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Electrical load forecasting using unsupervised learning

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***Abstract**: Electrical load forecasting plays an important role in the power systems. It helps in taking many decisions regarding energy purchasing and generation, maintenance, etc. This paper focuses on the significance of unsupervised learning and its application in the short term load forecasting. We propose self organizing feature map network to illustrate the use of unsupervised learning in load forecasting.*
***Keywords**: Load forecasting, unsupervised learning, Self organizing feature map network.*

I. Introduction:

Load forecasting is important for the electric power industry in the deregulated market. To provide users continuous supply of electricity, there must be accurate assessment of present and future demand of electrical power. Operational decisions such as economic scheduling of the generating capacity, scheduling of fuel purchase and system security assessment are based on such estimate.

It is used by power companies to foresee the amount of power needed to supply the demand. It tells about the scenario of present and future load demand. Basic operating functions such as unit commitment, economic dispatch, fuel scheduling and unit maintenance, can be performed efficiently with an accurate forecast [1]-[2]. Load forecasting is however a difficult task. First, because the load series is complex and exhibits several levels of seasonality. Second, the load at a given hour is dependent not only on the load at the previous day, but also on the load at the same hour on the previous day and previous week, and because there are many important exogenous variables that must be considered. Most of the researches were simultaneously concentrated on the number of input variables to be considered for the load forecasting problem. Temperature and relative humidity were considered by Khotanzad [3] in 1997, while the effect of humidity and wind speed were considered through a linear transformation of temperature in the improved version of Khotanzad [4] in 1998. An improved weather forecast is incorporated by K. Methaprayoon in 2007 [5].

II. Types Of Load Forecasting

Load forecasts can be divided into three categories as shown in figure 1.1.

i). Short-term forecasts: These forecasts are used to supply necessary information for the system management of day- to-day operations and unit commitment. The importance of the short term load forecasting is given in figure1.1.

ii). Medium-term forecasts: These forecasts are used for the purpose of scheduling fuel supplies and unit maintenance.

iii). Long-term forecasts: These forecasts are used to supply electric utility company management with prediction of future needs for expansion, equipment purchases, or staff hiring.

The forecasts for different time perspectives are important for different operations within a utility company. The nature of these forecasts is different as well. For example, for a particular region, it is possible to predict the next day load with an accuracy of approximately 1-3%. However, it is impossible to predict the next year peak load with the similar accuracy since accurate long-term weather forecasts are not available. For the next year peak forecast, it is possible to provide the probability distribution of the load based on past weather observations.

Weather normalized load is the load calculated for the normal weather conditions which are the average of the weather characteristics for the peak historical loads over a certain period of time. The duration of this period varies from one utility to another. Most companies take the last 25-30 years of data. Load forecasting has always been important for planning and operational decision. However, with the deregulation of the energy industries, load forecasting is even more important. With supply and demand fluctuating and the changes of weather conditions and energy prices increasing by a factor of ten or more during peak situations, load forecasting is vitally important for utilities.

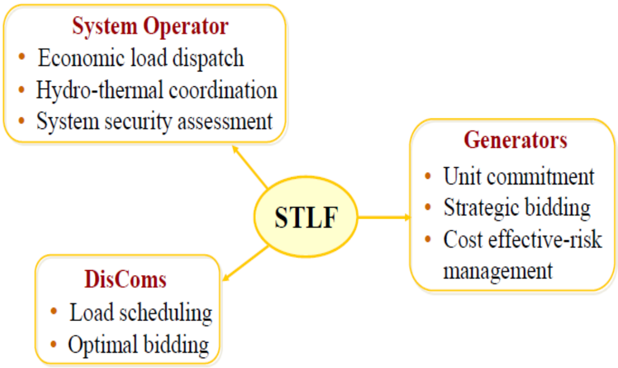

Figure.2.1 Importance of Short Term Load forecasting

III. Techniques for Load forecasting

There are various techniques available for electrical load forecasting.
1. Traditional methods like regression etc
2. Neural networks
3. Fuzzy logic
4. Hybrid intelligence techniques like neuro fuzzy etc**.**

We propose to use regression and neural network approach to predict the electrical load in this paper.

