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Learning Rates in Generalized Neuron Model for Short Term Load Forecasting

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ABSTRACT
In this paper, Short Term Load Forecasting (STLF) can be applied using Generalized Neuron Model (GNM) for under sum square error gradient function for different learning rates,η with various training epochs and constant leaning rate,η by having 30,000 training epochs. The simulation results were the root mean square testing error, maximum testing error, minimum testing error were predicted.

General Terms
Short Term Load Forecasting , Generalized Neuron Model, Sum square error gradient.

Keywords
Sum Squared Error Gradient, Generalized Neuron Model, Short Term Load Forecasting.

1. INTRODUCTION
Short Term Load Forecasting (STLF) is done from an hour to a week which is required for control, unit commitment, security assessment, optimum planning of power generation etc. Different methods such as general exponential smoothing, Kalman filter, multiple regressions, Auto Regressive Moving Average(ARMA) , stochastic time series methods.

In-order to decrease the complexity, decrease the computation time, artificial technique has been suggested such as artificial neural network fuzzy logic, knowledge based systems are used.

The deterministic models provide only the forecast values, not a measure for the forecasting error. The stochastic models 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 which 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.

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.

In order to improve the accuracy of model, better modeling result, include the feature of adaptivity, an artificial neural network (ANN) has been used for STLF. 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, hidden nodes. Chandragiri Radha Charan, Manmohan has proposed that the sum square error gradient by applying STLF with the help of generalized neuron model decreases the non adaptive load and adaptive load with weather parameters.

2. GENERALIZED NEURON MODEL
Generalized Neuron Model over comes the above draw backs. The GNM has less number of unknown weights. The number of weights in the case of GNM is equal to twice the number of inputs plus one, which is very low in comparison to a multi layered feed forward ANN. By reducing number of unknown weights, training time can be reduced. The number of training patterns required for GNM training is dependent on the number of unknown weights. The number of training patterns must be greater or equal to number of GNM weights. The number of GNM weights are lesser than multilayered ANN, hence the number of training patterns required is also lesser. In GNM usage of flexible neuron model reduces the total number of neurons, less training time, no hidden layer is required and a single neuron is capable of solve most of the problems .

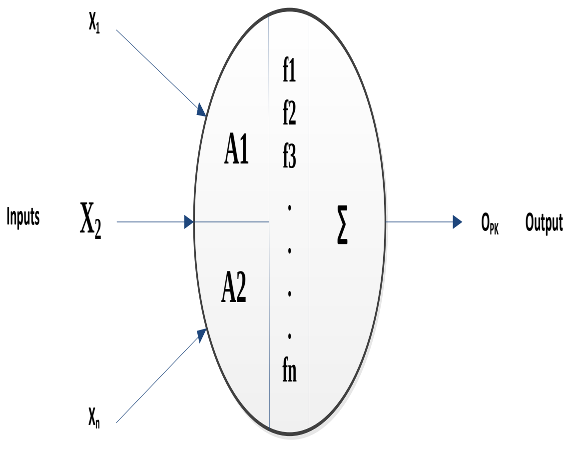


Fig. 1. Generalized Neuron Model

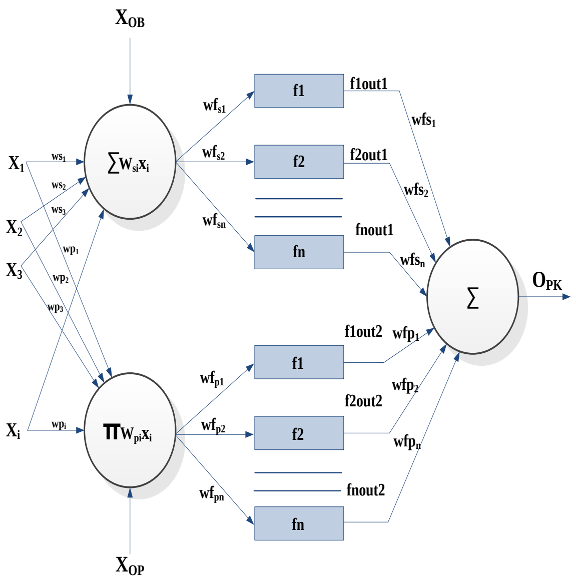


Fig.2. Structure of Generalized Neuron Model

The complexity of GNM is less as compared to multi layered ANN. The flexibility of GNM has been improved by using more number of activation functions and aggregation functions.

