International Journal of Electrical, Electronic and Communication Sciences
ISSN: 2517-9438
Vol:12, No:12, 2018

Load Forecasting Using Neural Network Integrated with Economic Dispatch Problem

Mariyam Arif, Ye Liu, Israr Ul Haq, Ahsan Ashfaq

***Abstract*—**High cost of fossil fuels and intensifying installations of alternate energy generation sources are intimidating main challenges in power systems. Making accurate load forecasting an important and challenging task for optimal energy planning and management at both distribution and generation side. There are many techniques to forecast load but each technique comes with its own limitation and requires data to accurately predict the forecast load. Artificial Neural Network (ANN) is one such technique to efficiently forecast the load. Comparison between two different ranges of input datasets has been applied to dynamic ANN technique using MATLAB Neural Network Toolbox. It has been observed that selection of input data on training of a network has significant effects on forecasted results. Day-wise input data forecasted the load accurately as compared to year-wise input data. The forecasted load is then distributed among the six generators by using the linear programming to get the optimal point of generation. The algorithm is then verified by comparing the results of each generator with their respective generation limits.

***Keywords*—**Artificial neural networks, demand-side management, economic dispatch, linear programming, power generation dispatch.

I. Introduction

Since electrical energy has non-storable characteristics, therefore balancing electrical power network is necessary to ensure that demand remains equal to supply. The difference in the consumption and generation of power creates voltage or frequency deviations. Such deviations can cause serious damage to electric network devices and consumers. To avoid such unfavorable situations, equilibrium can be kept by accurate forecasting of the load for various timeframes, i.e. very short-term, short-term, medium-term, and long-term. Load forecasting needs a thorough analysis of the implemented system and techniques.

Various techniques for prediction of load forecast are available in literature with different levels of accuracy [2]-[5]. These techniques can be classified as statistical and artificial intelligence such as fuzzy logic, neural networks, and hybrid systems, that can model the non-linearity of load demand empirically. To overcome accuracy problems existing in classical models of forecasting in many fields, soft computing, and intelligent engineering theory has been discussed [1].

ANN is an appropriate technology to forecast electric load under different circumstances to optimize complex non-linear trend with the help of training the network using historical data to achieve desired load curves [2]. Feasibility of hybrid network techniques has been discussed for short-term load forecasting (STLF) [3]. Combination of a neural network with stochastic learning techniques such as genetic algorithm (GA) or particle swarm optimization (PSO), etc. can be used to evaluate forecast of the short-term load. Another technique for evaluation of STLF is Bagging Neural Network (BNN) that is based on the creation of multiple sets of data by sampling randomly and producing results with minimum error [4].

This paper is based on load forecasting using dynamic ANN with a systematic way of data division into multiple sample sets for input data; to train the network by selecting data in two different ways, one is the selection of whole year data and the other is corresponding days' data. Effects of selection of input data on forecast results are compared in order to verify more appropriate approach. The forecasted load is then subjected to the economic load dispatch problem (ELD). Economic dispatch orders per minute demand of load that is associated to generating plant so that the cost of generation can be minimized while considering the transmission losses and other equality and inequality constraints. A significant amount of fuel can be saved by considering the economic dispatch in power system as well as increase the reliability of the system. The generators have different fuel cost curves that are quadratic in nature. For that, they need to be linear in order to apply linear programming. In this paper, the quadratic and nonlinear behavior of fuel cost curve of generators [5], [6] are converted into linear function with modified objective function and equality constraints to solve ELD problem by using linear programming [7], [8].

