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Short-Term (Seven Day Basis) Load Forecasting Of a Grid System in Bangladesh Using Artificial Neural Network

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Abstract: *Load forecasting is the technique for prediction of electrical load. In a deregulated market it is much need for a generating company to know about the market load demand for generating near to accurate power. If the generation is not sufficient to fulfil the demand, there would be Problem of irregular supply and in case of excess generation the generating company will have to bear the loss. Neural network techniques have been recently suggested for short-term load forecasting by a large number of researchers. This paper proposes the load forecasting for the Power Grid Company Bangladesh Ltd. (PGCB) by using Artificial Neural Network (ANN). It uses the advanced back propagation algorithm and the data from PGCB to train the system. This thesis has proposed to train the network in summer and winter to minimize the power as well as the cost of generation. It consists with the daily data of all seasons and the data of Friday, public holidays, Eid festival and Durga puja which represent the holiday. The input pattern is considered from the load variation events. And only that kind of inputs are chosen for which the shows a great performance by providing the output nearer to the actual value. The network is implemented by MATLAB programming language and then the results are compared and analyzed in terms of accuracy. For this thesis, more variables are used in the Neural Network model to achieve more accuracy for better short-term load forecasting results*

Key Word*: Short Term Load Forecasting, Artificial Neural Network (ANN), Power GRID Company Bangladesh (PGCB); MATLAB Simulink.*

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I. Introduction

The electricity is the necessity in daily life and it is one of the main driving factors for country economic. In order to provide sufficient electricity and make the economic grown continuously, the load forecasting is required for the related electricity producers. At present, there is no substantial energy storage in the electric transmission and distribution system. For optimal power system operation, electrical generation must follow electrical load demand. The generation, transmission, and distribution utilities require some means to forecast the electrical load so they can utilize their electrical infrastructure efficiently, securely, and economically. Generation utilities use electrical load forecasting techniques to schedule their generation resources to meet the future load demand. Transmission utilities use electric load forecasting techniques to optimize the power flow on the transmission network to reduce congestion and overloads. Distribution utilities would not have much interest in short-term electric load forecasts as their distribution systems are predominantly radial with predictable maximum load demands. Thus, the distribution systems are sized conservatively, and short-term load changes have little effect on the distribution system. Long- and medium-term load forecasts predict the electrical load over time ranges measured in months or years. The short-term load forecast (STLF) represents the electric load forecast for a time interval of a few hours to a few days. This thesis will define STLF as a 30 days-ahead load forecast whose results will provide a daily electric load forecast in megawatts (MW) for the future 30 days (a 30 days load profile).

II. Designing Neural Network For Forecasting

A. Factor Affecting Short Term Load Forecasting

The basic objective of short-term load forecasting is to predict the near future load for example next hour load prediction or next day load prediction etc. There are various factors which influence the behavior of the consumer load and also impact the total losses in transmission lines. These factors can be categorized as Time factor, weather, economy and random disturbances. In this research paper these factors and their impact on consumption of electric power and their significance in short term load forecasting is evaluated.

B. TIME FACTOR

Time is the most important factor in short term load forecasting because its impact on consumer load is highest. From observing load curve of several different grid stations, it is found that the load curve has “time of the day” property; also it has “day of week”, “week of month” and “month of season” property.

C. WEATHER

Weather is the most important independent variable for load forecasting. The effect of weather is most prominent for domestic and agricultural consumers, but it can also alter the load profile of industrial consumers. Load forecasting models use weather forecast and other factors to predict the future load, thus to minimize the operational cost. Weather data is taken from the site
https://www.timeanddate.com/weather/bangladesh/dhaka/historic?month=6&year=2018
The weather factor includes the following

- Temperature
- Humidity
- Precipitation
- Wind speed and wind chill index
- Cloud cover and light intensity

D. Temperature

The results of the D Paravan [25], shows that there is a high positive correlation between temperature and load during summer season and there is a negative correlation between temperature and load during winter.

This means that during summer increase in temperature will result in increase in load and decrease in temperature will result in decrease in not only average daily load but also will lower the peak demand. But in winter the opposite of the above will happen, during winter decrease in per degree temperature will results in increase of electric load.

F. HDD

"Heating degree days", or "HDD", are a measure of how much (in degrees), and for how long (in days), outside air temperature was lower than a specific "base temperature" (or "balance point"). They are used for calculations relating to the energy consumption required to heat building

G. CDD

"Cooling degree days", or "CDD", are a measure of how much (in degrees), and for how long (in days), outside air temperature was higher than a specific base temperature. They are used for calculations relating to the energy consumption required to cool buildings.

H. Humidity

Humidity is a term used for the amount of water vapors in air. Formally humid air was called not just the moist air but was referred as the mixture of water vapors and other constituents of air and humidity was defined in terms of water contents of this mixture called the absolute humidity [26]. In everyday life it is called relative humidity and is expressed in percentage.

I. Wind Speed and Wind Chill Index

Wind speed can affect weather forecast, it is now measured with anemometer, but it can also be measured using the older Beaufort scale which is based on people’s observation on specially defined effects of wind.

Wind chill temperature is always less than the air temperature and is undefined at temperature above 10˚C. Any hot body makes the surrounding air warmer. The warmer air surrounding the body then acts as insulator preventing the further heat loss. But if the wind blows then the colder air takes the place of the warmer air thus causing further heat loss. The speed of the heat loss is directly proportional to the wind speed. Greater the wind speed higher will be the heat loss. The above phenomenon is called wind chill.

