Short Term Load Forecasting Using Adaptive Neuro Fuzzy Interface.

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ABSTRACT

Load forecasting has become one of the major areas of the research in the electrical engineering. Short-term load forecasting (STLF) is essential for effective power system planning, economic load dispatch, and unit commitment. A variety of mathematical methods has been developed for load forecasting. This paper discusses the influencing factors of STLF and an artificial intelligence (AI) based STLF model for MGVCL load. It includes Adaptive neuro-fuzzy interface approach applied for load forecasting. Our main objective is to develop the best suited STLF model for MGVCL, by critically evaluating the ways in which the AI techniques proposed are designed and tested

Keywords: Short-term load forecasting, Power system Planning, Artificial Intelligence, Adaptive Neuro-Fuzzy Interface

1. Introduction

Load forecasting is one of the critical factors for economic operation of power systems. Forecasting of future loads is also crucial for network planning, infrastructure development, and Economic load dispatch. The accurateness of the forecast is a demanding feature in power system load forecasting. A fallacious load forecast misguides planners and often results in erroneous and uneconomical expansion plans. From the consumer forecast view, rigorous load forecasting is crucial for distribution system investments, electric load management strategies.[1] Added to this is playing a key role in improving the reliability of the power system, it is also required to reduce the generation cost. The system operators use the load forecasting result as a base of off-line network analysis to decide if the system might be accessible. If so, corrective actions should be planned, such as power purchases, load shedding and bringing peaking units online. Since in power systems the next days' power generation must be scheduled every day, a day ahead short-term load forecasting (STLF) is an essential daily task for power dispatch. [2] The forecasting of electric loads with lead times from a few minutes to seven days is generally assign as short-term load forecasting (STLF). STLF plays a crucial role in the secure and economic operation of power systems.

One of the most popular techniques used for load forecasting is the similar-day approach, time series based models, and intelligent system based models. Some of the traditional forecasting methods have major disadvantage especially their ineffectiveness to map the non-linear characteristic of the load, thus an alternative of conventional methods with intelligent system based models is to a great extent essential.

2. ADAPTIVE NEURO-FUZZY INTERFACE SYSTEM (ANFIS)

ANFIS consists of a combination of fuzzy logic and artificial neural network and generates mapping scheme between input parameters and output results. The system is trained with the entered information as an expert system. Then, the rules are formed and the corresponding outputs are specified. Compared with that of a neural network the training process is more complicated. In supervised learning ANN system, the data sets are expressed by several subsets of entry-exit. The transfer function and value of saturation known as bias are only needed for the construction of the model. However, in fuzzy interference systems, it also needs to define processes such as fuzzification and defuzzification. [3]The ANFIS method can be applied to a special problem as follows:

1. Fuzzification: converting crisp data into linguistic or fuzzy variables by using membership functions.
2. IF-THEN rules: defining the relations between fuzzy input and fuzzy output variables by IF-THEN rules.
3. Implication: identifying output weighting factors from the preceding part.
4. Defuzzification: converting the recent fuzzy results into a crisp value.

2.1 Sugeno Model

Assume that the fuzzy inference system has two inputs x and y and one output z. A first-order Sugeno fuzzy model has rules as the following: [4]