II. Load Forecasting

A. Electricity Load Profiles

Electricity load profile varies throughout the year with varying consumer needs. Many factors affect load profiles, amongst which seasonal element has the main contribution, e.g. offload seasons are spring, autumn and winter, whereas peak load occurs during summer when the usage of cooling system increases for maintaining the temperature to a comfortable level. Similarly, load demand goes high during afternoon and evening because of increased commercial activities. Load profile drops to lowest value during the night time since most of the population sleeps and switches off their electric appliances. Also, load profile goes high during

Mariyam Arif is with the Electrical Engineering Department, Xi'an Jiaotong University, Xi'an, Shaanxi 710049 China (corresponding author, phone: 155-0297-0717; e-mail: m_arif_mariyam@hotmail.com).

Ye Liu is with Xi'an Jiaotong University, Xi'an, Shaanxi 710049 China.

Israr ul Haq with the Department of Aeronautical Structural Engineering, Northwestern Polytechnical University, Xi'an, Shaanxi, China.

Ahsan Ashfaq is doctoral student in the field of Electrical Engineering at Electrical Engineering Department, Xi'an Jiaotong University, Xi'an, Shaanxi, China.

International Journal of Electrical, Electronic and Communication Sciences
ISSN: 2517-9438
Vol:12, No:12, 2018

occasions and festivals and drops during pleasant weather. To conclude, load profile depends on a large number of parameters from daily life like population, economy, electricity prices, and geographical situations.

Fig. 1 shows hourly based load data of Karachi city in Pakistan from 1st January 2017 to 31st December 2017. Each data point in the hour direction shows hourly data for the one complete week. In the weeks' direction, complete 53 weeks are shown, whereas in third axis, corresponding load data in MW are presented. A similar trend of the data can be seen as described earlier in this section.

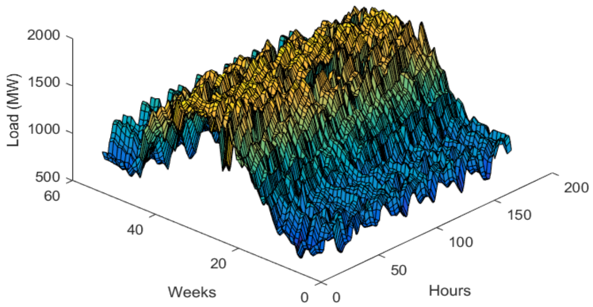

Fig. 1 Hourly based load data of Karachi, Pakistan for the year 2017

B. ANN Modeling

ANN technique is developed after being inspired by the human brain because of its ability to actually learn from everyday experiences. It is based on highly interconnected simple processing units.

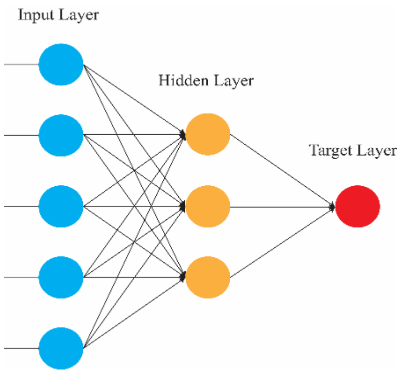

Fig. 2 Three-layered generic ANN model

One of the simplest cases can be considered as a three-layered feed-forward ANN model as shown in Fig. 2, where it is composed of input layer, a hidden layer and the target layer. All the layers are interconnected to form a feed-forward artificial neural network.

In this study, MATLAB Neural Network Toolbox [9] is utilized to model dynamic neural network with 20 hidden layers, the 'transig' transfer function is considered amongst the hidden layers and network is trained using Levenberg-Marquardt algorithm. Three days from last week of the year 2017 are selected for load forecasting, i.e. Sunday, Monday, and Tuesday (24-26 December, 2017). Two types of input datasets based on the range are analyzed, i.e. complete data since the first day of the year 2017 and corresponding day-wise data.

Fig. 3 shows result for day-wise comparison of forecasted load parallel to the actual load. Hourly forecasted data for Sunday, Monday, and Tuesday of last week of the year 2017 is compared with real load, where it can be seen that forecasted load from ANN is following the actual load. Figs. 4-6 show results for the Sunday, Monday, and Tuesday of last week of the year 2017 respectively, here again, outcomes from day-wise and yearly input data are analyzed with real load data. Amongst both approaches used in this research, it is observed that forecast made from input data of only corresponding day-wise data is following actual load accurately as compared to the forecast done using yearly input data.

