Short-Term Load Forecasting of Toronto Canada by Using Different ANN Algorithms

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***Abstract*—In the field of power system, electrical load forecasting has got wide acceptance due to the determination of future trends of demand. Electrical load forecasting is used to predict the future power demand of the consumers which is estimated on the basis of the historical load data. The forecast model processes the exogenous relation of the provided data and consequently anticipates the future load demand. In this paper different ANN algorithms i.e Levenberg Marquardt back propagation, Bayesian Regularization & Scaled Conjugate Gradient algorithms has been applied for short-term load forecasting i.e. the one hour-ahead hourly forecast of the electricity load of Toronto, Canada using MATLAB R14a. The data used in the forecasting are hourly historical data of the temperature & the electricity demand of Toronto, Canada. The simulation results obtained is highly accurate and well forecasted.**

***Index Terms*--- Mean absolute error (MAE), mean absolute percentage error (MAPE), neural network (NN), power system, short-term load forecasting.**

I. Introduction

Load forecasting is defined as the mechanism to use the historical power demand data to determine the direction of future trends of power requirements. In power system, our aim is to decide new as well as upgradable existing system elements, to satisfy the loads for an expected future is baptized as the load forecasting. Elements can be Generation, Transmission line, Substations, Capacitors or Reactors, etc. The first crucial step of any power system planning study is forecasting and for the further study of this planning we plot different load curve i.e. daily load curves, monthly load curves and annual load curves which give us the details about variation of load during different time, total number of units generated, maximum demand, average load on a power station and load factor [1]-[5].

There are basically four types of methods which we use to plot load curve in order to get forecasted values these methods are namely, very short-term load forecasting, short-term load forecasting, medium- term load forecasting and long term load forecasting. Short term load forecasting (STLF) aims to predict electrical loads for a period of hours, days, or weeks. STLF is a very important issue to have efficient economic and accurate power system operations which can be unit commitment, maintenance scheduling, etc. [5]-[10].

The factors which mainly affect the demand of load are due to the weather difference of different locations. Weather causes variation in domestic load, public lighting, commercial loads, etc. Main weather variables that affect the power consumption are namely, temperature, cloud cover, visibility and precipitation. Here first two variables affect heating/cooling of load while other affect lighting loads. Average temperature is the most significant weather dependent factor that influences load variations. In this model of load forecasting we used proper temperature ranges & used a typical average temperature which cover all regions of the area served by the electrical utilities [10]-[15].

In this paper, different ANN algorithms i.e Levenberg Marquardt back propagation, Bayesian Regularization & Scaled Conjugate Gradient algorithms has been used to compute the forecasted load of Toronto, Canada using MATLAB R14a. Both the hourly temperature and hourly electricity load, historical data have been used in forecasting. The temperature variable is included because temperature has a high degree of correlation with electricity load. The neural network models are trained on hourly data from 2007 to 2013 and tested on out-of-sample data from 2014. The simulation results obtained have shown that artificial neural network (ANN) is able to make very accurate short-term load forecast.

The paper has been organized in five sections. Section II presents the overview of neural network used**.** Section III discusses the selection of various data and model of ANN for one hour-ahead load forecasting. Results of simulation are presented in Section IV. Section V discusses the conclusion and future work.

II. ANN For Load Forecasting

Neural networks are composed of simple elements called neuron, operating in parallel. A neuron is an information processing unit that is fundamental to the operation of a neural network. The three basic elements of the neuron model are-

- A set of weights.
- An adder for summing the input signals.
- Activation functions for limiting the amplitude of the output of a neuron.

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The neural network is trained with Levenberg-Marquardt back propagation, Bayesian Regularization & Scaled Conjugate-Gradient algorithm.

In mathematics the Levenberg–Marquardt algorithm (LMA), also known as damped least-squares (DLS) method, is used to solve non-linear least squares problems. These minimization problems occurs frequently in least squares curve fitting [16]-[18].