III. Forecasting System

The load forecasting task in this thesis depends on the variation of the parameters affecting the load of a grid system where loads taken daily basis on 30 days (observing days). The load forecasting is calculated according to the following procedures:

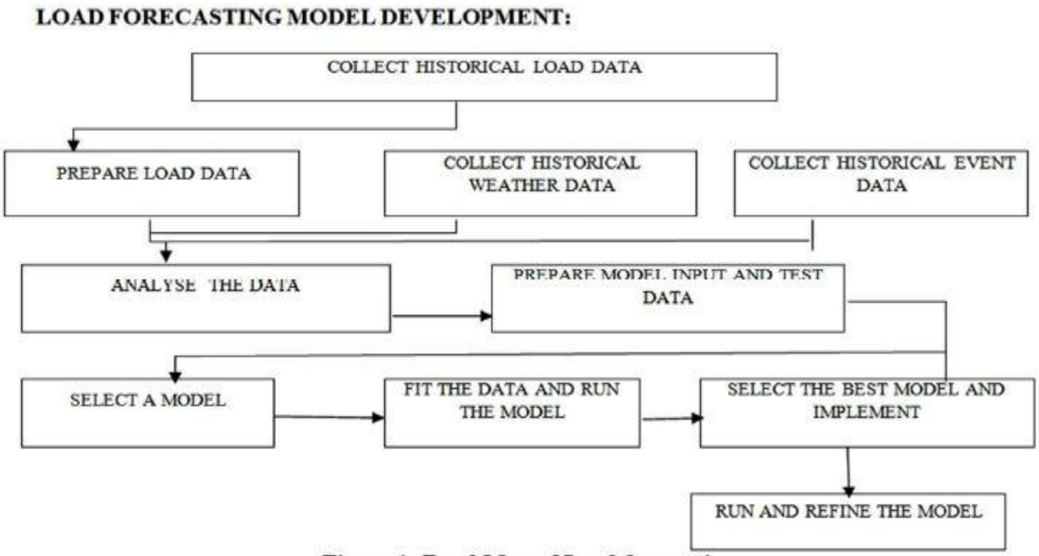

Fig 1: Road map of Load Forecasting

IV. Simulation Result

Successful operation of ANN based load forecasting requires an appropriate training data set that can adequately covers the entire solution space with a view to recognize and generalized the relations among the problem variables.

A. Implementation of ANN using MATLAB.16

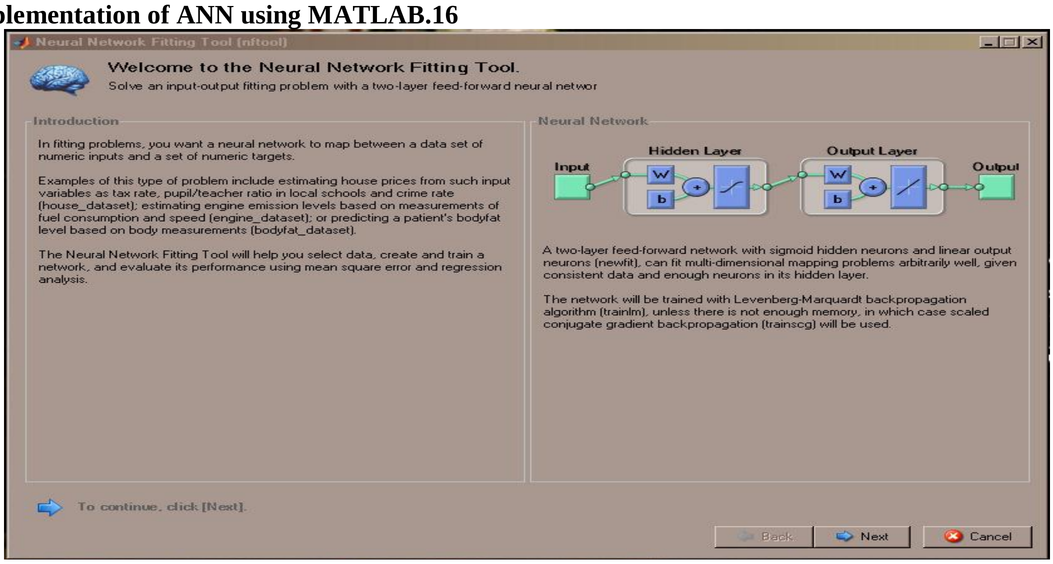

Fig 2: Open NF tool in MATLAB.16

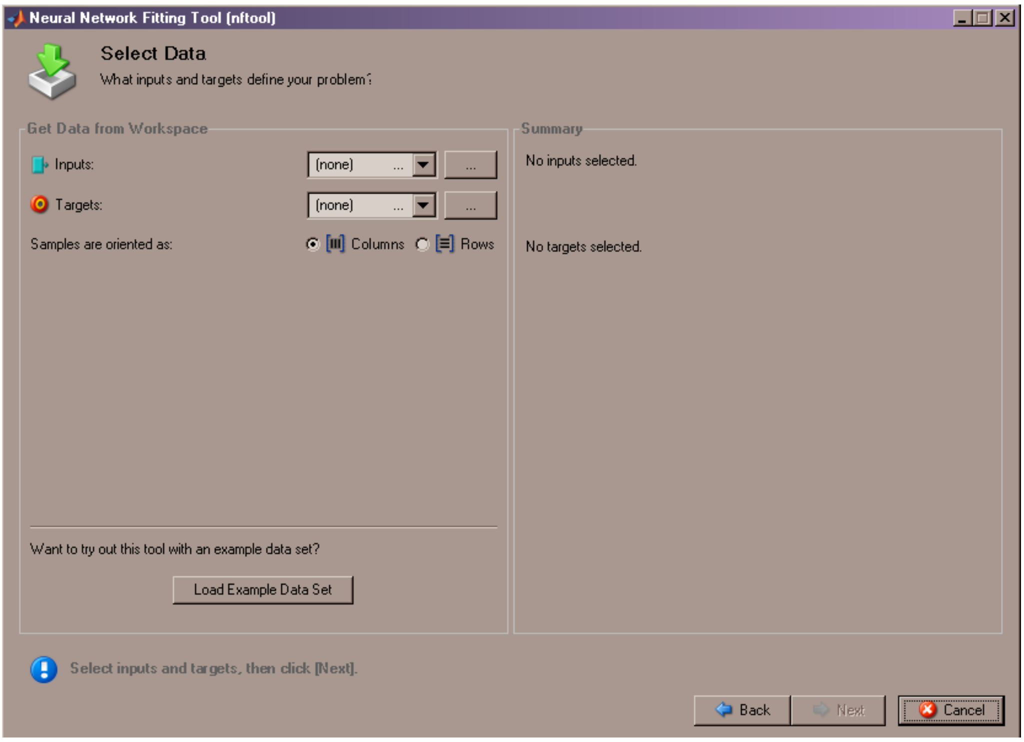

Fig. 3: Prepare input data and output data in Workspace. Import the prepare data from workspace