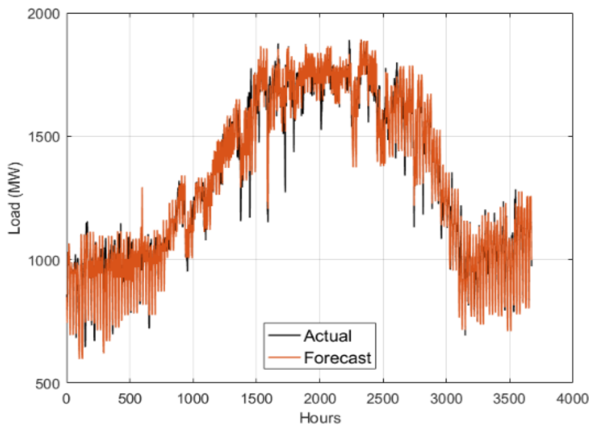

Fig. 3 Day-wise forecast comparison with actual load

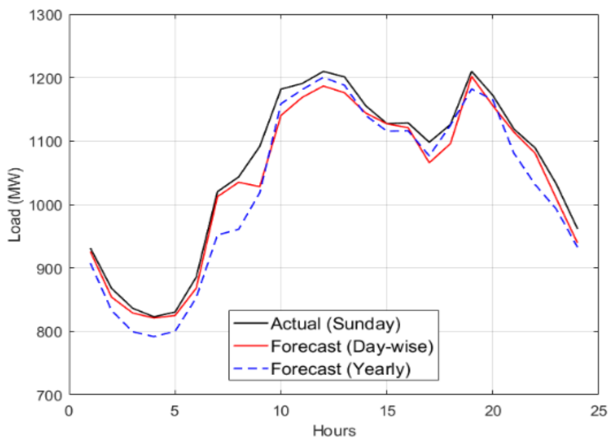

Fig. 4 Forecast load of Sundays and year input data with actual load

It is observed that load data for Monday and Tuesday are quite higher than that of Sunday, because most of the industries, offices, etc. remain closed during holiday. During daytime, for all the three days, load data are higher because of more and more utilization of electric appliances, and minimum load has been observed in late night since the majority of people usually sleep.