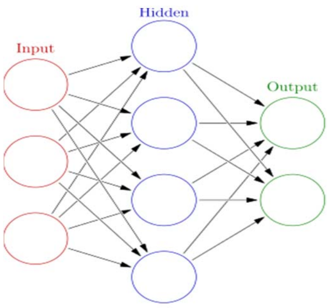
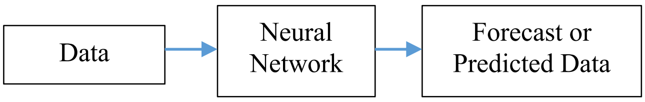


Fig. 1. Working model of an ANN.

Most input signals are time series in their raw format. Most signals are measured as functions of time. The forecast model for electricity load is described in block diagram shown below. Here the raw data input is a time series pattern, which can affect the accuracy of the forecast model's prediction. To produce the best quality of the raw input signal for time series forecast, the neural network model is used.



III. Data Inputs and ANN Model

The models are trained on historical hourly data of Toronto, Canada from 2007 to 2013 and tested on out-of-sample data from 2014 [19]. The data used in the ANN model are historical data of both the temperature and hourly electricity load. The relationship between power demand and average temperature for Toronto, Canada is shown in Fig. 2, where a close relationship between load and temperature can be observed.

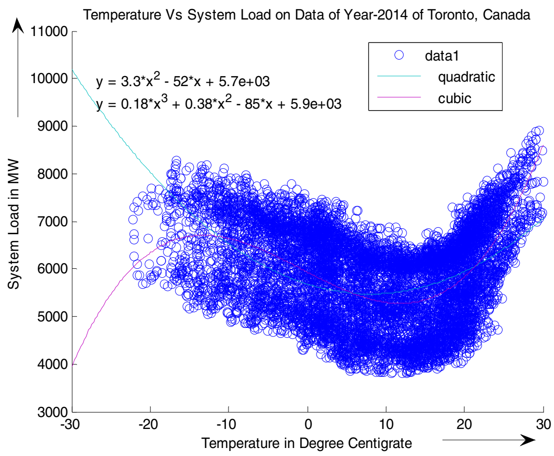


Fig. 2. Scatter plot of system load Vs. temperature with quadratic fitting equation.

The ANN model includes creating a matrix of inputs from the historical data, selecting and calibrating the chosen model and then running the model. For the load forecast, the inputs include

- Hour of day
- Day of the week
- Holiday/weekend indicator (0 or 1)
- 01-hr lagged load
- 02-hr lagged load
- 24-hr lagged load
- Previous 24-hr average load
- 168-hr (previous week) lagged load
- Hourly temperature data
- Hourly dew point temperature data

IV. Simulation & Results

In this paper hourly one hour ahead load forecasting has been done for sample of each day & month of data of year 2014 using neural network tool box of MATLAB R14a. The ANNs are trained with data from 2007 to 2013 and tested on out-of-sample data from 2014. The test sets are completely separate from the training sets and are not used for model estimation or variable selection.

The model accuracy on out-of-sample periods is computed with the Mean Absolute Percent Error (MAPE) metrics. The principal statistics used to evaluate the performance of these models, mean absolute percentage error (MAPE), is defined in eq. 1 below.

$$MAPE\ [\%] = \frac{1}{N}\sum_{i=1}^{N}\frac{|L_A^i - L_F^i|}{L_A^i} \times 100 \qquad (1)$$

Where L_A is the actual load, L_F is the forecasted load, N is the number of data points.

Various plots comparing the one-hour ahead actual and forecasted load for each day, week for the year 2014 are also generated. Simulation results is discussed below.

A. Load Forecast Using Levenberg-Marquardt Back Propagation Algorithm

The ANN model used in the forecasting is shown below in Fig. 3. It has input, output and one hidden layers. Hidden layer has 60 neurons. Inputs to the input layer are as listed above for load forecast. After simulation the average MAPE obtained is 0.63% for load forecasting for the year 2014 as shown in Fig. 4.

Multiple series plots between actual load & forecasted load from 01-07 January, 2014 & from 09 -15 April, 2014 and also plots of MAPE with 0.68% and 0.63% for one hour ahead weekly forecast in year 2014 have been shown in Fig. 5 and

Fig. 6. The simulation results show that the highest & least error occurred with MAPE of 1.83% & 0.28% for day-ahead hourly forecast. Here 16 October, 2014 is for highest & 28 January, 2014 and 11 February, 2014 are for least error. respectively. It is observed that maximum MAPE (0.72%) is for September, 2014 and minimum MAPE (0.5%) is for February, 2014.