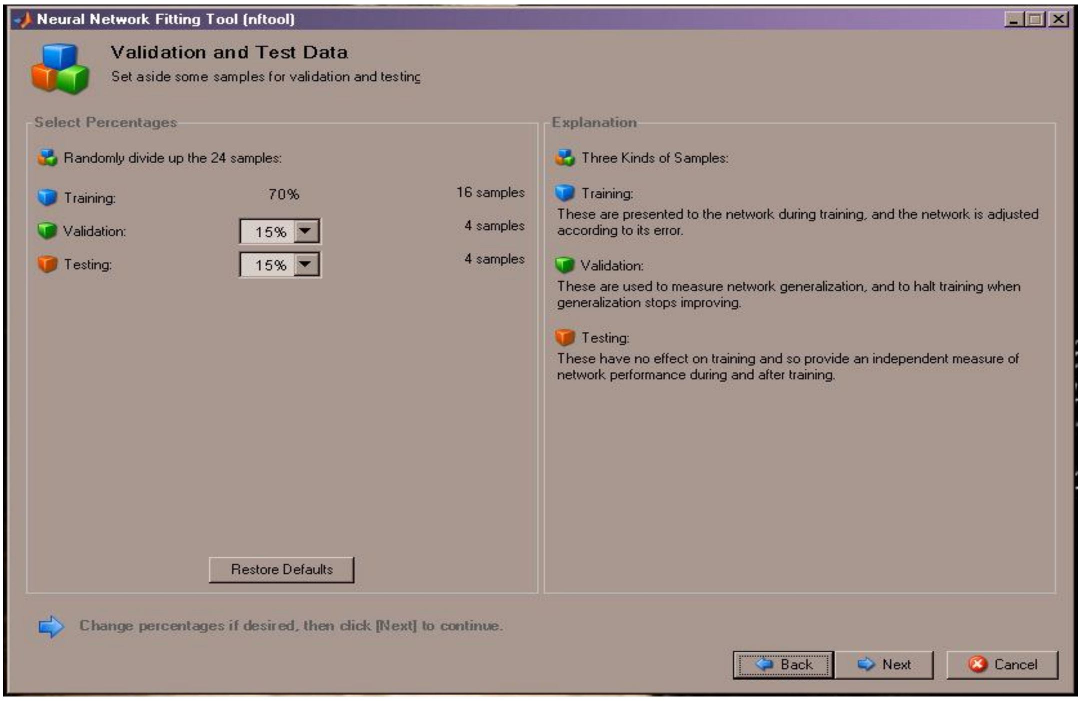

Fig. 4: Training validation and testing percentage can be set according to the need.
In this paper Training was set to 70%, Validation was 15% and Testing was 15%

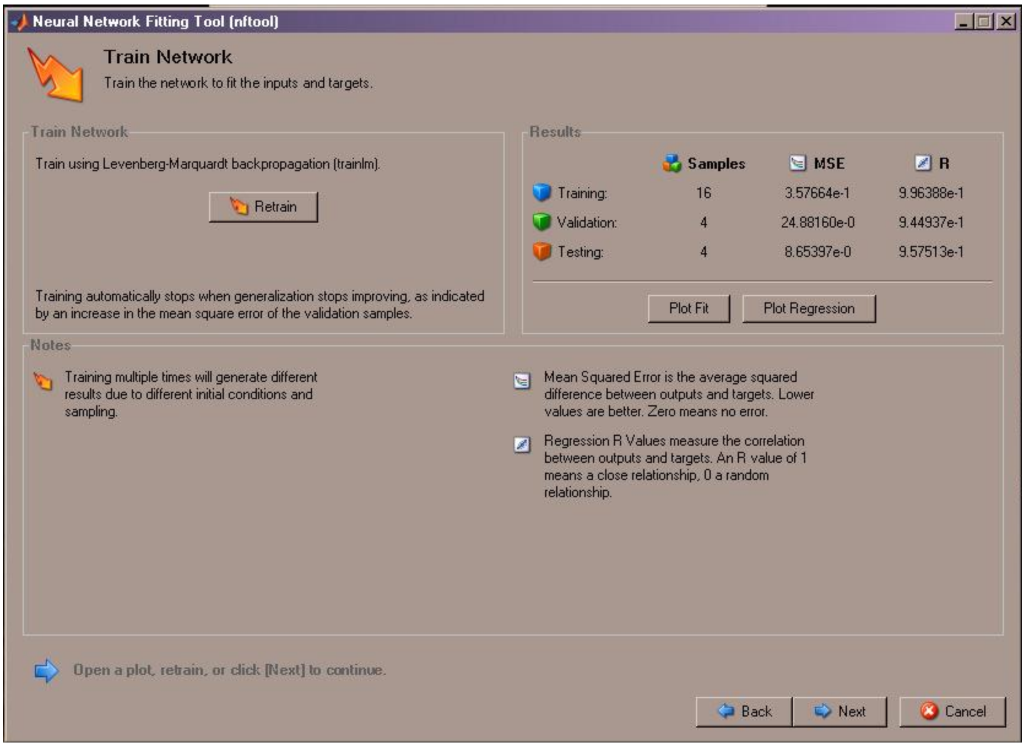

Fig. 5: Error Retrain If error is high, and then to minimize the error Retrain is done. Then we can get plots of performance, Training state, Fit and Regression.

