Application of Error Gradient Functions by Generalized Neuron Model under Electric Short Term Load Forecasting

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ABSTRACT - Utilization of Generalized Neuron Model (GNM) has paved a way to Electric Short Term Load Forecasting (ESTLF) an new arena. By using Error Gradient Functions, Generalized Neuron Model can solve Electric Short Term Load Forecasting for non adaptive, adaptive learning which is more precise, more flexible, no hidden nodes etc. A practical electric load data has been taken for the simulation through MATLAB 7.0®. The outputs were root mean square testing error, maximum testing error, minimum testing error.

Keywords: Adaptive Learning, Electric Short Term Load Forecasting , Error Gradient Functions, Generalized Neuron Model, Normalizing Function, Non Adaptive Function.

1.0 Introduction:

Electric Short Term Load Forecasting (ESTLF) will take part in an important responsibility in power system planning, operation and control. ESTLF is generally prepared for an hour to a week. ESTLF can be used for unit commitment, optimum planning of power generation, security assessment etc. 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. performance. F. D. Galiana has proposed Identification of Stochastic Electric Load Models from Physical Data in 1974[7]. In 1990 Rahaman [8] and Ho [9] proposed the application of KBES. In 1991-92 Park [10] and Peng[11] used Artificial Neural Networks (ANN) for STLF, which did not consider the dependency of weather on load.

In artificial neural networks the drawbacks are limited to accuracy, large training time, huge data requirement, relatively large number of hidden layer to train for nonlinear complex load forecasting problem. In-order to train the total number of neurons, it requires large amount of time. In 2002, Man Mohan, et al. [12] proposed a generalized neuron model (GNM) for training and testing of short-term load forecasting.

In order to reduce local minima and other deficiencies, the training and testing performances of the models have been compared by Chaturvedi D. K. et al. in 2003 [13]. In ANN, the training time required training the neurons, size of hidden layer can cause training difficulties, size of training data, learning algorithm is comparatively large. To overcome these difficulties with ANN, a new neuron model with development for short term load forecasting has been done in 2003 by Man Mohan et al. [14]. C. Radha Charan and Manmohan has found the best suitable error gradient function for Short Term Load Forecasting with weather parameters with Generalized Neuron Model [15].

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2.0 Architecture of Generalized Neuron Model:

A. Generalized Neuron Model (GNM)

GNM consists of supervised learning which is feed forward neuron (Fig. 1). There are so many advantages of GNM. The advantages are : Number of unknown weights are less. Weights in case of GNM = 2(number of inputs) +1 which is very low. Training time, training patterns can be reduced as the no of weights are less.

The weights of multi layered ANN is more than the GNM weights. GNM consists of flexibility as the total neurons are reduced resulting in less training time, no hidden nodes and single neuron is capable of solving the STLF problem by using error gradient functions. The complexity of GNM is less as compared to the multi layered artificial neural network.

B. Mathematical Equations of GNM

The architecture consists of Gaussian activation function , straight line activation function and sigmoid activation function were the three activation functions used and summation aggregation function (Σ) and product aggregation function(Π) were the two aggregation functions used. This were non linear functions which will produce an output. In Fig. 2., the output,

$$Opk=f_1out_1\times w_1s_1+f_2out_1\times w_1s_2+.....+f_nout_1\times w_1s_n+f_1out_2\times w_1p_1+f_2out_2\times w_1p_2+.....+f_nout_2\times w_1p_n \quad (1)$$

Here f_1out_1, f_2out_1,…. ,f_nout_1 are outputs of activation functions $f_1,f_2,…,f_n$ related to aggregation function Σ, and f_1out_2, f_2out_2,…., f_nout_2 are outputs of activation functions $f_1,f_2,…,f_n$

related to π. Output of activation function f_1 for aggregation function, $\Sigma f_1 out_1 = f_1(w_{s1}.sumsigma)$. Output for activation functions f_1 for aggregation function of π, $f1out2= f1(wfp1.product)$.

3.0 Data Set for ESTLF Using GNM:

Data set which is only load is taken from Dayalbagh electricity and water supply department, Dayalbagh, Agra, Uttar Pradesh. Data set was taken from January 1st -19th February 2003, out of which six data sets will act as input and one set will act as output in the given neural network (Table 1).

C. Normalization Value

Normalization value =

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

Y_{max} = 0.9, Y_{min} = 0.1, L= electrical load of variable, L_{min}= minimum value in that electrical load set and L_{max} = maximum value of electric load in that set.