The box-plot of the error distribution of forecasted load as a function of hour of the day is presented in Fig. 7. It shows the percentage error statistics of hour of the day in year 2014. It is also evident that the maximum error is for the 7th hour of the day and minimum error for 23rd hour of the day in year 2014. The box-plot of the error distribution of forecasted load as a function of day of the week is evaluated in Fig. 8 which shows the percentage error statistics of day of the week in year 2014. The maximum error is for the Thursday and minimum error for Saturday in year 2014.

Regression R Values measure the correlation between outputs and targets. If R value is 1 means a close relationship, 0 a random relationship. If training performance is worse, then increase the number of neurons. Mean squared error which is the average squared difference between outputs and targets indicates the accuracy of forecasting. Fig. 09 shows the plot of regression obtained from simulation.

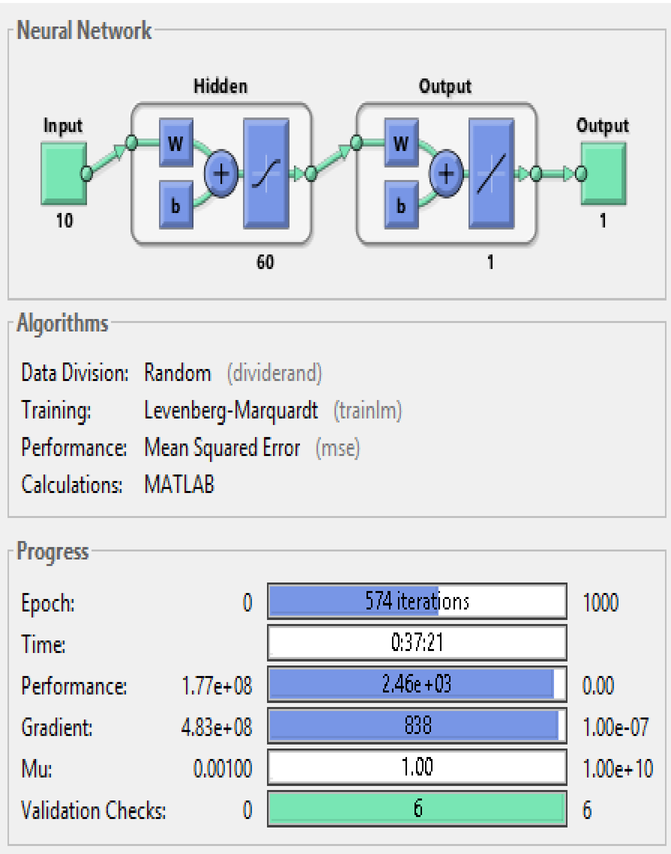


Fig. 3. Showing ten different input data for one target data with 60 neurons in hidden layer using Levenberg-Marquardt algoritm.

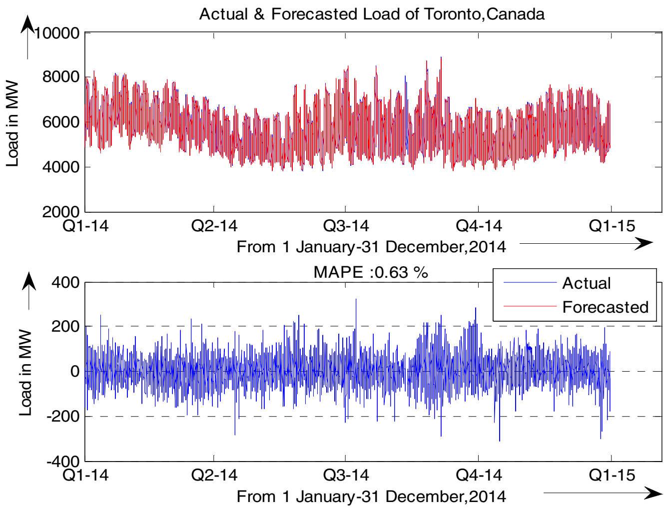


Fig. 4. Multiple series plot between actual & forecasted load in the year 2014 using Levenberg-Marquardt algoritm.

