalized Neural Network (GNN) Approach," Journal of Institution of Engineers, vol. 78, pp. 83-91, August 1997.
6. D.K.Chaturvedi, O.P.Malik," Performance of a generalized Neuron-Based PSS in a Multi machine Power System," IEEE Trans. on Energy Conversion, vol.19, no.3, pp. 625-632, September 2004.
7. Leszek Rutkoski, "Generalized Regression Neural Networks in Time-Varying Environment," IEEE Trans. on Neural Networks, vol. 15, no.3, pp. 576-582, May 2004.
8. T. Yildirm, H.K. Cigizoglu, "Comparison of Generalized Regression Neural Network and MLP Performances on Hydrological Data Forecasting," IEEE Trans. on Proc. of the 9th International Conference on Neural Information Processing (ICONIP'02), vol. 6, pp. 2488-2491.
9. EsaAleksiPaaso, and Yuan Liao, "Development of New Algorithms for Power System Short-Term Load Forecasting", International Journal of Computer and Information Technology Volume 02– Issue 02, pp. 201-209, March 2013.
10. Wei Guo, MinHan, "Generalized Predictive Controller based on RBF Neural Network for a class of Nonlinear System," IEEE Trans. on Proc. of the 2006 American Control Conference Minneapolis, Minnesota, USA, pp. 1569-1574, June 14-16, 2006.
11. Filipe Rodriguez, Carlos Cardeira and J.M.F. Calado, "The daily and hourly energy consumption and load forecasting using artificialneural network method: a case study using a set of 93 households in Portugal", Energy Procedia 62, pp. 220 – 229, 2014.
12. Ying Chen, Peter B. Luh, Che Guan, Yige Zhao, Laurent D. Michel, Matthew A. Coolbeth, Peter B. Friedland, and Stephen J. Rourke, "Short-Term Load Forecasting: Similar Day-Based Wavelet Neural Networks", IEEE transactions on power systems, vol. 25, no. 1, pp. 322-330 , Feb. 2010.
13. "Application of Neural Networks for Short-Term Load Forecasting," IEEE Trans. on Power India Conference, pp. 5-10, 10-12 April 2006.
14. You Yong, Wang Sun'an, and Sheng Wanxing, " Short-Term Load Forecasting using Artificial Immune Network," IEEE Trans. on Power System Technology 2002, Proceeding of Power International Conference 2002, vol.4, pp. 2322-2325, 13-17 Oct. 2002.
15. ManMohan, D.K.Chaturvedi, A.K.Saxena, P.K.Kalra, "Short Term Load Forecasting by Generalized Neuron Model," Journal of Institution of Engineers, vol.83, pp. 87-91, September 2002.
16. J.K. Mandal, A.K. Sinha, G. Parthasarathy, "Application of Recurrent Neural Network for Short-Term Load Forecasting in Electric Power System," IEEE Trans. on Power Systems vol. 5, pp. 2694-2698, 27 Nov. - 1 Dec. 1999.
17. NahiKandil, Vijay Sood, MaaroufSaad, "Use of ANNs for Short-Term Load Forecasting," IEEE Transactions on Electrical and Computer Engineering Canadian Conference, vol. 2, pp. 1057-1061, 9-12 May 1999.

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