ISSN 1512-1232

004.8 (AI), 1698(EE)

NON ADAPTIVE GENERALIZED NEURON MODEL FOR SHORT-TERM LOAD FORECASTING WITH ERROR FUNCTIONS

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Abstract:

Artificial Neural Networks (ANN's) has the disadvantages such as large size of data, large number of hidden layers and hidden nodes, local minima etc. Generalized Neuron Model (GNM) has less data, no hidden layers, hidden nodes, aggregation of summation and product etc. In this paper, GNM having short-term load forecasting (STLF) with error functions has been applied to the non -adaptivity has been proposed. Testing and training of data is there, which will compute root mean square (RMS) error, maximum testing error and minimum testing error with error functions.

Keywords*: Artificial neural network, Error Functions, Generalized neural Network, Short term load forecasting.*

1. Introduction

Load forecasting plays an important role in power system planning, operation and control. There are three types of load forecasting. Short term load forecasting, medium term forecasting and long term forecasting. Short term load forecasting is usually done for an hour or for one day. Medium load forecasting is done few months ahead. Long term forecasting is done few year ahead demands.

Short term load forecasting is required for control, unit commitment, security assessment, optimum planning of power generation, and planning of both spinning reserve and energy exchange, also as inputs to load flow studies and contingency analysis. Medium term forecasting planning is done for seasonal peak winter, summer. Long term load forecasting is used to determine the capacity of generation, transmission and distribution in system planning, annual hydrothermal maintenance scheduling etc.

Various methods such as general exponential smoothing, state space and kalman filter and multiple regression, auto regressive moving average (ARMA), stochastic time series models etc. are available for STLF. In order to improve the model accuracy and to decrease the computation time, artificial intelligence (AI) techniques like artificial neural networks (ANN), knowledge based expert systems (KBES) etc are being used.

In 1980-81 the IEEE load forecasting working group [1], [2] has published a general philosophy load forecasting on the economic issues. Some of the techniques are general exponential smoothing [3], state space and kalman filter [4] and multiple regression [5].

In 1987 Hagan [6] proposed stochastic time series model for short term load forecasting. Load forecasting depends on weather according to ARMA mode [7], which falls under time series category. The combination of both these models gives the better performance.

In 1990 Rahaman [8] and Ho [9] proposed the application of KBES. In 1991-92 Park [10] and Peng[11] used ANN for STLF, which did not consider the dependency of weather on load. In 1995 Kalra [12] incorporated the feature of weather dependency also for STLF. Later in 1996 Khincha [13] developed online ANN model for STLF.

In artificial neural networks the drawbacks are limited to accuracy, large training time, huge data requirement, relatively large number of hidden layers to train for non-linear complex load

ISSN 1512-1232

forecasting problem. So the fuzzified neural network approach for load forecasting, D K Chaturvedi et.al [14] has been developed in 2001. In-order to reduce the training time, total number of neurons required to train a complex non-linear variation in 2002, Man Mohan, et.al [15] proposed a generalized neuron model (GNM) for short-term load forecasting.

In order to reduce local minima and all another deficiencies, the training and testing performances of the models have been compared by Chaturvedi D K et.al in 2003 [16]. In ANN, the training time, size of hidden layers, size of training data, their normalization, error functions, learning algorithm also. Here an attempt has been made to develop new neuron model, using neuro-fuzzy approach by Man Mohan et.al in 2003 [17]. By having all these difficulties with ANN, so a new neuron model development for short term load forecasting has been done in 2003 by Man Mohan et.al [18]. In 2005 R C Bansal has listed out all the overview and literature of ANN applications to power systems [19].

The deterministic models provide only the forecast values, not a measure for the forecasting error. The stochastic models, on the other hand, provide the forecast as the expectation of the identified stochastic process. They allow calculations on statistical properties of the forecasting error. Regression models are among the oldest methods suggested for load forecasting. They are quite insensitive to occasional disturbances in the measurements.

The stochastic time series models have many attractive features. The properties of the model are easy to calculate. The model identification is also relatively easy. Moreover, the estimation of the model parameters is quite straightforward, and the implementation is not difficult.

The weakness in the stochastic models is in the adaptability. In reality, the load behavior can change quite quickly at certain parts of the year. While in ARMA models the forecast for a certain hour is in principle a function of all earlier load values, the model cannot adapt to the new conditions very quickly, even if model parameters are estimated recursively.