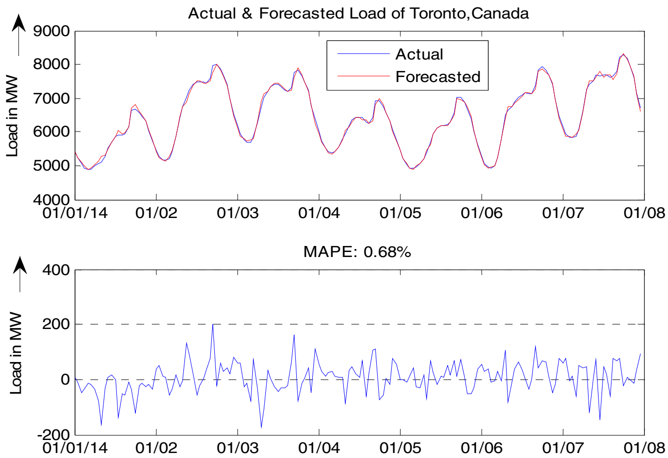


Fig. 5. Load forecast from 01-07 January, 2014.

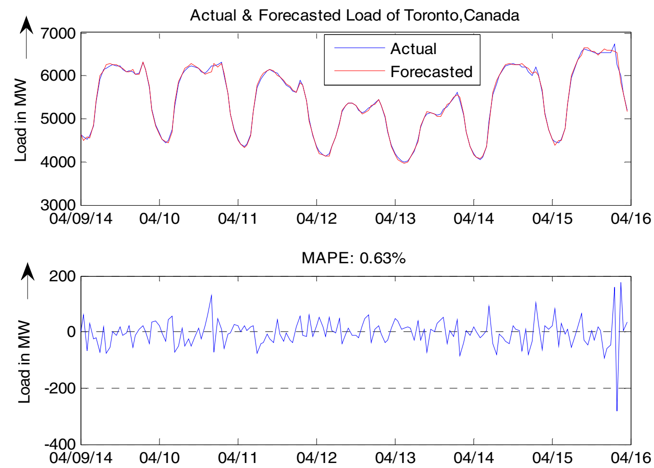


Fig. 6. Load forecast from 09 -15 April, 2014.

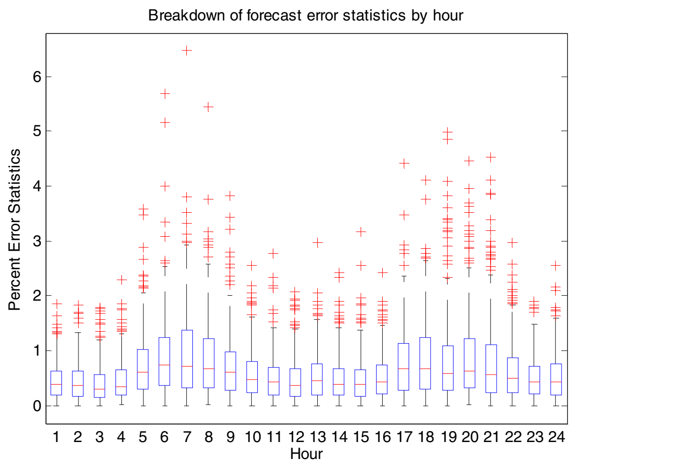


Fig. 7. Box-plot of the error distribution of forecasted load as a function of hour of the day for year 2014 using Levenberg-Marquardt algoritm.

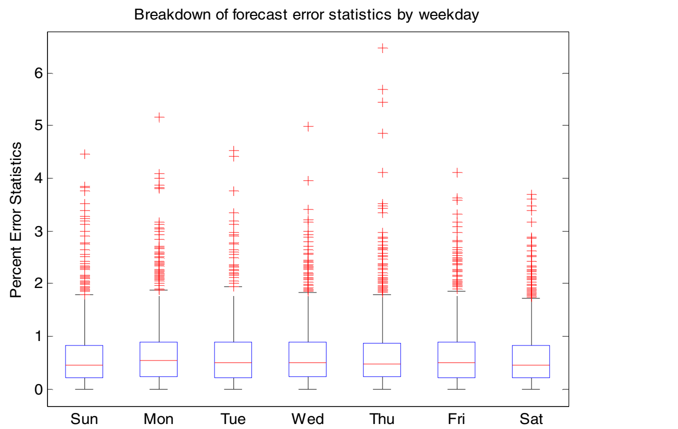


Fig. 8. Box-plot of the error distribution for the forecasted load as a function of day of the week in the year 2014 using Levenberg-Marquardt algoritm.