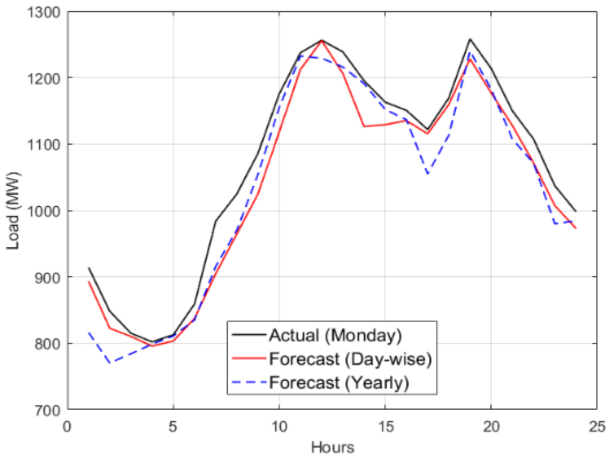

Fig. 5 Forecast load of Mondays and year input data with actual load

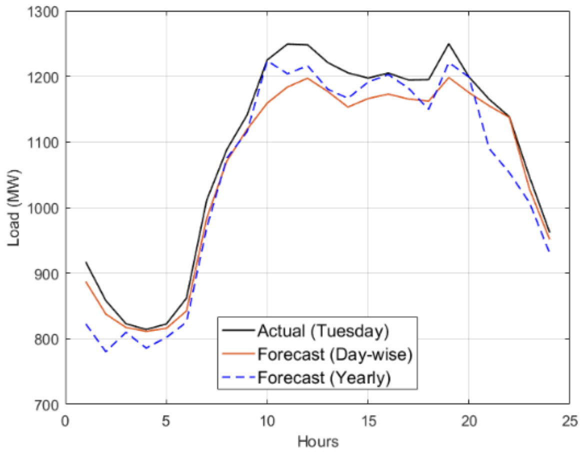

Fig. 6 Forecast load of Tuesdays and year input data with actual load

In order to sum up the analysis, a proper parameter is needed to be evaluated for judging the performance of forecasted results using different data sets, for this, mean absolute percentage error (MAPE) is usually used to analyze the accuracy of ANN.

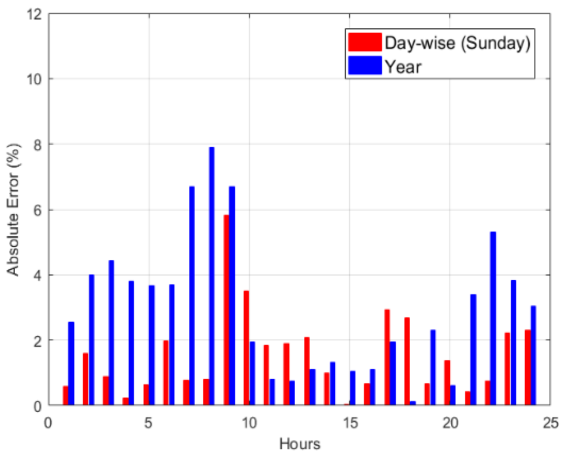

Fig. 7 Absolute error comparison of Sunday and yearly load data

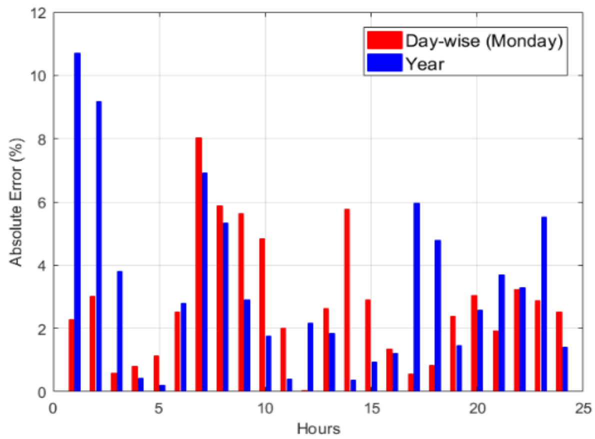

Fig. 8 Absolute error comparison of Monday and yearly load data

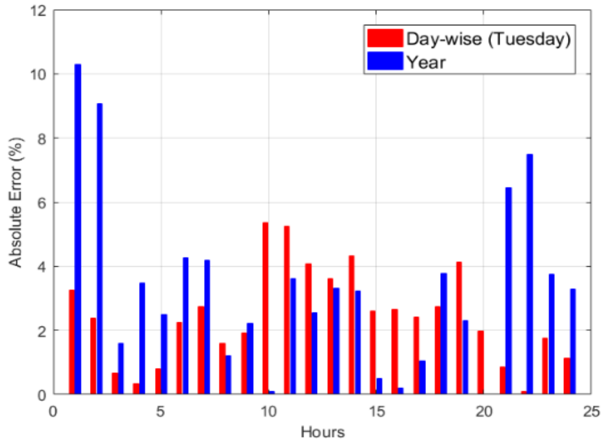

Fig. 9 Absolute error comparison of Tuesday and yearly load data

In equation form, it can be represented as,

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{\left|P_{i,actual} - P_{i,\,forecast}\right|}{P_{i,actual}} * 100 \qquad (1)$$

where n is number of load data points, and P is the load. MAPE for day-wise input data of Sunday is 0.63%, whereas for yearly input data it has a percentage of 1.2. For Monday, day-wise forecast MAPE is 1.11%, and yearly data have 1.32%. Similarly, for Tuesday, day wise forecasted result of MAPE is 0.98% and yearly 1.38%.