Another problem is the handling of the anomalous load conditions. If the load behavior is abnormal on a certain day, this deviation from the normal conditions will be reflected in the forecasts into the future. A possible solution to the problem is to replace the abnormal load values in the load history by the corresponding forecast values. But the drawback of ANN model is the requirement of large training time which depends on size of training file, type of ANN, error functions, learning algorithms.

2. Generalized Neuron Model (GNM):

2.1 Generalized Neuron Model over comes the above draw backs. In GNM usage of flexible neuron model reduces the total number of neurons as well as training time required for ANN. The flexibility of GNM has been improved by using more number of activation functions and aggregation functions.

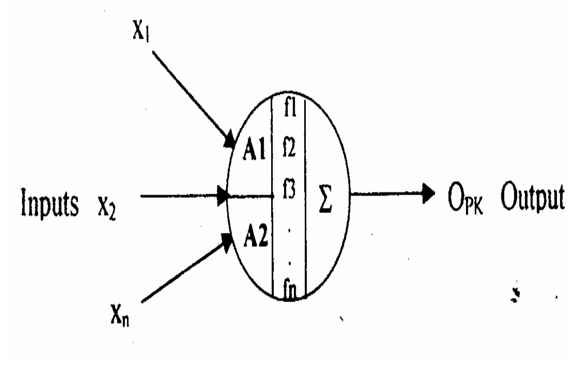

Fig.1 Generalized Neuron Model (GNM)

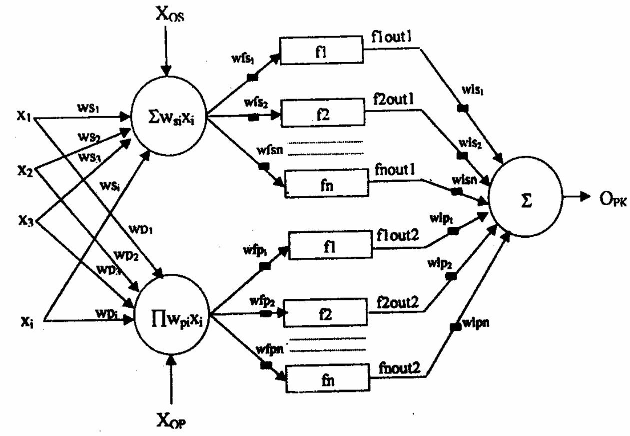

Fig.2 Structure of Generalized Neuron Model

ISSN 1512-1232

In this type of model of Fig.1, contains three activation functions: sigmoid, gaussian, straight line, with two aggregation functions ∑, ∏.The summation and product of an aggregation function have been incorporated and aggregated output passes through non-linear activation function. In Fig.2, the output of generalized neuron is

$$Opk = f1\text{out}1\times w1s1 + f2\text{out}1\times w1s2 + \ldots\ldots\ldots + fn\text{out}1\times w1sn + f1\text{out}2\times w1p1 + f2\text{out}2\times w1p2 + \ldots\ldots fn\text{out}2\times w1pn. \quad (1)$$

Here *f1*out1, *f2*out1,…. ,*fn*out1 are outputs of activation functions *f1,f2,…,fn* related to aggregation function ∑**,** and *f1*out2, *f2*out2, *fn*out2 are outputs of activation functions *f1,f2,…,fn* related to ∏. Output of activation function $f1$ for aggregation function Σ, $f1$out1=$f1$(ws1× sumsigma).Output for activation functions $f1$ for aggregation function of π, $f1$out2= $f1$(wfp1×product)

2.2 Data for short term load forecasting (STLF)

Data for the short term load forecasting has been taken from Dayalbagh Electricity and water works, Agra and weather conditions from children science museum, Dayalbagh, Agra. Different types of conditions have been considered which are mentioned below as different types. The data consists of load of different weeks; maximum temperature, minimum temperature and humidity have been considered for the month of January 2003. There are six inputs, one output.

$$\text{Normalization value} = [(Y_{\max} - Y_{\min}) * (\frac{L - L_{\min}}{L_{\max} - L_{\min}})] + (Y_{\min}) \quad (2)$$

where: Y_{max}=0.9, Y_{min}=0.1, L= values of variables, L_{min}= minimum value in that set, L_{max}= maximum value in that set. Data is tabulated in three types where in the inputs are six and output is one.