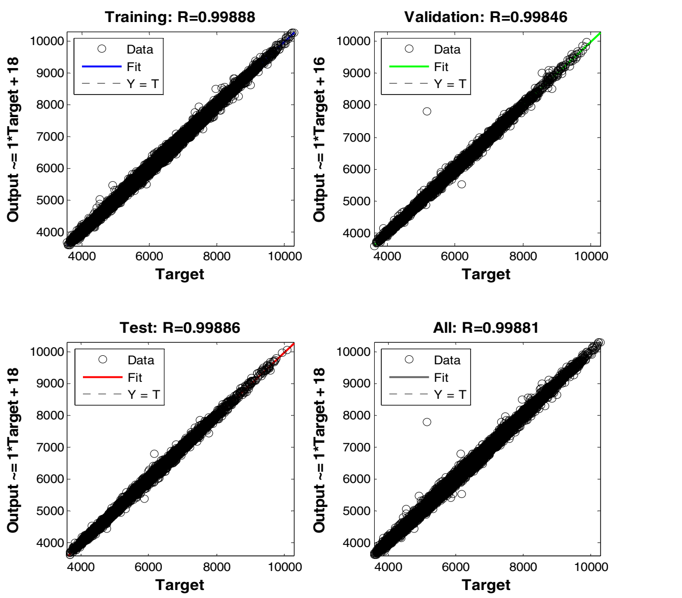


Fig. 9. Regression plot during training, testing & validation using Levenberg-Marquardt algoritm.

B. *Load Forecast Using Bayesian Regularization Algorithm*

The ANN model used in the forecasting is shown below in Fig. 10. It has input, output and one hidden layers. Hidden layer has 60 neurons. Inputs to the input layer are as listed above for load forecast. After simulation the average MAPE obtained is 0.62% for load forecasting of the year 2014.

The simulation results show that the highest & least error occurred with MAPE of 1.94% & 0.32% for day-ahead forecast of 29 January & 16 October, 2014 respectively. It is observed that maximum MAPE (0.72%) is for September, 2014 and minimum MAPE (0.52%) is for February, 2014.

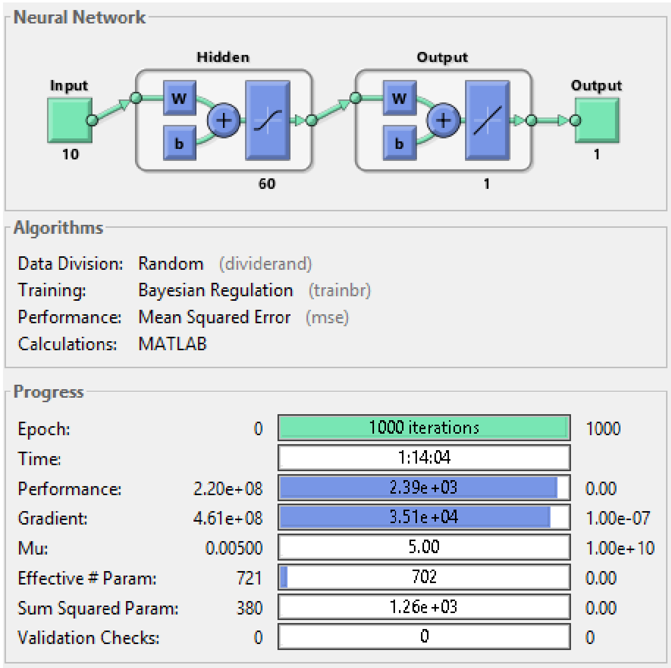


Fig. 10. Showing ten different input data for one target data with 60 neurons in hidden layer.