Regression Method

The goal in regression analysis is to identify a function that describes, as closely as possible, the relationship between these variables so that the value of the dependent variables can be predicted using a range of independent variables values. Table 3.1 presents the predicted values of load using multi-linear regression. Graphical presentation of the values is given in figure 3.1.

Table.3.1. Prediction table for Multi linear regression

Hour	Actual(MW)	Predicted(MW)	MAPE
0	55	54.18018	1.490586
1	55	54.47511	0.954345
2	50	55.73478	11.46955
3	55	54.52524	0.863194
4	50	58.45109	16.90219
5	50	56.63929	13.27858
6	50	59.05217	18.10434
7	55	59.43088	8.056145
8	56	58.15978	3.856754
9	55	57.41915	4.398455
10	60	55.25544	7.9076
11	60	55.10684	8.155272
12	55	58.06827	5.578672
13	50	59.93793	19.87585
14	50	61.43945	22.8789
15	50	62.35461	24.70922
16	45	60.77442	35.05428
17	45	61.46286	36.58413
18	65	62.43675	3.943463
19	65	63.863	1.749234
20	65	67.48716	3.826405
21	65	67.08395	3.206074
22	65	69.8374	7.442148
23	60	70.22351	17.03918
			11.555

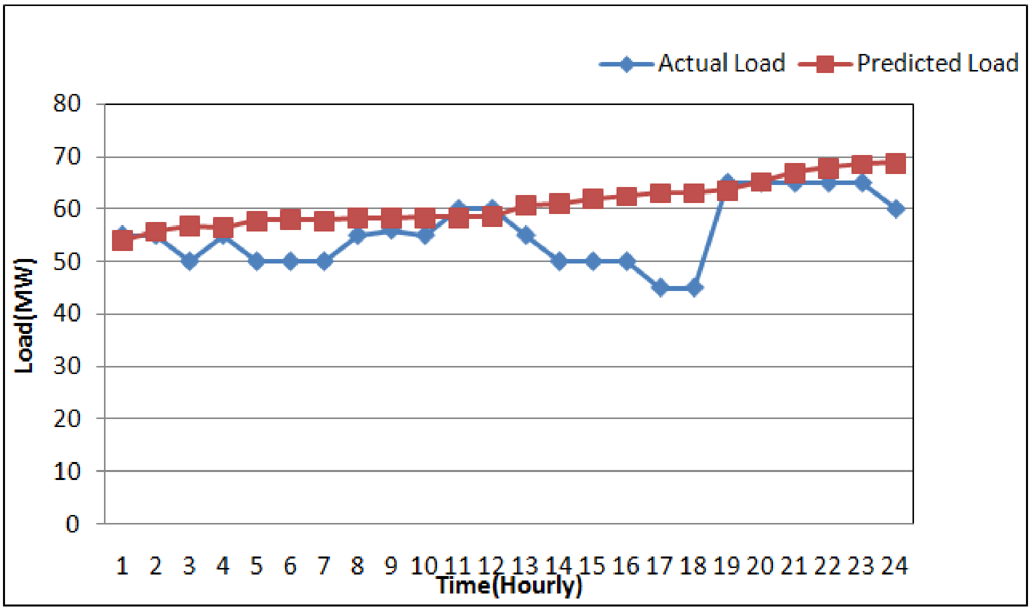

Figure.3.1. Graph of actual load and predicted load for Multi-Linear Regression

Neural Networks

ANN has been proved as powerful alternative for Short Term Load Forecasting that it is not relying on human experience [6].A neural network is a machine that is designed to model the way in which the brain performs a particular task. The network is implemented by using electronic components or is simulated in software on a digital computer. A neural network is a massively parallel distributed processor made up of simple processing units, which has a natural propensity for storing experimental knowledge and making it available for use.

