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Short Term Load Forecasting using Generalized Neuron Model with Error Gradient Functions

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Abstract: Short Term Load Forecasting(STLF) varies from an hour to hour and is used for requirement 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. Artificial neural networks (ANN's) has drawbacks like inputs nodes or hidden nodes which can cause training file difficulties, more computation time, large size data, less flexibility etc. Generalized neuron model (GNM) have more flexibility, no hidden layers, less computation time, usage of $\sum$ and $\prod$ neurons etc. In this paper, development of STLF using GNM under different error gradients functions is obtained.

Keywords: Artificial neural networks, Error gradient functions, Generalized Neuron model, Short term load forecasting.

1. Introduction

Various methods such as general exponential smoothing, state space and Kalman filter and multiple regressions, ARMA, ARIMA, ARMAX, ARIMAX, 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 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, and relatively large number of hidden layer to train for non-linear complex load 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 train the total number of neurons, it requires large amount of time. In 2002, Man Mohan, et al [15] 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 [16]. 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. Here an attempt has been made to develop new neuron model, which is using Neuro-fuzzy approach by Man Mohan et al in 2003 [17]. By having all these difficulties with ANN, so a new neuron model with 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 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 behaviour 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 can not adapt to the new conditions very quickly, even if model parameters are estimated recursively. If the load behaviour 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 modelling result, include the feature of adaptively, 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.

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 multilayered 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 . 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 (∏).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

$$Opk = f1out1 \times w1s1 + f2out1 \times w1s2 + ... + fnout1 \times w1sn +$$

$$f1out2 \times w1p1 + f2out2 \times w1p2 + ... + fnout2 \times w1pn (1)$$

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 ∏.

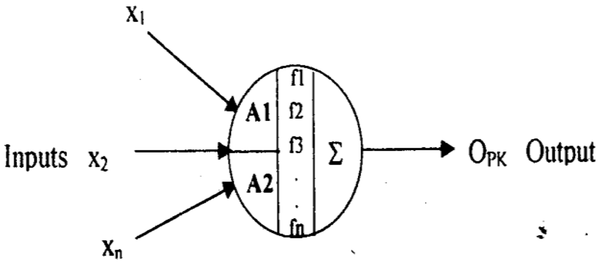

Fig.1. Generalized neuron model

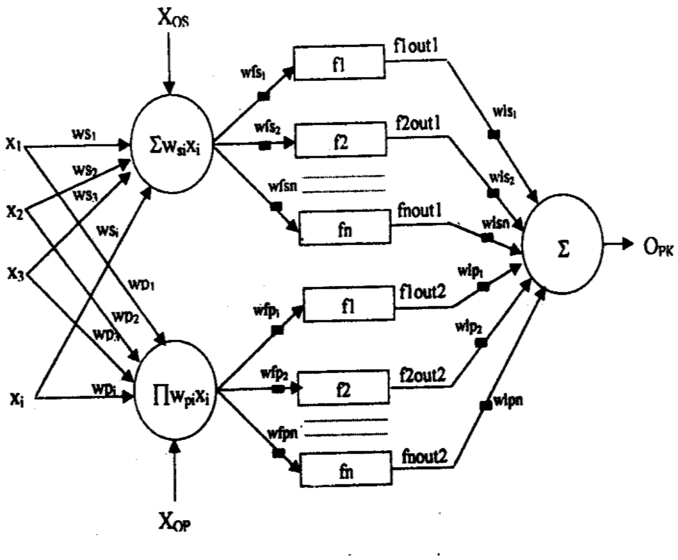

Fig.2. Structure of Generalized Neuron Model

Output of activation function $f1$ for aggregation function, Σ $f1$out1=$f1$(ws1× sum sigma).Output for activation functions $f1$ for aggregation function of π, $f1$out2= $f1$(wfp1×product)

3. Data for STLF under error gradient functions

Data for the short term load forecasting has been taken from Department of Electricity and water supply, Dayalbagh and Dayalbagh science museum, Agra, India. 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.

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

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.

The mathematical expression for sum squared error gradient function is given by

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

The mathematical expression for Geman-Mc clure error gradient function is given by

$$\frac{\delta E}{\delta Wsi} = -sum(\frac{error^3 + error * 2}{((error^2 + 1)^2)} * \frac{\delta opk}{\delta Wsi}) \qquad (4)$$

The mathematical expression for Cauchy error gradient function is given by

$$\frac{\delta E}{\delta Wsi} = -sum(((cauchy^2) * \frac{error}{(cauchy^2 + error^2)}) * \frac{\delta opk}{\delta Wsi}) \qquad (5)$$

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

$$\frac{\delta E}{\delta Wsi} = -sum(4 * ((D - opk)^3 * (\frac{\delta opk}{\delta Wsi}))) \qquad (6)$$

where δE=change in error, δWsi= change in weights, opk= actual output, δopk= change in output ,D = desired output, Cauchy = 2.3849.

Type I (I,II,III weeks of load, average maximum temperature, average minimum temperature, average humidity as input and week load as output

I week load	II week load	III week load	Avg. max. temp.	Avg. min. temp.	Avg. Humd.	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	Avg. max. temp.	Avg. min. temp.	Avg. Humd.	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

Table: 1

4. Result of STLF under GNM

STLF under GNM has been trained with the sum square error gradient using Equation (3), Geman Mc clure error gradient using Equation (4), Cauchy error gradient function using Equation (5), mean 4th error gradient function using Equation (6). These results are obtained when learning factor, η is 0.0001, momentum factor, α is 0.75, gain scale factor = 1.0, tolerance = 0.002, all initial weights = 0.95 and training epochs = 30,000. The Equations were compared with for comparing root mean square (RMS) testing error, maximum testing error and minimum testing error, elapsed time in training in seconds with MATLAB 7.0. Comparing the results of error gradients

Type I Error gradient	RMS testing error	Maximum testing error	Minimum testing error	Elapsed time (seconds)
Sum squared	0.0168	0.0209	-0.0256	231.391
Geman Mc clure	10.0088	0.0139	-0.0140	538.562

Cauchy	0.0227	0.0249	-0.0322	369.969
Mean 4^{th} power	0.0735	0.0925	-0.1166	307.984

Table 2

5. Conclusion

The variation of short term load forecasting with different types of error gradients using GNM has been applied. In these comparisons, there is a sum squared error gradient with GNM is having less computation time. The accuracy will be developed with respect to learning factor, momentum factor, different types of activation functions etc.

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