C. *Load Forecast Using Scaled Conjugate Gradient Algorithm*

The ANN model used in the forecasting is shown below in Fig. 11. It has input, output and one hidden layers. Hidden layer has 60 neurons. Inputs to the input layer are as listed above for load forecast. After simulation the average MAPE obtained is 96.77% for load forecasting for the year 2014. Therefore it must not be considered for forecasting the load & price.

The Mean Absolute Percentage Error (MAPE) between the forecasted and actual loads for sample of each day & month during one hour ahead forecast has been calculated and presented in the Table I-III respectively for the year 2014.

The author tried to perform the load forecasting with other available ANN algorithms using MATLAB, but it was found that the data set used was very large therefore it could not perform. It might perform by using other data sets which were small in size.

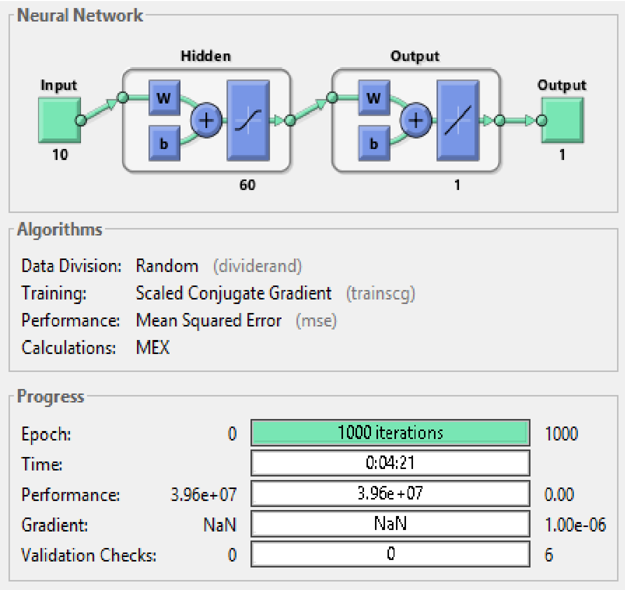


Fig. 11. Showing ten different input data for one target data with 60 neurons in hidden layer.

TABLE I

RESULTS FOR OUT-OF-SAMPLE DAILY TEST FROM JANUARY TO APRIL IN YEAR 2014

Day	MAPE (%) for Each Day of the Month in Year 2014 During One Hour-Ahead Load Forecast for Toronto, Canada Using Different ANN Algorithms							
	Levenberg-Marquardt				Bayesian Regularization			
	Jan.	**Feb.**	**Mar.**	**April**	**Jan.**	**Feb.**	**March**	**April**
1	0.74	0.44	0.58	0.56	0.78	0.4	0.56	0.6
2	0.69	0.43	0.48	0.71	0.83	0.42	0.6	0.72
3	0.82	0.39	0.54	0.75	0.57	0.5	0.57	0.73
4	0.68	0.54	0.49	0.71	0.64	0.45	0.5	0.68
5	0.52	0.68	0.58	0.76	0.49	0.61	0.6	0.88
6	0.62	0.37	0.57	0.67	0.66	0.4	0.6	0.58
7	0.72	0.32	0.59	0.57	0.76	0.47	0.62	0.6
8	0.49	0.34	0.5	0.62	0.59	0.33	0.5	0.59
9	0.53	0.31	0.68	0.54	0.54	0.45	0.75	0.55
10	0.69	0.45	0.76	0.67	0.65	0.45	0.85	0.63
11	0.59	**0.28**	0.57	0.49	0.51	0.37	0.56	0.55
12	0.56	0.58	0.85	0.52	0.6	0.48	0.68	0.52
13	0.66	0.5	0.83	0.6	0.66	0.51	0.81	0.54
14	0.41	0.4	0.56	0.61	0.44	0.4	0.61	0.67
15	0.67	0.4	0.9	0.94	0.65	0.49	0.65	0.91
16	0.43	0.51	0.67	0.69	0.36	0.42	0.75	0.61
17	0.61	0.48	0.67	0.55	0.61	0.56	0.73	0.58
18	0.58	0.59	0.66	1.08	0.49	0.63	0.58	1.24
19	0.37	0.67	0.52	0.58	0.41	0.65	0.49	0.63
20	0.88	0.57	0.64	0.54	0.65	0.53	0.68	0.47
21	0.56	0.63	0.53	0.56	0.46	0.58	0.6	0.55
22	0.49	0.57	0.56	0.73	0.41	0.55	0.5	0.72
23	0.51	0.7	0.74	0.53	0.61	0.64	0.73	0.51
24	0.6	0.69	0.69	0.43	0.57	0.69	0.61	0.45
25	0.63	0.54	0.74	0.7	0.47	0.55	0.66	0.77
26	0.48	0.49	0.66	0.85	0.41	0.66	0.68	0.83
27	0.6	0.66	0.6	0.83	0.53	0.82	0.62	0.69
28	**0.28**	0.47	0.73	0.45	0.38	0.56	0.69	0.56
29	0.41	----	0.59	0.62	**0.32**	-----	0.5	0.59
30	0.54	----	0.76	0.63	0.63	----	0.71	0.64
31	0.54	-----	0.77	------	0.52	----	0.76	----
Avg.	**0.58**	**0.5**	**0.65**	**0.65**	**0.55**	**0.52**	**0.64**	**0.65**