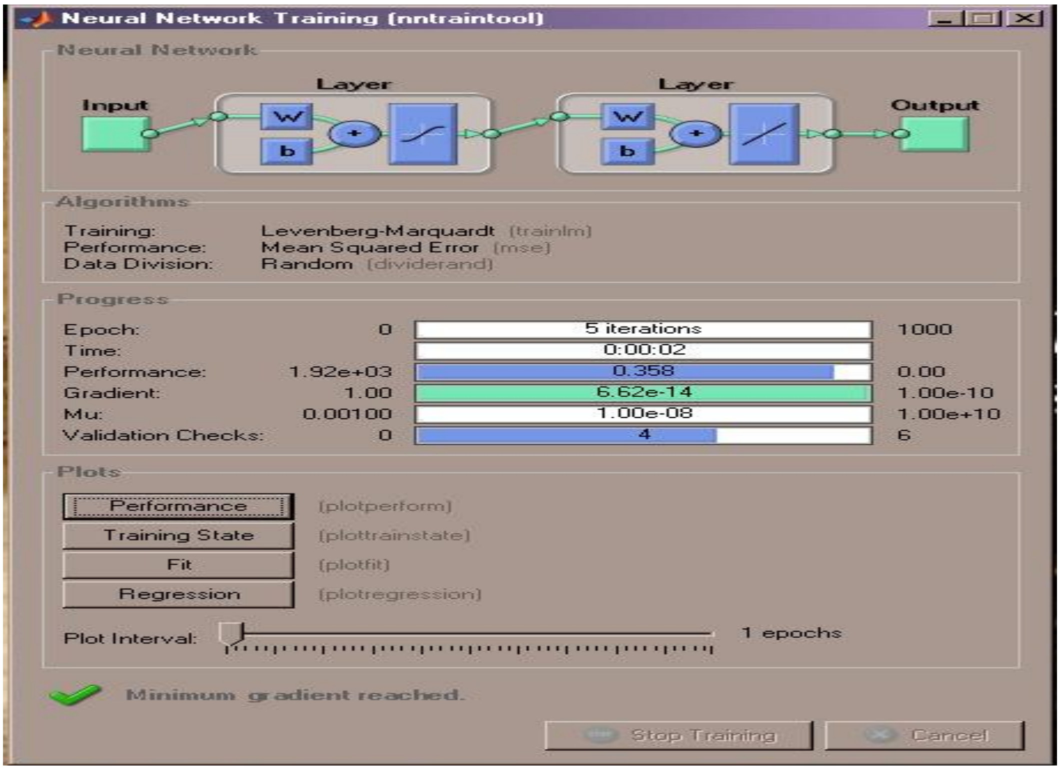

Fig. 6: Training state, Fit and Regression

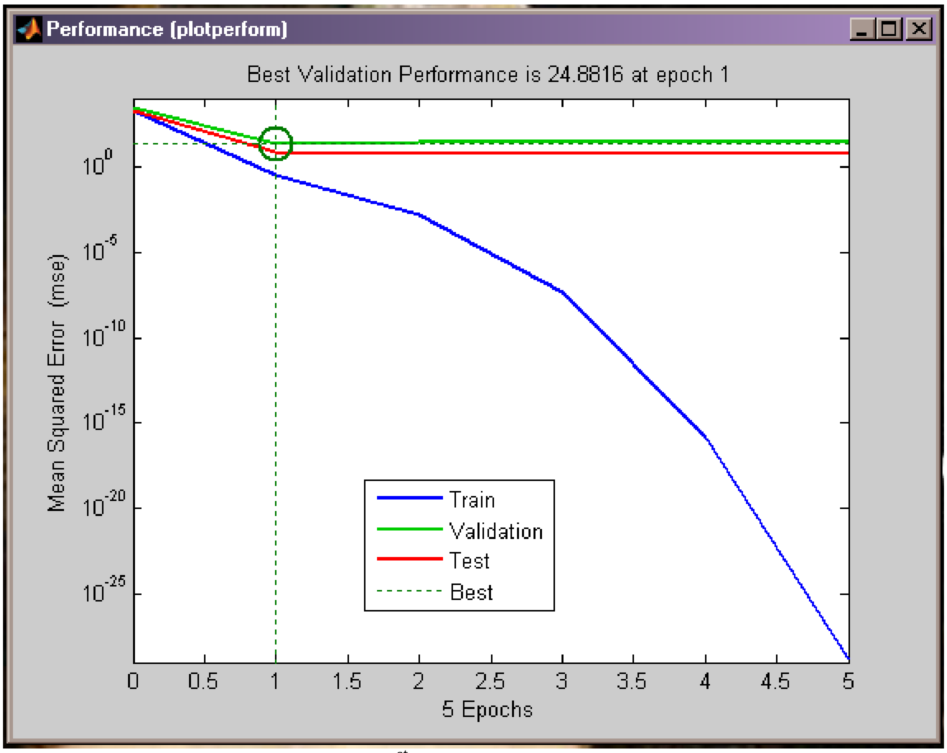

Fig. 7: This shows the performance plot for 1st July 18 with 5 Epochs. This plot is Mean squared error vs. Epochs.