- RULE1: IF X IS A1 AND Y IS B1, THEN F1 = P1X + Q1Y + R1
- RULE2: IF X IS A2 AND Y IS B2, THEN F2 = P2X + Q2Y + R2

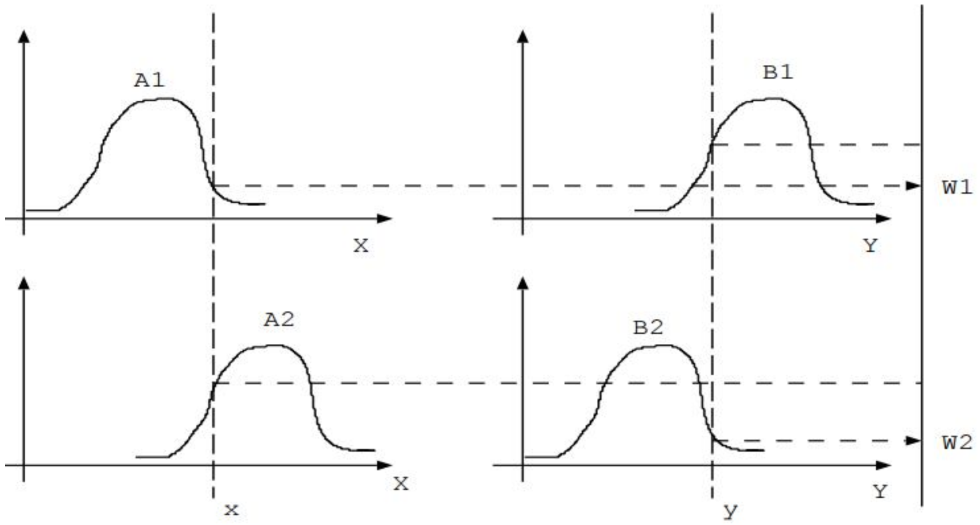

Figure 2.1: Sugeno Model

$$F = \frac{W1.f1 + W2.f2}{W1 + W2}$$

2.2 ANFIS Architecture

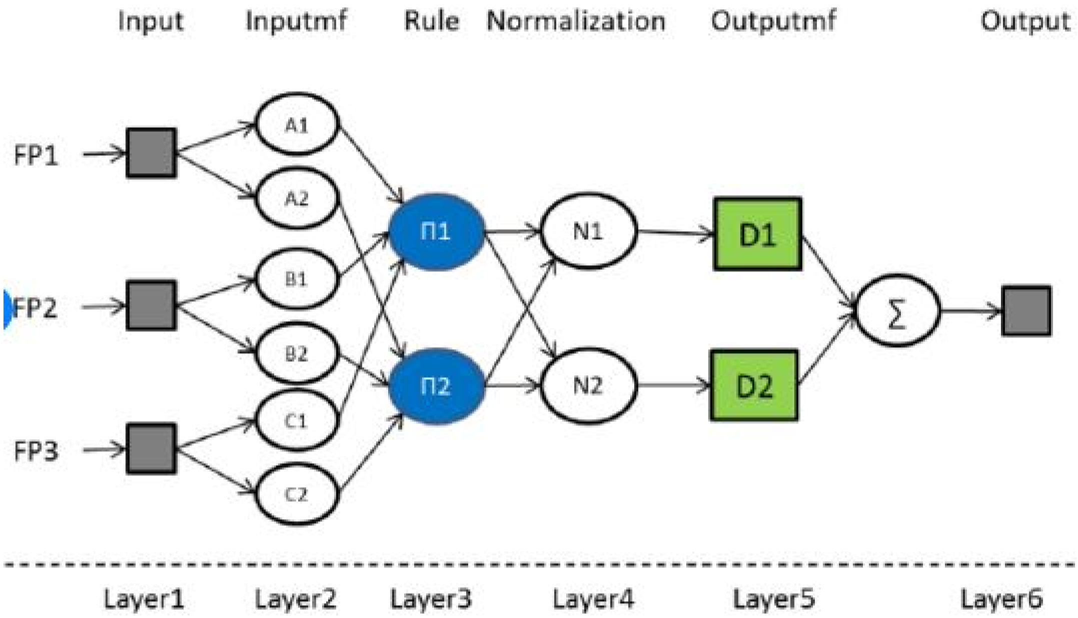

Figure 2.2 ANFIS Architecture

In ANFIS architecture as shown above in Fig.2.2 each joint in the same layer has the analogous function. Level 1 shows that with each input in terms of its association grade a linguistic tag is associated; this is also called as membership grade.[5] It can be defined by suitable membership functions with appropriate parameters. The foundation parameters are associated with functions are called nonlinear parameters.