Figs. 7-9 show absolute error comparison of day-wise input for Sunday, Monday, and Tuesday respectively with yearly input data. It can be observed that in all the three cases, day-wise input data have much lower error as compared to yearly data. From Fig. 7, cumulative error for day-wise input data of Sunday is 37.7%, whereas for yearly input data, it is 72%. Cumulative error for day-wise data has 66.8% and yearly 79.6% in case of Monday (Fig. 8). Correspondingly, for Tuesday (Fig. 9), day-wise error is 59% and yearly data is 80.5%.

TABLE I
ACTUAL & DAYWISE LOAD FORECAST DATA

Actual	Forecast (Sunday)	Error (%)	Actual	Forecast (Monday)	Error (%)	Actual	Forecast (Tuesday)	Error (%)
931.5	925.9	0.59	914.2	893.4	2.27	917.3	887.4	3.26
867.9	854.0	1.60	848.2	822.6	3.02	858.1	837.6	2.39
836.4	829.0	0.89	815.0	810.2	0.59	822.9	817.3	0.68
823.0	821.1	0.24	802.1	795.6	0.81	814.1	811.3	0.35
830.4	825.0	0.65	812.6	803.4	1.14	822.4	815.8	0.80
885.5	868.1	1.97	859.0	837.3	2.52	862.0	842.5	2.26
1020.2	1012.4	0.77	983.8	904.7	8.04	1011.3	983.5	2.74
1043.3	1035.0	0.80	1024.9	964.7	5.87	1088.5	1071.1	1.60
1091.7	1028.2	5.82	1086.2	1025.1	5.63	1141.0	1119.1	1.92
1181.8	1140.4	3.50	1175.6	1118.6	4.85	1225.1	1159.3	5.37
1190.7	1168.8	1.84	1237.4	1212.4	2.02	1249.3	1183.8	5.24
1209.8	1186.8	1.90	1256.2	1255.6	0.05	1248.2	1197.2	4.08
1201.1	1176.1	2.08	1238.7	1206.0	2.63	1221.2	1177.0	3.62
1155.7	1144.2	0.99	1195.2	1126.3	5.77	1205.4	1153.2	4.33
1127.5	1127.1	0.03	1163.0	1129.1	2.91	1197.4	1166.2	2.61
1128.7	1121.2	0.67	1150.6	1135.1	1.34	1205.1	1173.0	2.67
1098.1	1065.8	2.94	1121.7	1115.4	0.56	1194.5	1165.5	2.42
1126.1	1095.8	2.69	1169.4	1159.6	0.84	1195.0	1162.2	2.74
1210.0	1202.0	0.66	1258.1	1228.0	2.40	1249.9	1198.3	4.13
1172.0	1155.8	1.38	1213.6	1176.8	3.03	1199.2	1175.3	1.99
1118.8	1114.0	0.43	1149.8	1127.6	1.93	1165.1	1155.1	0.86
1089.0	1080.7	0.76	1107.3	1071.3	3.24	1138.4	1137.4	0.09
1032.2	1009.2	2.23	1037.1	1007.2	2.88	1046.6	1028.2	1.76
961.5	939.2	2.32	998.1	972.8	2.53	961.9	951.1	1.12

Table I shows the calculated results of day-wise data for Sunday, Monday, and Tuesday. For Sunday, maximum absolute error in forecasted result from day-wise input is 5.8%, whereas it is 7.8% for yearly input. Similarly, maximum absolute error results for Monday in case of day-wise input data are 8% and 10.7% for yearly data input. Maximum absolute error for day-wise and yearly input data of Tuesday are 5.3% and 10.3%, respectively.