Type I consists of I, II, III weeks load, I, II, III week average temperatures, as inputs and IV week load as output. Type II consists of II, III week load, III week maximum temperature, III week minimum temperature, III week humidity as inputs and IV week load as output. Type III consists of I, II, III week load, average maximum temperature, average minimum temperature, average humidity as inputs and IV week load as output.

TABLE I: Type I (I, II, III weeks of load, I, II, III week average temperatures as inputs and IV week load as output)

I week load	II week load	III week load	I week average temperature	II week average temperature	III week average temperature	IV week load
2263.2	2479.2	2166	10.75	8	7.25	2461.2
2238	3007.2	2227.2	12	8	8.5	2383.2
2482.2	3016.8	2802	11.5	7.75	8.25	2025.6
2384.4	3285.6	2022	9.5	7	7.5	2557.2
2196	2295.6	2014.8	9.5	7.5	6.75	2548.8
2678.4	2286	3087.6	8.5	8	7.75	2560.8
2887.6	2458.8	2618.4	9.5	8.75	9.25	2800.8
Normalized data						
I week load	II week load	III week load	I week average Temperature	II week average temperature	III week average temperature	IV week load
0.17	0.25	0.20	0.61	0.55	0.26	0.54
0.14	0.67	0.25	0.90	0.55	0.66	0.46
0.43	0.68	0.68	0.78	0.44	0.58	0.10
0.31	0.90	0.10	0.32	0.10	0.34	0.64

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0.10	0.10	0.09	0.32	0.32	0.10	0.63
0.65	0.10	0.90	0.10	0.55	0.42	0.65
0.90	0.23	0.54	0.32	0.90	0.90	0.90

TABLE II: Type II (I, II, III week load, III week maximum temperature, III week minimum temperature, III week humidity as inputs and IV week load as output)

I week load	II week load	III week load	III Week maximum temperature	III week minimum temperature	III week humidity	IV week load
2263.2	2479.2	2166	9.5	5	95	2461.2
2238	3007.2	2227.2	11	6	99	2383.2
2482.2	3016.8	2802	10.5	6	98	2025.6
2384.4	3285.6	2022	10	5	88	2557.2
2196	2295.6	2014.8	8.5	5	92	2548.8
2678.4	2286	3087.6	10.5	5	90	2560.8
2887.6	2458.8	2618.4	13.5	5	81	2800.8
Normalized data						
I week load	II Week load	III week load	III Week maximum temperature	III week minimum temperature	III week humidity	IV week load
0.17	0.25	0.20	0.26	0.10	0.72	0.54
0.14	0.67	0.25	0.50	0.90	0.90	0.46
0.43	0.68	0.68	0.42	0.90	0.85	0.10
0.31	0.90	0.10	0.34	0.10	0.41	0.64
0.10	0.10	0.09	0.10	0.10	0.58	0.63
0.65	0.10	0.90	0.42	0.10	0.50	0.65
0.90	0.23	0.54	0.90	0.10	0.10	0.90

TABLE III: Type III (I, II, III weeks of load, average maximum temperature, average minimum temperature, average humidity as inputs and IV week load as output)

I week load	II Week load	III week load	Average maximum temperature	Average minimum temperature	Average humidity	IV week load
2263.2	2479.2	2166	11.5	5.83	87	2461.2
2238	3007.2	2227.2	12	6.66	95	2383.2
2482.2	3016.8	2802	11.5	6.83	88.6	2025.6
2384.4	3285.6	2022	10.83	5.16	95	2557.2
2196	2295.6	2014.8	10.16	5.66	90	2548.8
2678.4	2286	3087.6	10.5	6.33	90	2560.8
2887.6	2458.8	2618.4	12.5	5.83	85.6	2800.8
Normalized data						
I week load	II Week load	III week load	Average maximum temperature	Average minimum temperature	Average humidity	IV week load
0.17	0.25	0.20	0.55	0.42	0.21	0.54
0.14	0.67	0.25	0.72	0.81	0.90	0.46
0.43	0.68	0.68	0.55	0.90	0.35	0.10
0.31	0.90	0.10	0.32	0.10	0.90	0.64
0.10	0.10	0.09	0.10	.33	0.64	0.63
0.65	0.10	0.90	0.21	0.66	0.47	0.65
0.90	0.23	0.54	0.90	0.42	0.10	0.90