Layer 2 shows fuzzy AND operations using an appropriate operator on the input signals to generate the output can be given as,

$$Oi^2 = Wi = \mu pi(x)\mu qi(x); \quad i = 1,2$$

The throughput of this level is normally known as the analogous rule of firing power. The ratio of a rule's firing strength is the summation of the firing strengths of all the rules is calculated in layer 3. This is known as firing strengths of normalization. The throughput of layer 3 can be given by:

$$Oi^3 = Wi = \frac{Wi}{W1 + W2}; \quad i = 1,2$$

The throughput of layer 4 is given by:

$$Oi^4 = W1d1 = w1(aix + biy + ci); \quad i = 1,2$$

In this, resulting parameters are ai, bi and ci where i = 1, 2 of the ANFIS. The amount of parameters of ANFIS is the sum of the premise and resultant parameters.
Lastly, in layer 5, the overall output of ANFIS which can be given below is the summation of incoming signals.

$$Oi^5 = \sum_i w1di = \frac{\sum_i widi}{\sum_i wi}$$

The above structure of an ANFIS is a meaningful assignment of node functions and because of this several configurations are possible. ANFIS is an amalgamation of fuzzy logic and neural network. So it holds the benefits of neural network and fuzzy logic respectively. Because of this ANFIS is a better option.

3. INPUT DATA FOR ANFIS MODEL

Table 3.1 Input Data for ANFIS Model

	Input					Target
Hour	Previous day Actual Load (MW)	Previous day Temperature (C)	Previous day Humidity	Same day Temperature (C)	Same day Humidity	Actual Load (MW)
1	903	16	82	13	54	859
2	878	15	82	13	44	834
3	857	14	88	13	44	823
4	831	14	88	13	44	811
5	856	14	82	11	50	831
6	910	13	88	10	54	883
7	995	13	88	9	58	978
8	1032	12	94	8	62	1053
9	1078	13	94	12	51	1114
10	1110	15	82	13	51	1125
11	1100	15	82	18	40	1134
12	1097	23	50	22	38	1128
13	1076	25	47	24	36	1097
14	1069	26	42	24	36	1087
15	1055	27	37	26	30	1093
16	990	27	39	26	28	1073
17	983	27	37	26	28	1057
18	1008	25	41	24	31	1050
19	1088	23	41	21	38	1116
20	1071	20	43	18	45	1114
21	1033	18	64	17	42	1049
22	976	17	48	16	39	1015
23	970	15	51	15	45	990

24	897	15	48	14	48	950

Table 3.1 gives details of input data required for the ANFIS model of STLF; the target is the hourly actual load in MW as given in the table. The training data set is used to train a fuzzy system by adjusting the membership function parameters that best model this data, and appears in the plot in the center of the app as a set of circles. Initialize your FIS using Grid partition, choose the number of membership functions, MFs, and the type of input and output membership functions.

Optimization method used for FIS training is hybrid (the default, mixed least squares, and backpropagation). Error Tolerance is used to create a training stopping criterion, which is related to the error size. The training will stop after the training data error remains within this tolerance. This is best left set to 0 if you are unsure how your training error may behave.

4. RESULTS

Table 4.1 ANFIS Model Result January

Hour	Actual Load (MW)	Temp	Humidity	ANFIS output (MW)	ANFIS error	ANN error	Forecasted Error
1	859	16	82	859	0	0.002608451	-4.880093132
2	834	15	82	834	0	0.031400898	-5.092304004
3	823	14	88	823	0	-0.014723582	-4.901603499
4	811	14	88	811	0	1.301535573	-7.155193684
5	831	14	82	831	0	2.333328556	-5.109051517
6	883	13	88	883	0	-0.04268522	-6.144894725
7	978	13	88	978	0	-0.13339033	-3.479541735
8	1053	12	94	1053	0	-0.05805595	-3.013862514
9	1114	13	94	1114	0	0.043630862	-2.958348294
10	1125	15	82	1125	0	3.064016911	-1.951644444
11	1134	15	82	1134	0	-0.06422431	-3.63633157
12	1128	23	50	1128	0	-3.25474180	-0.301347996
13	1097	25	47	1097	0	-0.16066863	-0.760663507
14	1087	26	42	1086.9	0.009199632	-0.06861795	0.764759978
15	1093	27	37	1093	0	0.052007041	-1.480688267
16	1073	27	39	1073	0	0.128444783	-2.148797315
17	1057	27	37	1057	0	-2.12781849	-2.776621903
18	1050	25	41	1050	0	-0.01881424	-4.654541992
19	1116	23	41	1116.9	-0.08064516	-0.14879840	-1.651496148
20	1114	20	43	1114	0	-3.12386737	-4.045772752
21	1049	18	64	1049	0	-3.76104661	-5.870949295
22	1015	17	48	1015	1.12007E-14	-0.81525185	-7.266495962
23	990	15	51	990	0	0.10286304	-2.468497577
24	950	15	48	950	0	0.380679885	-1.106315789