D. Error Gradient Functions

Sum square error gradient function, Cauchy error gradient function, mean fourth power error gradient function, mean median error gradient function and hyperbolic square error gradient function were the five error gradient functions. The mathematical expression for each of the error gradient function is given below:

1.Sum square error gradient function:

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

2. Cauchy error gradient function :

$$\frac{\delta E}{\delta W_{si}} = -sum(((Cauchy^2)*\frac{error}{(Cauchy^2+error^2)})*\frac{\delta opk}{\delta W_{si}})$$

(4)

3. Mean fourth power error gradient function :

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

4. Mean median error gradient function :

$$\frac{\delta E}{\delta Wsi} = -sum((\frac{1+error}{2})^{-0.5}*\frac{\delta opk}{\delta Wsi} \quad (6)$$

5. Hyperbolic square error gradient function :

$$\frac{\delta E}{\delta W_{si}} = -sum((\frac{4*error}{error^4-1}))*\frac{\delta opk}{\delta W_{si}} \quad (7)$$

δE = change in error, δWsi= change in weights, opk = output, δopk = change in output,

D = desired value, Cauchy = 2.3849.

E. Simulation Results of ESTLF with GNM by Using Error Gradient Functions

The ESTLF was simulated through GNM by using sum square error gradient function using (3), Cauchy error gradient function using (4), mean fourth power error gradient function using (5), mean median error gradient function using (6) and hyperbolic square error gradient function using (7). The outputs were root mean square testing error, maximum testing error, minimum testing error. These results were taken at momentum factor, α = 0.95, learning rate, η = 0.001, gain scale factor = 1.0, all initial weights = 0.95, tolerance = 0.002 and training epochs = 30,000. Simulated results are shown in tabular form as well as graphical plot.

F. Simulation Results of ESTLF with GNM under Non Adaptivity

The results in tabular form are shown in Table 2 and Fig 3 shows the graphical plot

G. Simulation Results of ESTLF with GNM under Adaptivity

Without applying adaptivity the sum square error gradient is taking less rms testing error, maximum testing error, minimum testing error. Usage of adaptive learning will decrease the error gradient to a maximum extent. Simulation results of sum square error gradient function and graph is given below. Adaptive Learning is given by

$$\eta=\eta_{old}*(\frac{\frac{\delta E}{\delta t_{old}}}{\frac{\delta E}{\delta t_{new}}}) \quad (8)$$

The results are shown in Table 3 and Fig. 4

4.0 Conclusions:

Five error gradient functions were used for comparison of the rms testing error, maximum testing error, minimum testing error. Sum square error gradient function has given the optimized result i.e. rms testing error = 0.2730, maximum testing error = 0.4405 and minimum testing error = -0.3590. After the application of adaptivity for ESTLF through GNM for sum square error gradient function is rms testing error = 1.058×10^{-12}, maximum testing error = 2.0825×10^{-12} and minimum testing error = -1.6288×10^{-12}. By using the feature of adaptivity, reduction of error gradient has reached to the 10^{-12}. The application of different hybrid techniques will further decrease the error gradient for both non adaptivity and adaptivity.

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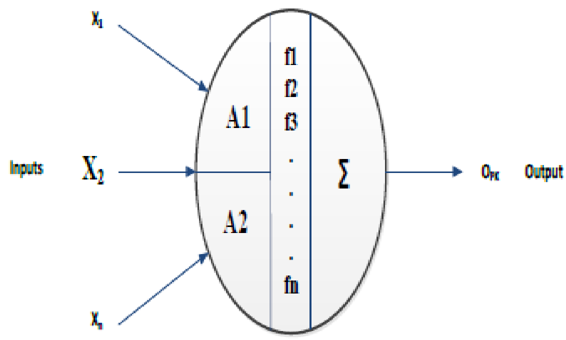