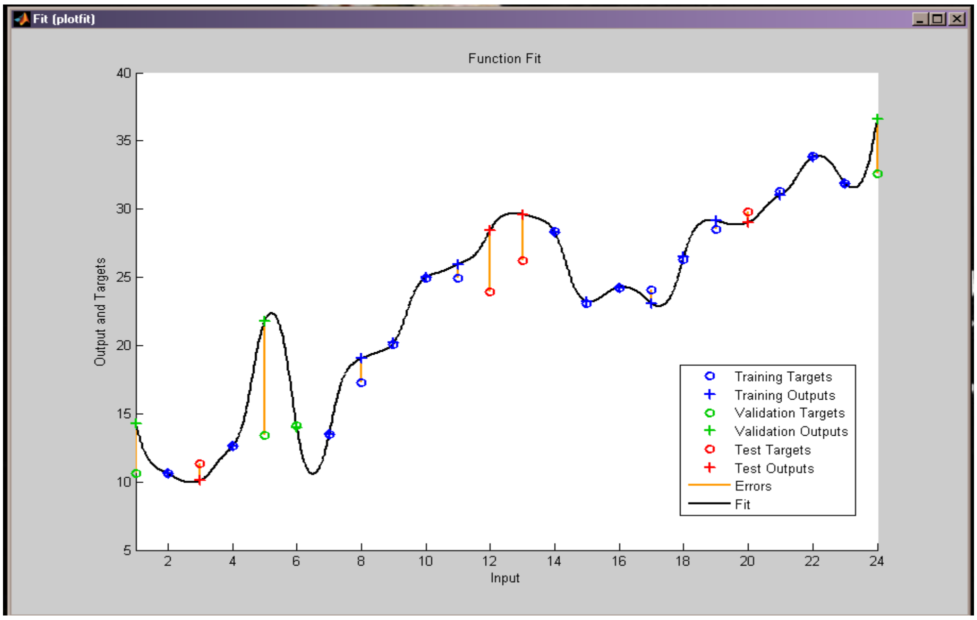

Fig. 8: This is the plot fit for output and targets. This error is difference between actual data and predicted data. (1stJuly, 18)

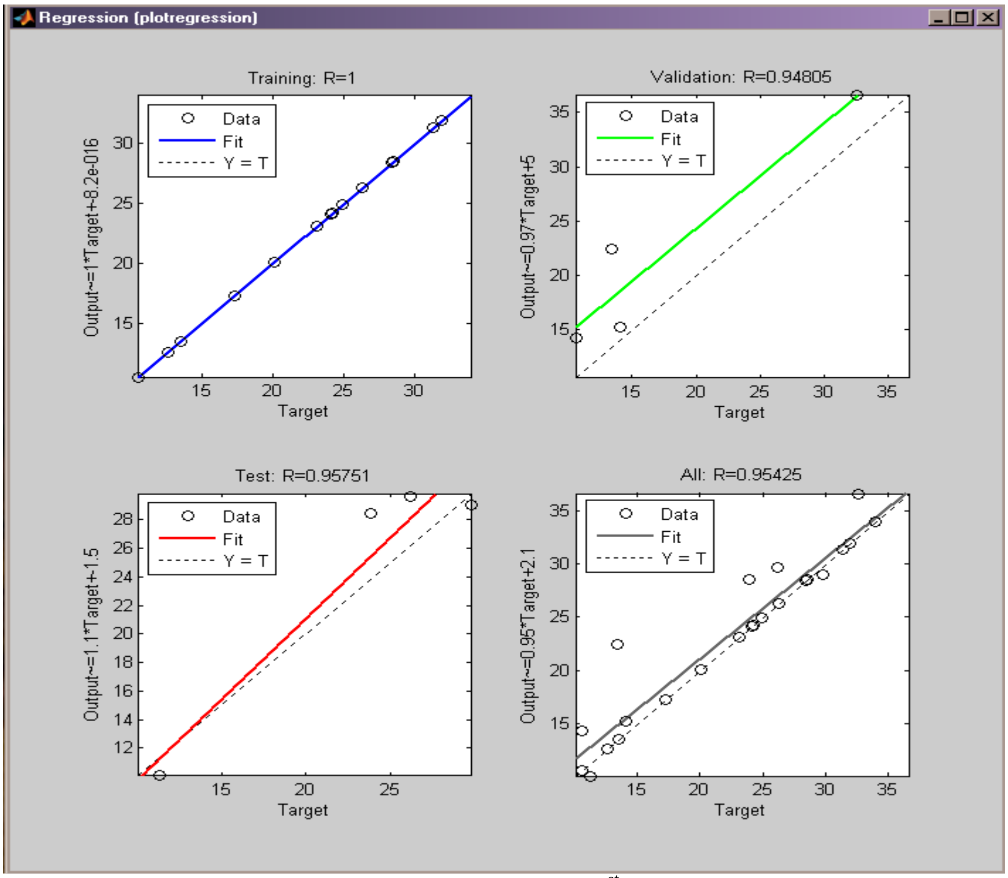

Fig. 9: Regression plot for 1st July, 18

Similarly, various plots can be found for 2nd July, 3rd July, 4th July, 5th July, 6th July and 7th July