Table4.1 shows results of the ANFIS model. 6th column indicates % ANFIS error for MGVCL load, 7th column indicates % ANN error and 8th column indicates forecasted error of MGVCL load. It shows ANFIS error is very less as compared to forecasted error. Hence it improves load forecasting accuracy drastically.

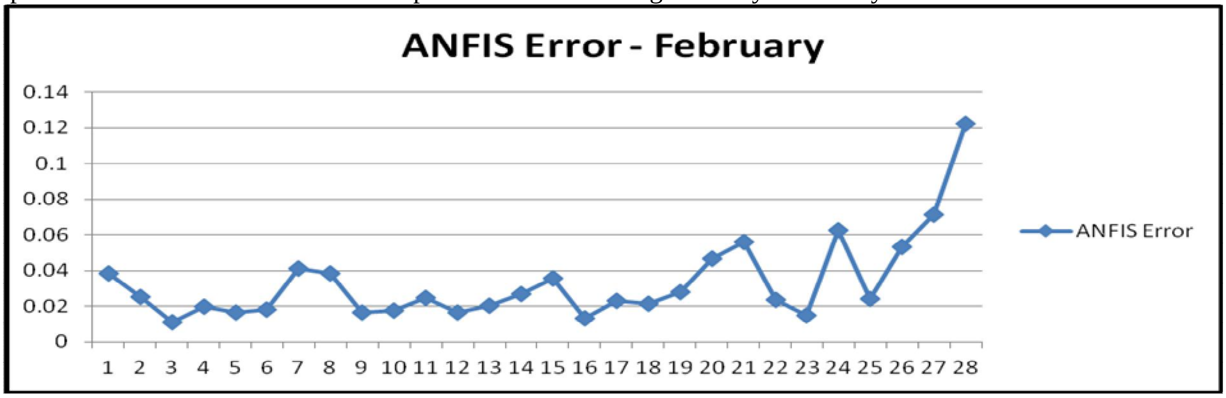

Figure 4.1 February month error

The figure 4.1 shows ANFIS error for the month of February. It varies between 0.01 % to 0.12% which is very less as compared to forecasted error.