Fig.1. Generalized Neuron Model

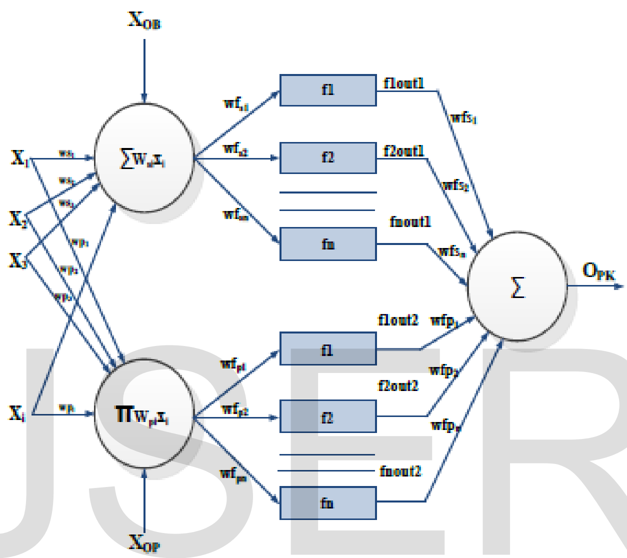

Fig. 2: Architecture of Generalized Neuron Model

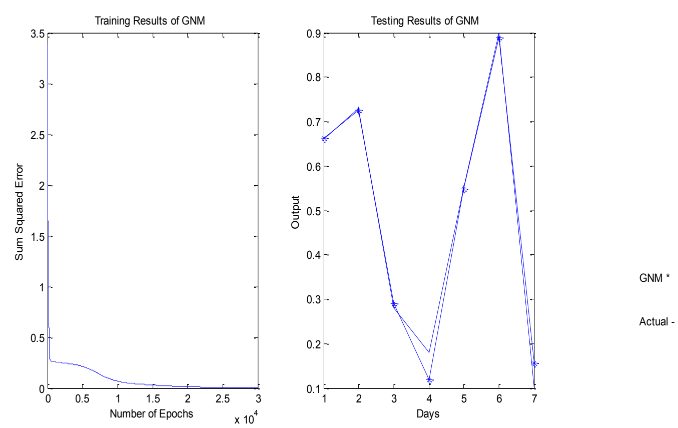

Fig. 3. Graphical plot of Sum Square Error Gradient for ESTLF by using GNM without adaptivity

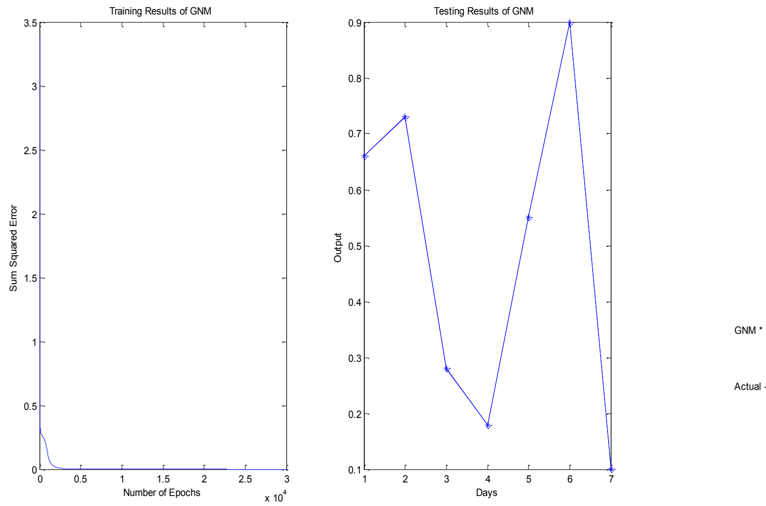

Fig. 4. Graphical plot of Sum square error gradient function with adaptivity

TABLE 1. Type I (I,II, III,IV, V, VI Weeks of Load As Input and VII week as Output)

I Week Load	II Week Load	III Week Load	IV Week Load	V Week Load	VI Week Load	VII Week Load
2263.2	2479.2	2166	2461.2	2522.4	2984.4	2943.6
2238	3007.2	2227.2	2383.2	1261.2	2870.4	3001.2
2482.2	3016.8	2802	2025.6	2400	3004.4	2608.8
2384.4	3285.6	2022	2557.2	2744.4	3010.8	2522.6
2196	2295.6	2014.8	2548.8	3266.4	2678.4	2846.1
2678.4	2286	3087.6	2560.8	2878.8	3025.2	3146.4
2887.6	2458.8	2618.4	2800.8	2512.8	2983.2	2446.8
Normalized Data						
I Week Load	**II Week Load**	**III Week Load**	**IV Week Load**	**V Week Load**	**VI Week Load**	**VII Week Load**
0.17	0.25	0.20	0.54	0.60	0.80	0.66
0.14	0.67	0.25	0.46	0.10	0.54	0.73
0.43	0.68	0.68	0.10	0.55	0.85	0.28
0.31	0.90	0.10	0.64	0.69	0.86	0.18
0.10	0.10	0.09	0.63	0.90	0.10	0.55
0.65	0.10	0.90	0.65	0.74	0.90	0.90
0.90	0.23	0.54	0.90	0.59	0.80	0.10

Table 2: I,II,III,IV,V and VI weeks electric load as input and VII week electric load as output

Type of Error Gradient Function	Root Mean Square (RMS) Testing Error	Maximum Testing Error	Minimum Testing Error
Sum square Error Gradient Function	0.2730	0.4405	-0.3590
Cauchy Error Gradient Function	0.2731	0.4406	-0.3593
Mean Fourth Error Gradient Function	0.3033	0.2978	-0.5023
Mean Median Error Gradient Function	7.1331 - 8.7688i	-7.5246 + 8.7775i	-6.7250 + 8.7781i
Hyperbolic Square Error Gradient Function	4.1175	4.5206	3.7174

Table 3. Simulation Results with Sum Square Error Gradient Function

	Root Mean Square Testing Error	Maximum Testing Error	Minimum Testing Error
Sum Square Error Gradient Function	1.058×10^{-12}	2.0825×10^{-12}	-1.6288×10^{-12}

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