The mathematical expression for sum squared error function is given by

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$$\frac{\delta E}{\delta Wsi} = -sum((D - Opk) * \frac{\delta opk}{\delta Wsi} \quad (3)$$

The mathematical expression for Cauchy error function is given by

$$\frac{\delta E}{\delta Wsi} = -sum(((cauchy^2) * \frac{error}{(cauchy^2 + error^2)}) * \frac{\delta opk}{\delta Wsi}) \quad (4)$$

The mathematical expression for mean 4th power error function is given by

$$\frac{\delta E}{\delta Wsi} = -sum(4 * ((D - opk)^3 * (\frac{\delta opk}{\delta Wsi}))) \quad (5)$$

where δE=change in error, δWsi= change in weights, opk=actual output, δopk= change in output ,D = desired output.

2.3 Results of STLF

With the help of the data, GNM has been applied to train the network. Types of error functions that have been considered are sum squared error function using Equation (3), Cauchy error function using Equation (4), mean 4th power error function using Equation (5) is used for obtaining root mean square (RMS) error, maximum testing error, minimum testing error.

TABLE IV: Sum square error for type of load data I, II, III

Type of load data	RMS testing error	Maximum testing error	Minimum testing error
I	0.0420	0.0486	-0.0738
II	0.0685	0.1059	-0.1146
III	0.0175	0.0236	-0.0233

TABLE V: Cauchy error function for type of load data I, II, III

Type of load data	RMS Testing error	Maximum testing error	Minimum testing error
I	0.0429	0.0499	-0.0754
II	0.0686	0.1061	-0.1150
III	0.0177	0.0239	-0.0237

TABLE VI: Mean 4th power error for type of load data I, II, III

Type of load data	RMS testing error	Maximum testing Error	Minimum testing error
I	0.2273	0.3941	-0.4047
II	0.1849	0.3312	-0.3264
III	0.2183	0.3833	-0.3904

ISSN 1512-1232

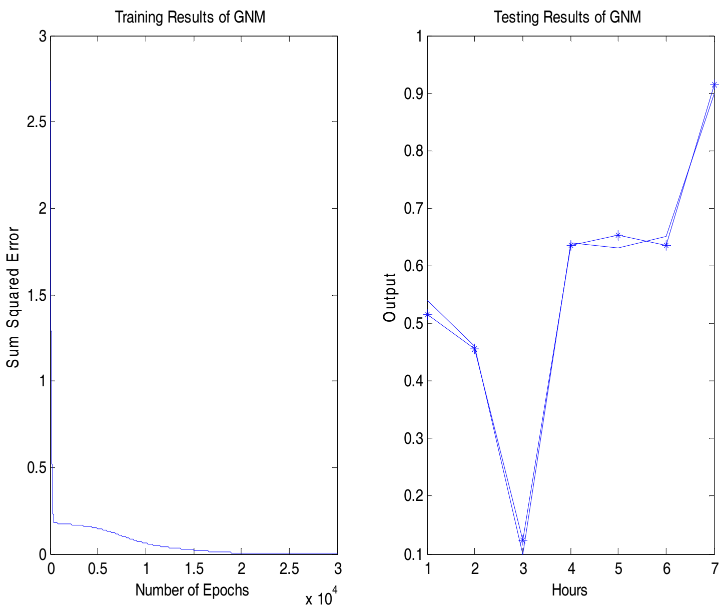

Fig.3. Training, testing results of type III with sum square error

In Fig.3. the training and testing results of type III with sum square error in which the momentum factor, $\alpha = 0.95$, learning rate, $\eta = 0.0001$, training epochs = 30,000

3. Conclusion

Short-term load forecasting using generalized neuron model with non- adaptivity under error functions has been calculated. In that, sum square error, the training, test is found to be least error between actual load (-) versus GNM (*) load with root mean square testing error = 0.0175, maximum testing error =0.0236 and minimum testing error = - 0.0233.

Acknowledgements: The author Mr. C. Radha Charan would like to thank Mr. V.Prem Prakash, Assistant Professor, Computer Science department, Anand Engineering College, Agra, India.

ISSN 1512-1232

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Article received: 2010-01-04