The purpose of learning rule is to train the network to perform some task. They fall into three broad categories:

i) Supervised learning

The learning rule is provided with a set of training data of proper network behavior. As the inputs are applied to the network, the network outputs are compared to the targets. The learning rule is then used to adjust the weights and biases of the network in order to move the network outputs closer to the targets.

ii) Reinforcement learning

It is similar to supervised learning, except that, instead of being provided with the correct output for each network input, the algorithm is only given a grade. The grade is a measure of the network performance over some sequence of inputs.

iii) Unsupervised learning

The weights and biases are modified in response to network inputs only. There are no target outputs available. Most of these algorithms perform some kind of clustering operation. They learn to categorize the input patterns into a finite number of classes. In this paper it is proposed to use self organizing feature map for short term electrical load forecasting.

Self-organizing feature map

Self-organizing feature map (SOFM) network is an excellent method to cluster the data according to their similarity [7]. Self-organizing feature maps (SOFMs) are a data visualization technique invented by Professor Teuvo Kohonen which reduces the dimensions of data through the use of self-organizing neural networks. Self-organizing feature maps (SOFMs) transform the input of arbitrary dimension into a one or two dimensional discrete map subject to a topological (neighborhood preserving) constraint. The feature maps are computed using Kohonen unsupervised learning. The output of the SOFM can be used as input to a supervised classification neural network such as the MLP. SOFMs are very easy to understand and simple. This network's key advantage is the clustering produced by the SOFM which reduces the input space into representative features using a self-organizing process. Hence the underlying structure of the input space is kept, while the dimensionality of the space is reduced. The major problem with SOFMs is that they are very computationally

expensive which is a major drawback since as the dimensions of the data increases, dimension reduction visualization techniques become more important, but unfortunately then time to compute them also increases.
The self-organization process involves four major components:

Initialization: All the connection weights are initialized with small random values.
Competition: For each input pattern, the neurons compute their respective values of a discriminant function which provides the basis for competition. The particular neuron with the smallest value of the discriminant function is declared the winner.
Cooperation: The winning neuron determines the spatial location of a topological neighborhood of excited neurons, thereby providing the basis for cooperation among neighboring neurons.
Adaptation: The excited neurons decrease their individual values of the discriminant function in relation to the input pattern through suitable adjustment of the associated connection weights, such that the response of the winning neuron to the subsequent application of a similar input pattern is enhanced. Fig 3.2 shows a self-organizing feature map with input layer and weight matrix. The table 3.2 shows the mean absolute percentage error for the self-organizing feature map network. The graphical representation of its prediction ability is given in figure 3.3.

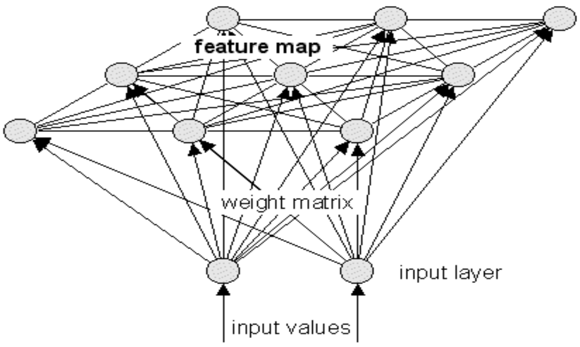

Figure.3.2 Self-organizing Feature Map

Table.3.2 Prediction table for Self-Organizing Feature Map Network

Hour	Actual(MW)	Predicted(MW)	MAPE (%)
0	51	50.49997	0.980455
1	50	50.98134	1.962674
2	48	50.95093	6.147776
3	50	50.94294	1.88587
4	50	50.94288	1.885766
5	52	50.94288	2.032928
6	55	50.96918	7.328755
7	56	56.25714	0.459185
8	54	56.99637	5.548832
9	50	52.38665	4.773304
10	56	50.95272	9.013
11	59	51.27043	13.10097
12	50	51.16855	2.337106
13	55	52.51333	4.52122
14	55	51.13523	7.026858
15	55	51.06457	7.155328
16	50	51.1296	2.259195
17	54	52.22417	3.288576
18	60	53.32726	11.12124
19	66	53.38399	19.11517
20	65	59.21248	8.903871
21	65	53.55044	17.61471
22	60	63.66172	6.102866
23	55	65.72184	19.49425
			6.83