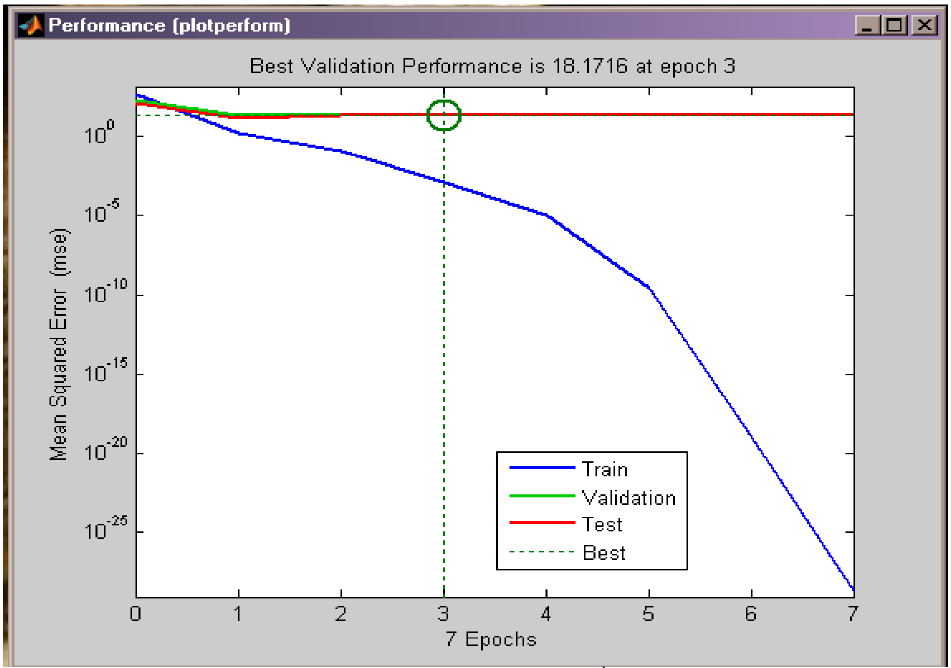

Fig. 10: Performance plot for 2nd July, 18

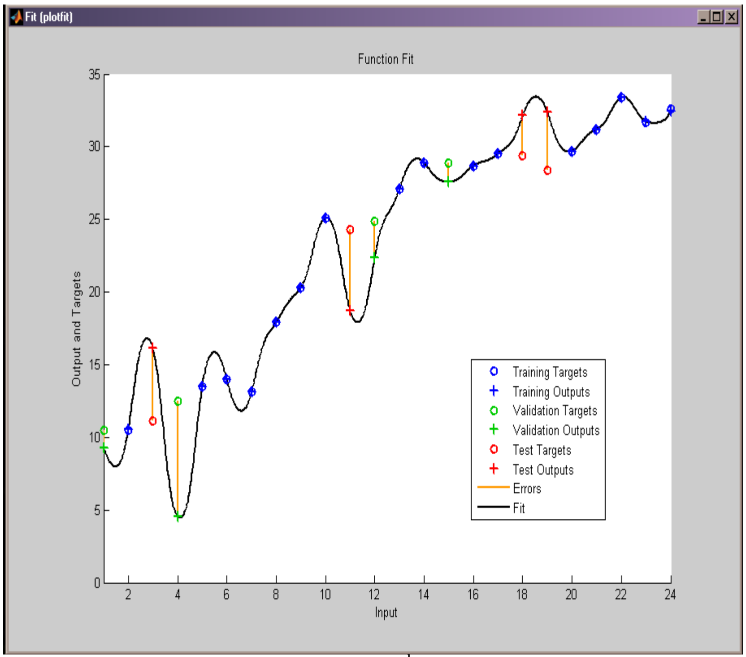

Fig. 11: For 2nd July, 18

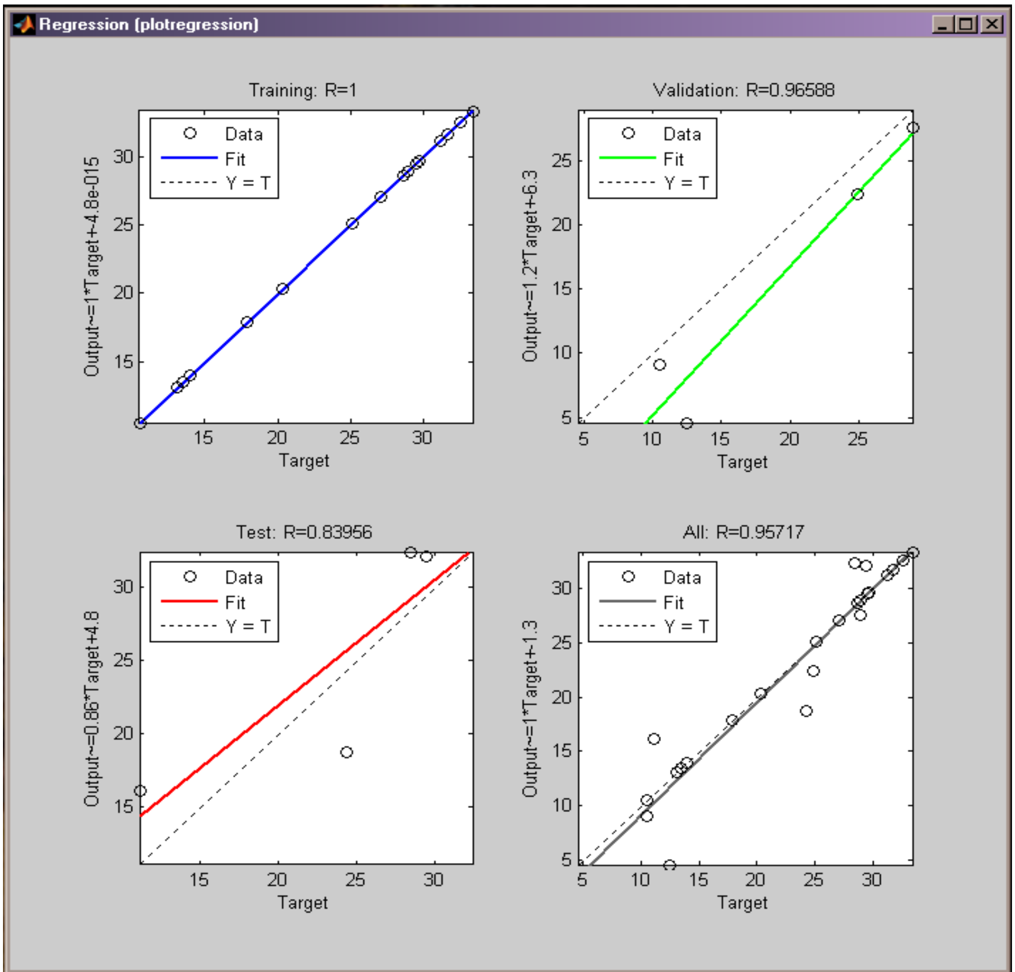

Fig. 12: Regression plot for 2nd July, 18

V. COMPARISONS OF ACTUAL AND PREDICTED RESULT

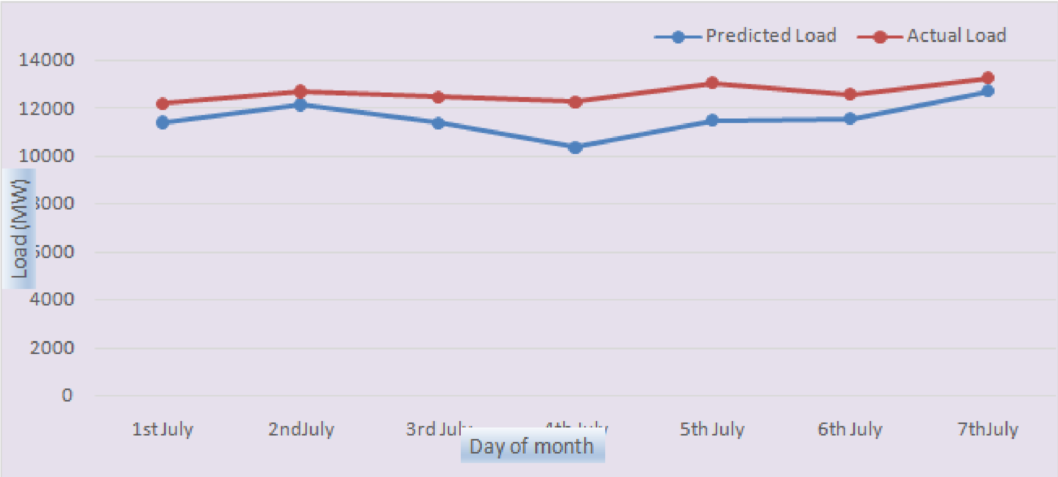

Fig. 13: Comparison between actual and forecasted values

VI. TABULATION OF RESULTS & CALCULATION OF ERROR

Date	ACTUAL LOAD (MW)	PREDICTED LOAD (MW)
01-07-18	12256	11433
02-07-18	12742	12177
03-07-18	12518	11423
04-07-18	12307	10402
05-07-18	13108	11527
06-07-18	12633	11595
07-07-18	13299	12750

Table -1

A. Error Calculation for 1st July 2018:

$$MAPE = \sum \frac{1}{N} \left(\frac{Actual - Predict}{Actual} \right) \times 100\%$$

MAPE = {[12256-411433] /12256} *100/7
= 0.959 %
Similarly, calculation of error for 2nd July to 7th July can be done.

Days	MAPE %
01-07-18	0.959
02-07-18	0.633
03-07-18	1.249
04-07-18	2.211
05-07-18	1.723
06-07-18	1.173
07-07-18	0.589

Table-2

Data sets for Training and Testing	
Historical Daily Load (Training)	Jan 1- Jan 5
	Feb 1 - Feb 5
	Mar 1 - Mar 5
	April 1 - April 5
	May 1 - May 5
	Jun 1 - Jun 5
Test Weeks	July 1 - July 7

Table-3

VII. CONCLUSIONS

Based on the results obtained from this work, it can be concluded that ANN models with the developed structure could perform good prediction with least error and finally this neural network could be an important tool for short term power load forecasting. In this work, simulations and programming of short-term power load forecasting problem presented for PGCB by using necessary ANN model. The results obtained showed the effectiveness of the developed method. Based on the results obtained from this work, it can be concluded that ANN models with the developed structure could perform good prediction with least error and finally this neural network could be an important tool for short term power load forecasting

References

[1]. Y. Al-Rashid and L.D. Paarmann, "Short-term electric load forecasting using neural network models," Circuits and Syst., Ames, IA, 1996, pp. 1436-1439.