In this the model of Fig.1.GNM, contains sigmoid, gaussian, straight line activation functions, with two aggregation functions summation (∑), product (π).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

$$Opk = f1out1 \times w1s1 + f2out1 \times w1s2 + \ldots.. + fnout1 \times w1sn +$$
$$f1out2 \times w1p1 + f2out2 \times w1p2 + \ldots.. + fnout2 \times w1pn (1)$$

Here f1out1, f2out1,…. ,fnout1 are outputs of activation functions f1,f2,…,fn related to aggregation function ∑, and f1out2, f2out2, fnout2 are outputs of activation functions f1,f2,…,fn related to π. 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)

3. DATA FOR STLF UNDER GNM

3.1 Normalized Value for data

Data for the short term load forecasting has been taken from Department of Electricity and water supply, Dayalbagh and Dayalbagh science museum, Agra, India. Different types of conditions have been considered which are mentioned below as different types. The data consists of load of different weeks, weather conditions (maximum temperature, minimum temperature and humidity) have been considered for the month of January 2003. Normalization value:

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

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

3.2 Sum Square Error Gradient Function

The mathematical expressions were given below. The mathematical expression for the sum squared error gradient function is $\frac{\delta E}{\delta Wsi} = -sum((D - Opk) * \frac{\delta opk}{\delta Wsi}$ (3)

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

3.3 Data for STLF

Table 3: I, Ii, Iii Weeks Load, Average Maximum Temperature, Average Minimum Temperature, Average Humidity As Inputs And Iv Week Load As Output

First week load	Second week load	Third week load	Average maximum temperature	Average minimum temperature	Average humidity	Fourth 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
2263.2	2479.2	2166	11.5	5.83	87	2461.2
Normalized data						
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	0.33	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

4. RESULTS OF STLF UNDER GNM

By applying GNM, STLF problem can be done using learning rates, η in different epochs and at constant epoch. The root mean square testing error, maximum testing error, minimum testing error can be reduced. The result is being provided by keeping momentum rate, α = 0.95, gain scale factor = 1.0, all initial weights = 0.95.

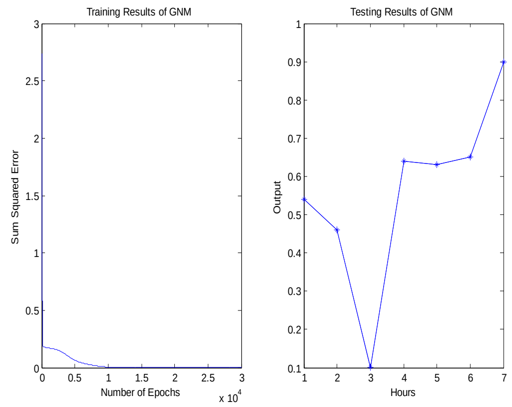
4.1 By considering different learning rates,η

The consideration of different learning rates, η along with different training epochs will lead to various root mean square testing error, maximum testing error, minimum testing error

4.1.1 Case 1

TABLE 4: Training Epochs Versus Learning Rate - I

Training epoch	Learning Rate, η	Result
1-8000	0.0003	Root mean square testing error $=2.133\times10^{-4}$ Maximum testing error= 2.7325×10^{-4} Minimum testing error=- 3.2884×10^{-4}
8001-30000	0.0002	