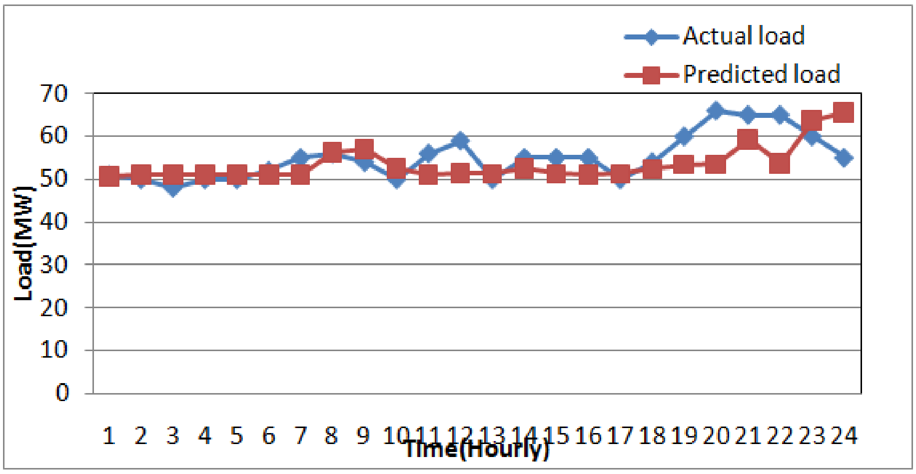

Figure.3.3 Prediction chart for Self-Organizing Feature Map Network

IV. Conclusion

Soft computing techniques play an important role in power system applications. In specific neural networks are widely used in electrical load forecasting. As short term load forecasting is very important in making decisions in daily operations of local power systems it is crucial to predict the electrical load with high precision. In this paper it has been shown that neural networks works better than the conventional regression techniques. Self organizing feature map network was used to predict the electrical load. It shows the influence of unsupervised learning and it dominates the traditional regression techniques. The performance of the neural network is satisfactory as the MAPE (Mean Absolute Percentage Error) is 6.83.This error can be reduced further by using hybrid intelligent techniques.

References

[1]. A. G. Bakirtzis, V. Petridis, S. J. Kiartzis, M. C. Alexiadis, and A. H. Maissis, "A neural network short term load forecasting model for the Greek power system," IEEE Transactions on Power Systems, vol. 11, pp. 858-863, 1996.

[2]. Eugene A. Feinberg & Dora Genethlion, "Applied Mathematics For Power Systems: Optimization, Control and Computational Intelligence", Springer Science and Business media, New York, 2005.

[3]. A. Khotanzad, R. Afkhami-Rohani, L. Tsun-Liang, A. Abaye, M. Davis, and D. J. Maratukulam, "ANNSTLF-a neural-network-based electric load forecasting system", IEEE Transactions on Neural Networks, vol. 8, pp. 835-846, 1997.

[4]. A. Khotanzad, R. Afkhami-Rohani, and D. Maratukulam, "ANNSTLF Artificial Neural Network Short-Term Load Forecaster generation three", IEEE Transactions on Power Systems, vol. 13,issue.4, pp. 1413-1422, 1998.

[5]. K. Methaprayoon, W.J. Lee, S. Rasmiddatta, J. R. Liao, and R. J. Ross, "Multistage Artificial Neural Network Short-Term Load Forecasting Engine With Front-End Weather Forecast" ,IEEE Transactions on Industry Applications, vol. 43, pp. 1410-1416, 2007.

[6]. A.J. Al-Shareef and M.F. Abbod," Intelligent Modelling Techniques of Power Load Forecasting for the Western Area of Saudi Arabia" Eng. Sci., vol. 21 No.1 pp.3-18,2010.

[7]. Dongxiao Niu, Dau liu, and Desheng dash wu, "A soft computing systems for day- ahead electricity price forecasting", ASOC 694, Elsevier, 2009.