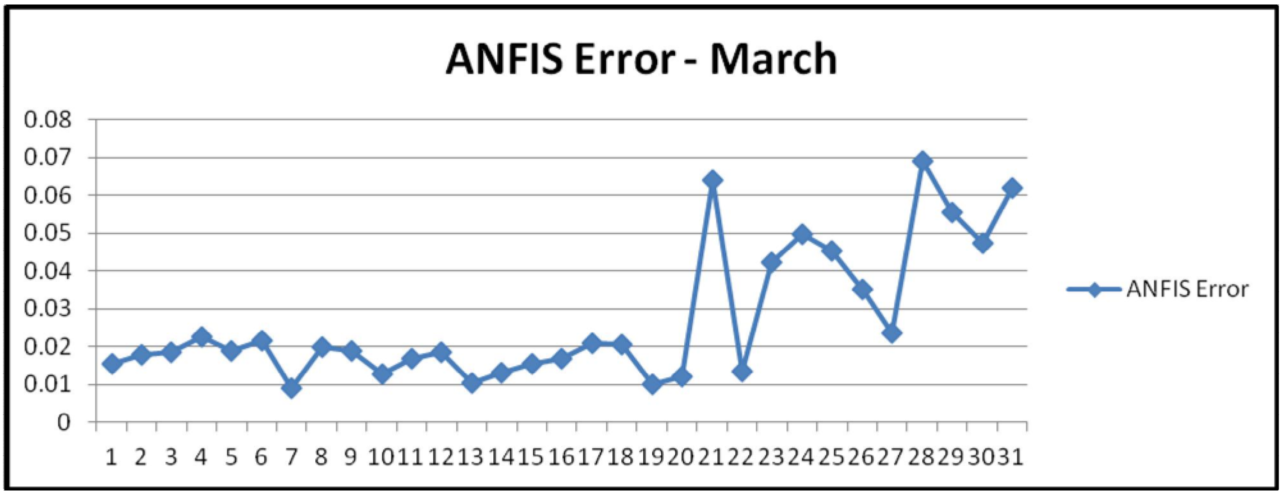

Figure 4.2 March month error

The figure 4.2 shows the ANFIS error for the month of March. It varies between 0.01 % to 0.07 %, hence it gives satisfactory results.

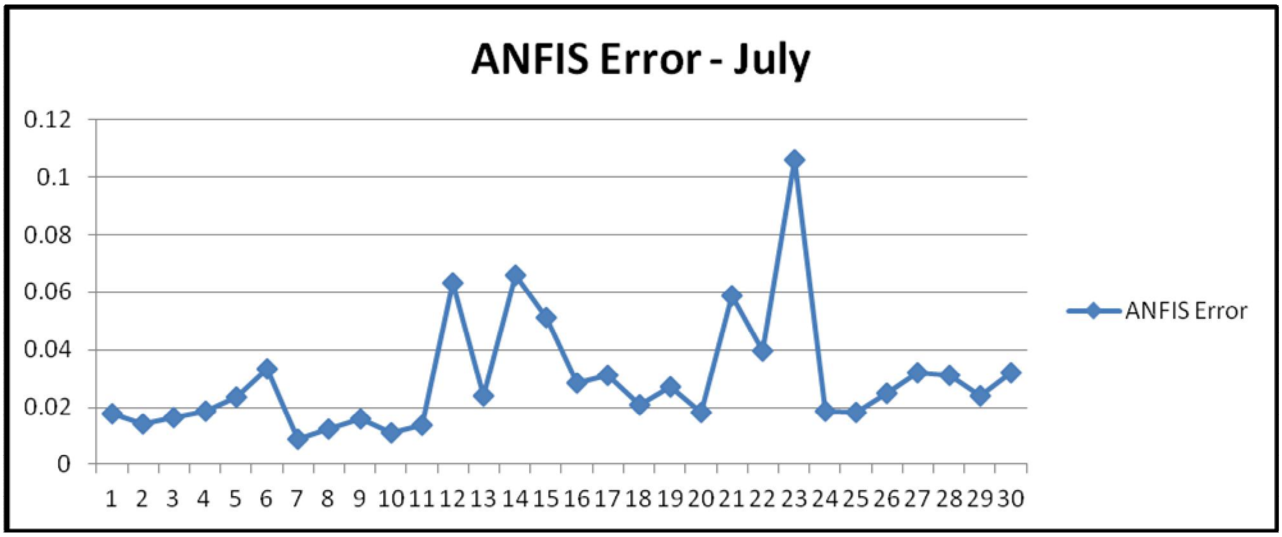

Figure 4.3 July month error

The figure 4.3 shows the ANFIS error for the month of March. It varies between 0.01 % to 0.11 %, hence it gives satisfactory results.

5. CONCLUSION

From the above discussion, it is observed that artificial intelligence techniques give an accurate result for short-term load forecasting. As the accuracy of short-term load forecasting is a very important factor for economic load dispatch, unit commitment, and spinning reserve requirements. The result obtained for the month of January, February, March, and July. Error varies between 0.01% to 0.12%, which is very less as compared to forecasted error. Hence Adaptive Neuro-Fuzzy Interface System based model is best suited for STLF.

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