[2]. I. Moghram and S. Rahman, "*Analysis and evaluation of five short-term load forecasting techniques*," IEEE Trans. Power Syst., vol. 4, pp. 1484-1491, Nov. 1989.
[3]. G. Gross and F.D. Galiana, "Short-Term Load Forecasting," Proc. IEEE, vol. 75, pp. 1558-1573, Dec. 1987.
[4]. Daily Load report of Bangladesh Power Development Board (BPDB) Available: http://www.bpdb.gov.bd/bpdb/index.php?option=com_content&view=article&id=20&Itemid=18
[5]. T. Hong, M. Gui, M. Baran, and H.L. Willis, "Modeling and forecasting hourly electric load by multiple linear regression with interactions," Power and Energy Soc. General
[6]. Meeting, Minneapolis, MN, 2010, pp. 1-8.
[7]. P.J. Santos, A.G. Martins, and A.J. Pires, "Short-term load forecasting based on ANN applied to electrical distribution substations," Universities Power Engineering Conf., Bristol, UK, 2004, vol. 1, pp. 427-432.
[8]. T.G. Manohar and V.C. Veera Reddy, "*Load forecasting by a novel technique using ANN*," ARPN J. of Eng. And Appl. Sci., vol. 3, pp. 19-25, Apr. 2008.
[9]. N. Amral, C.S. Ozveren, and D. King, "Short term load forecasting using multiple linear regression," Universities Power Engineering Conference, Brighton, 2007, pp. 1192-1198.
[10]. W.R. Christiaanse, "*Short-term load forecasting using general exponential smoothing*," IEEE Trans. Power App. and Syst., vol. PAS-90, pp. 900-911, Mar. 1971.

[11]. S. Rahman and R. Bhatnagar, "*An expert system based algorithm for short term load forecast*," IEEE Trans. Power Syst., vol. 3, pp. 392-399, May 1988.

[12]. M. Ramezani, H. Falaghi, and M. Haghifam, "Short-term electric load forecasting using neural networks," Int. Conf. on Computer as a Tool, Belgrade, 2005, pp. 1525- 1528.

[13]. K.Y. Lee, Y.T. Cha, and J.H. Park, "*Short-term load forecasting using an artificial neural network*," IEEE Trans. Power Syst., vol. 7, pp. 124-132, Feb. 1992.

[14]. T. Senjyu, P. Mandal, K. Uezato, and T. Funabashi, "Next day load curve forecasting using recurrent neural network structure," Proc. Inst. Elect. Eng., vol. 151, pp. 388-394, May 2004.