III. ECONOMIC LOAD DISPATCH

A. Objective Function

Objective function of the problem is to find optimum point of generation for each generation unit at which we can minimize the total cost of generation by meeting necessary constraints and bounds. The above statement makes problem as the constrained optimization problem that can be expressed mathematically as

$$\min F(t) = \sum_{i=1}^{N} F_i(P_i) \tag{2}$$

As the fuel cost curve is known for every generation unit [10], so the objective function can be turned as.

$$\min F(t) = \sum_{i=1}^{N} [(a_i * P_i^2) + (b_i * P) + (c_i)] \tag{3}$$

B. Equality Constraint

Power balance of the system must be fulfilled for the concerned optimization problem. Total power generation in a system must be equal to the power demand, in addition with transmission losses in a system that is written as

$$\sum_{i=1}^{N} P_i = P_r + P_l \tag{4}$$

C. Inequality Constraint

This constraint holds the inequality as generation of each generator should remain between upper and lower limits, and mathematically it can be expressed as in (5).

$$P_{i,\min} < P_{i,gen} < P_{i,\max} \tag{5}$$

IV. MODIFIED METHODOLOGY FOR LINEAR PROGRAMMING

Since objective function is highly nonlinear in nature, therefore, a methodology has to be adopted to change the objective function into linear one. For this, “q” number of points on the fuel cost curve have been considered, and in order to attain linearity, point to point strategy is proceeded.

The fuel cost curve of generator i (i=1…N) starts from the minimum point of generation limit and ends at the maximum point. To generate q number of points on the curve, starting point will be P_{i1} followed by P_{i1}, P_{i2}….P_{iq}. Distance between two consecutive points can be calculated by two-point formula:

$$S_{liq} = \frac{(f_{cq} - f_{c(q-1)})}{(lb_q - lb_{(q-1)})} \tag{6}$$

Slope between each point on the curve is represented by (S_{li1}, S_{li2}, S_{liq}). Increase in the cost function *f(C)* consequent to each line segment is specified by

$$\Delta f(C) = S_{liq} * P_{iq} \tag{7}$$

These points symbolize the increments in generation range from 0 to maximum limit of generation for each unit. Linear form of curve after taking points will turn out to be:

$$f(P_i) = S_P + \sum_{j=1}^{q} \Delta S_{lij} * P_{ij} \tag{8}$$

Therefore, cost function can be estimated using set of line segments that can be improved to any desired level by escalating number of line segments used. Approximate linear cost curve is obtained by using values from (7) in (8), which is represented as:

$$f_i(P_{i1}, P_{i2}, ..., P_{iq}) = (C_i(P_{i,\min})) + (S_{li1} * P_{i1}) + (S_{li2} * P_{i2}) + ... + (S_{lij} * P_{iq}) \tag{9}$$

A. Modified Objective Function

By two-point method, slope between different points is calculated, leaving only one more variable to be calculated as P_{iq} where (i = 1 to N and q = No. of points on a curve), making objective function as:

$$\min \sum_{i=1}^{n} f(P_i) = \min[\sum_{i=1}^{n} C_i(P_{i,\min}) + \sum_{i=1}^{n}\sum_{j=1}^{q}(S_{liq} * P_{ij})] \tag{10}$$

B. Modified Power Balance Equality Constraint

Although it seems as if the sum of q numbers of variables is equivalent to total electrical load plus losses, but this is not relatively correct. The reason behind is that q number of variables are turned as additions instead of each unit's minimum generation level. Therefore, individual unit's total minimum generation level was subtracted from sum of total load and losses and can be expressed as:

$$[(P_{11} + P_{21} + ... + P_{i1}) + (P_{21} + P_{22} + ... + P_{i2}) + ... + (P_{i1} + P_{i2} + ... + P_{ii}) = [P_l + P_r - (P_{1,\min} + P_{2,\min} + ... + P_{i,\min})] \tag{11}$$

C. Modified Generation Limit Inequality Constraint

The generation limit inequality constraint can be transformed as:

1. Modified Lower Bounds

First, we distinguish that the value of all of the new variables must be nonnegative entities. This was realized from the fact that a negative amount of electrical generation increment cannot be achieved. But, the possible amount can only be generation increment between zero and the upper bound. Consequently, the lower bound on all $i \times q$ variables must be zero.