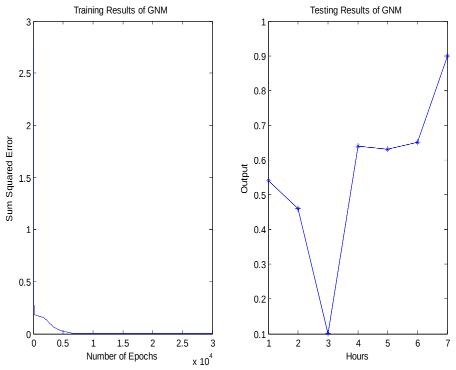


Graph 5: STLF using GNM for sum sqaured error gradient

4.1.2 Case II

TABLE 6: Training Epochs Versus Learning Rate - II

Training epoch	Learning Rate, η	Result
1-5000	0.0004	Root mean square testing error = 9.1784×10^{-7} Maximum testing error=1.1629×10^{-6} Minimum testing error=-1.4255×10^{-6}
5001-30000	0.0003	

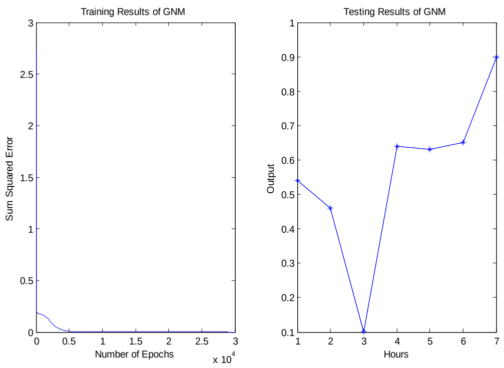


Graph 7: STLF using GNM for sum square error gradient

4.1.3 Case III

TABLE 8: Training Epochs Versus Learning Rate - III

Training epoch	Learning Rate, η	Result
1-250	0.0006	Root mean square testing error = 4.0420×10^{-9}, Maximum testing error=5.1181×10^{-9} Minimum error = -6.2830×10^{-9}
251-1000	0.0005	
1001 - 30000	0.0004	

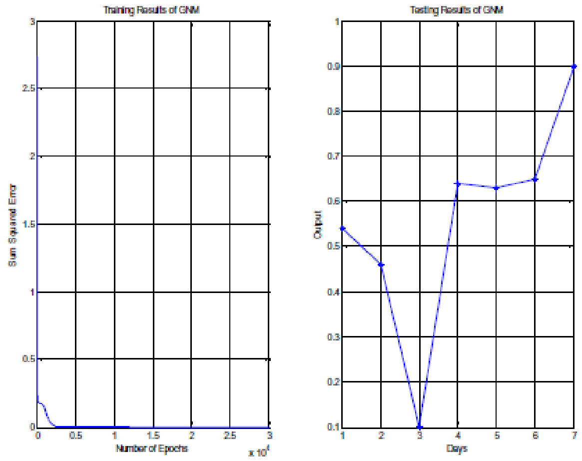


Graph 9: STLF using GNM for sum square error gradient

4.1.4 Case IV

TABLE 10: Training Epochs Versus Learning Rate - V

Learning rate, η	Training epochs	Results
0.001	1-30000	Root mean square testing error = 5.2307×10^{-15}, Maximum testing error=9.992×10^{-15}, Minimum testing error = -5.88475×10^{-15}



Graph 11: GNM for STLF , learning rate, η=0.001 under sum square error gradient, momentum factor, α=0.95,gain scale factor=1.0, tolerance=0.002,all initial weights=0.95,trainibg epochs = 30,000.

5. CONCLUSIONS

The comparision is made between different learning rate's, η with number of training epochs and constant learning rate, η at 0.001 with number of training epochs which can be simulated in MATLAB 7.0. The results were produced root mean square testing error = 4.0420×10^{-9}, maximum testing error=5.1181×10^{-9} , minimum error = -6.2830×10^{-9} by varying learning rate, number of training epochs. By keeping the learning constant as 0.001 under 30,000 epochs the result obtained is root mean square testing error = 5.2307×10^{-15}, maximum testing error=9.992×10^{-15}, minimum testing error = -5.88475×10^{-15} minimum. By keeping learning rate as constant will achieve very less error as compared to the variation of learning rate by including adaptivity.

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