[15]. Weather Information of Bangladesh. Available: https://www.timeanddate.com/weather/bangladesh/dhaka/historic?month=6&year=2018

[16]. Z.H. Osman, M.L. Awad, and T.K. Mahmoud, "Neural network based approach for short-term load forecasting," IEEE/PES Power Systems Conference and Exposition, Seattle, WA, Mar. 15-18, 2009.

[17]. F. Liu, R.D. Findlay, and Q. Song, "A neural network based short term electric load forecasting in Ontario Canada," Int. Conf. on Computational Intelligence for Modeling, Control, and Automation, Sydney, NSW, 2006, pp. 119-126.

[18]. W. Charytoniuk and M. Chen, "*Very short-term load forecasting using artificial neural networks*," IEEE Trans. Power Syst., vol. 15, pp. 263-268, Feb. 2000.

[19]. J.K. Mandal, A.K. Sinha, and G. Parthasarathy, "Application of recurrent neural network for short term load forecasting in electric power system," Int. Conf. on Neural Networks, Perth, WA, 1995, pp. 2694-2698.

[20]. D.C. Park, M.A. El-Sharkawi, R.J. Marks II, L.E. Atlas, and M.J. Damborg, "Electric load forecasting using an artificial neural network," IEEE Trans. Power Syst., vol. 6, pp. 442-449, May 1991.

[21]. B.S. Kermanshahi et al, "Artificial neural network for forecasting daily loads of a Canadian electric utility," Applications of Neural Networks to Power Systems, Yokohama,Japan, 1993, pp. 302-307.

[22]. Y. Hsu and C. Yang, "Design of artificial neural networks for short-term load forecasting. Part II: Multiplayer feed forward networks for peak load and valley load forecasting," Proc. Inst. Elect. Eng., vol. 138, pp. 414-418.

[23]. T. Senjyu, H. Takara, and K. Uezato, "Two-hour-ahead load forecasting using neural network," Int. Conf. on Power Syst. Technology, Perth, WA, 2000, pp. 1119-1124.

[24]. T. Senjyu, H. Takara, K. Uezato, and T. Funabashi, "*One-hour-ahead load forecasting using neural network*," IEEE Trans. Power Syst., vol. 17, pp. 113-118, Feb. 2002.

[25]. H. Demuth, M. Beale, and M. Hagan. (2009, Mar.). Neural network toolbox™ 6 user's guide [Online]. Available: http://www.varpa.org/Docencia/Files/nnet.pdf

[26]. Weisstein, Eric W. "Correlation Coefficient." MathWorld- [Online]. Available: http://mathworld.wolfram.com/CorrelationCoefficient.html.

[27]. H.S. Hippert, C.E. Perdreira, and R.C. Souza, "*Neural networks for short-term load forecasting: a review and evaluation*," IEEE Trans. Power Syst., vol. 16, pp. 44-55, Feb. 2001.

[28]. D. Paravan, A. Debs, C. Hansen, D. Becker, P. Hirsch, and R. Golob. "Influence of temperature on short-term load forecasting using the EPRI-ANNSTLF."

[29]. S. S. Wyer, "A treatise on producer-gas and gas-producers," The Engineering and Mining Journal, London, pp. 23, 1906.

[30]. Papalexopoulos, A. D., T. C. Hesterberg, 1990, "*A regression-based approach to short-term system load forecasting*", IEEE Transactions on Power Systems, Vol. 5,No. 4,November 1990, pp. 1535-1547.

[31]. Bangladesh govt. holiday: http://www.ofuran.com/2018/01/government-public-holidays-in-2018-bd-list.html

Appendix

Data Sheet For Neural Network Analysis Of Bangladesh

	Ref Temp = 25°C							Seasons						Weeks							Holidays					Months											
Target Value	Max temp	Min temp	Mean temp	Degree Days	HDD	CDD	Humidity	Summer	Rainy	Autumn	Late Autumn	Winter	Spring	Saturday	Sunday	Monday	Tuesday	Wednesday	Thursday	Friday	Weekly Holi	Govt HoliDays	Eid Festival	Durga Puja	Others	January	February	March	April	May	June	July	August	September	October	November	December
10955	32	25	29	4	0	4	0.85	1	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
12234	33	25	29	4	0	4	0.84	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
12453	34	25	30	5	0	5	0.77	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
12567	32	26	29	4	0	4	0.73	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
12734	34	25	30	5	0	5	0.77	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
12941	35	27	31	6	0	6	0.73	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
12935	35	28	32	7	0	7	0.72	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
12588	33	26	30	5	0	5	0.81	1	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
12219	35	28	32	7	0	7	0.78	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
12405	34	26	30	5	0	5	0.84	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
12550	32	26	29	4	0	4	0.87	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
11619	34	26	30	5	0	5	0.93	1	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
11966	32	25	29	4	0	4	0.92	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
11599	35	28	32	7	0	7	0.86	1	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
10455	33	26	30	5	0	5	0.9	1	0	0	0	0	0	0	1	0	0	0	0	1	1	1	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0
9365	31	25	28	3	0	3	0.79	0	1	0	0	0	0	1	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0
10031	35	27	31	6	0	6	0.82	0	1	0	0	0	0	0	1	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0
10693	35	26	31	6	0	6	0.76	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
10502	30	25	28	3	0	3	0.9	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
11211	34	26	30	5	0	5	0.77	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
11588	34	28	31	6	0	6	0.74	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
11641	34	28	31	6	0	6	0.75	0	1	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
11909	30	26	28	3	0	3	0.79	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
11507	33	27	30	5	0	5	0.79	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
11813	31	27	29	4	0	4	0.88	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
12016	34	27	31	6	0	6	0.79	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
11942	32	27	30	5	0	5	0.74	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
12030	32	26	29	4	0	4	0.69	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
11301	33	28	31	6	0	6	0.73	0	1	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
12445	33	28	31	6	0	6	0.77	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0