2. Modified Upper Bounds

For the consequent linear segments, the maximum possible increment on the variable can be regarded as the upper bounds. As q number of points were taken on a curve, we set all the lower bounds as zero. So, the upper bounds can be calculated as,

$$Ub(i_q) = P_{i,gen}(q) - P_{i,gen}(q-1) \tag{12}$$

D. Algorithm

The linear programming starts with getting the initial data of generation units. The program reads the cost curve data and make q no. of points on curve. The program reads the upper and lower limits of the generation units and also the transmission loss coefficient matrix to calculate the P_l. Total load is being calculated by load forecasting part and value is given to linear program to be distributed among the generation units. The upper and lower bounds are changed according to the modified constraints mentioned in (12). The quadratic nature of curve is changed into linear as the q no. of points are made on curve. The start of one segment is taken as lower bound and end is taken as upper bound. In this manner, the upper and lower bounds are made on the line. The program reads the value of forecasted load and begin the iterations to converge the objective function to its minimum value by considering the constraints. As the program is converged to a point, the objective that is achieved contains the following goals.

- The most economical way of generation electricity.
- Meets the forecasted load demand.

V. Case Study

To apply the above algorithm, six generation unit system has been selected. To solve the economic load dispatch problem the upper and lower bounds, generation limits for maximum and minimum value and loss coefficient which are used as in [7] are given in Table II.

Linear programming applied on the forecasted load in previous sections. Load is distributed between the six generation units to get the economic load dispatch Table III.

TABLE II
FUEL COST CURVE COEFFICIENT & GENERATION UNITS' LIMITS

Generation Unit	a_n	b_n	c_n	$P_{n,min}$	$P_{n,max}$
1	756.80	38.530	0.15240	10	125
2	451.33	46.159	0.10587	10	150
3	1045.00	40.397	0.02803	35	225
4	1243.53	38.306	0.03546	35	210
5	1658.57	36.328	0.02111	130	325
6	1356.66	38.270	0.01799	125	315

TABLE III
ECONOMIC LOAD DISPATCH BY USING LINEAR PROGRAMMING

S. No.	Forecast (MW) (Sunday)	P1 (MW)	P2 (MW)	P3 (MW)	P4 (MW)	P5 (MW)	P6 (MW)
1	**925.9**	38.75	10.00	130.00	166.25	276.25	304.65
2	**854.0**	38.75	10.00	130.00	131.50	276.25	267.50
3	**829.0**	38.75	10.00	130.00	122.50	276.25	251.50
4	**821.1**	38.75	10.00	130.00	122.50	276.25	243.60
5	**825.0**	38.75	10.00	130.00	122.50	276.25	247.50
6	**868.1**	38.75	10.00	130.00	145.60	276.25	267.50
7	**1012.4**	38.75	10.00	177.50	166.25	304.90	315.00
8	**1035.0**	38.75	10.00	177.50	168.75	325.00	315.00
9	**1028.2**	38.75	10.00	177.50	166.25	320.00	315.00
10	**1140.4**	38.75	26.65	225.00	210.00	325.00	315.00
11	**1168.8**	48.80	45.00	225.00	210.00	325.00	315.00
12	**1186.8**	66.80	45.00	225.00	210.00	325.00	315.00
13	**1176.1**	56.10	45.00	225.00	210.00	325.00	315.00
14	**1144.2**	38.75	30.45	225.00	210.00	325.00	315.00
15	**1127.1**	38.75	13.35	225.00	210.00	325.00	315.00
16	**1121.2**	38.75	10.00	222.45	210.00	325.00	315.00
17	**1065.8**	38.75	10.00	177.50	199.50	325.00	315.00
18	**1095.8**	38.75	10.00	197.05	210.00	325.00	315.00
19	**1202.0**	67.50	59.50	225.00	210.00	325.00	315.00
20	**1155.8**	38.75	42.05	225.00	210.00	325.00	315.00
21	**1114.0**	38.75	10.00	215.25	210.00	325.00	315.00
22	**1080.7**	38.75	10.00	181.95	210.00	325.00	315.00
23	**1009.2**	38.75	10.00	177.50	166.25	301.70	315.00
24	**939.2**	38.75	10.00	132.95	166.25	276.25	315.00

VI. CONCLUSION

STLF has been done using ANN where network is trained using two different types of input data, i.e. day-wise and yearly. It has been observed that the network trained by using day-wise data has performed better as compared to the yearly dataset. Maximum MAPE calculated for day-wise and yearly data for several days is 1.11% and 1.38%, respectively. Therefore, selection of input datasets has significant influence on STLF using ANN. Next, quadratic objective function transformed into linear and applied the linear programming. Non-varying results are achieved by using a heuristic algorithm to evaluate unpredictable results. Developed algorithm has been applied to six-unit system and verified the results by comparing them with the generation limits of the generators. The results can be improved by increasing the number of points constructed on the fuel cost curve to make it further closer to linear. Hence, a simple method has been attained to compete with the other complex methods to solve the STLF and its economic dispatch problem.

ACKNOWLEDGMENT

The authors would like to thank Professor Jiao Zaibin and Professor Ding Tao for introducing this area of research which has broadened our knowledge in respective area.

REFERENCES

[1] D. C. Montgomery, C. L. Jennings, and M. Kulahci, *Introduction to time series analysis and forecasting*. John Wiley & Sons, 2015.

[2] C. Barbulescu, S. Kilyeni, A. Deacu, G. M. Turi, and M. Moga, "Artificial neural network based monthly load curves forecasting," in *Applied Computational Intelligence and Informatics (SACI), 2016 IEEE 11th International Symposium on*, 2016, pp. 237-242: IEEE.

[3] A. Baliyan, K. Gaurav, and S. K. Mishra, "A review of short term load forecasting using artificial neural network models," *Procedia Computer Science,* vol. 48, pp. 121-125, 2015.

[4] A. Khwaja, M. Naeem, A. Anpalagan, A. Venetsanopoulos, and B. Venkatesh, "Improved short-term load forecasting using bagged neural networks," *Electric Power Systems Research,* vol. 125, pp. 109-115, 2015.

[5] J. S. Al-Sumait and J. K. Sykulski, "Solving economic dispatch problem using hybrid GA-PS-SQP method," 2009.

[6] C.-T. Su and C.-T. Lin, "New approach with a Hopfield modeling framework to economic dispatch," *IEEE Transactions on Power Systems,* vol. 15, no. 2, pp. 541-545, 2000.

[7] R. A. Jabr, A. H. Coonick, and B. J. Cory, "A homogeneous linear programming algorithm for the security constrained economic dispatch problem," *IEEE Transactions on power systems,* vol. 15, no. 3, pp. 930-936, 2000.

[8] A. Farag, S. Al-Baiyat, and T. Cheng, "Economic load dispatch multiobjective optimization procedures using linear programming techniques," *IEEE Transactions on Power systems,* vol. 10, no. 2, pp. 731-738, 1995.

[9] H. Demuth and M. Beale, "Neural network toolbox, user's guide version 4, The Mathworks Inc," ed, 2014.

[10] A. Ashfaq, S. Yingyun, and A. Z. Khan, "Optimization of economic dispatch problem integrated with stochastic demand side response," in *Intelligent Energy and Power Systems (IEPS), 2014 IEEE International Conference on*, 2014, pp. 116-121: IEEE.