TABLE II

RESULTS FOR OUT-OF-SAMPLE DAILY TEST FROM MAY TO AUGUST IN YEAR 2014

Day	MAPE (%) for Each Day of the Month in Year 2014 During One Hour-Ahead Load Forecast for Toronto, Canada Using Different ANN Algorithms							
	Levenberg-Marquardt				Bayesian Regularization			
	May	**Jun.**	**July**	**Aug.**	**May**	**Jun.**	**July**	**Aug.**
1	0.6	0.6	1.03	0.58	0.62	0.58	1.36	0.61
2	0.53	0.67	0.83	0.43	0.59	0.66	0.81	0.56
3	0.88	0.62	0.82	0.58	0.78	0.55	0.77	0.73
4	0.94	0.71	0.77	1.26	0.83	0.61	0.94	0.95
5	0.53	0.55	0.66	0.73	0.5	0.57	0.49	0.74
6	0.9	0.82	0.82	0.4	0.93	0.76	0.77	0.38
7	0.53	0.54	0.75	0.41	0.57	0.67	0.75	0.44
8	0.55	0.74	0.98	0.44	0.56	0.62	1.05	0.4
9	0.65	0.5	0.47	0.42	0.7	0.44	0.54	0.33
10	0.62	0.49	0.55	0.49	0.54	0.6	0.54	0.53
11	0.68	0.72	0.88	0.63	0.5	0.76	0.88	0.72
12	0.51	0.72	0.47	-----	0.49	0.7	0.47	----
13	0.62	0.68	0.62	0.86	0.57	0.6	0.6	0.77
14	0.47	0.54	0.85	0.85	0.49	0.46	0.85	0.68
15	0.49	0.68	0.71	0.43	0.54	0.65	0.72	0.39
16	0.62	0.67	0.71	0.41	0.61	0.69	0.63	0.43
17	0.83	0.71	0.55	0.62	0.76	0.71	0.58	0.47
18	0.77	0.85	0.7	0.67	0.7	0.8	0.7	0.6
19	1.29	0.39	0.39	0.76	1.18	0.46	0.43	0.74
20	0.58	0.67	0.53	0.73	0.62	0.61	0.51	0.7
21	0.66	0.7	0.48	0.68	0.65	0.68	0.58	0.65
22	0.58	0.59	0.4	0.73	0.67	0.62	0.45	0.65
23	0.54	0.63	0.83	0.57	0.57	0.6	0.91	0.57
24	0.5	0.56	0.59	0.7	0.48	0.46	0.83	0.57
25	0.76	0.41	0.59	0.72	0.6	0.37	0.58	0.73
26	1.25	0.73	0.46	0.89	0.95	0.7	0.47	0.7
27	0.59	0.56	0.78	0.85	0.59	0.64	0.7	0.71
28	0.86	0.52	0.85	0.92	1.08	0.54	0.92	0.72
29	0.55	0.57	0.6	0.71	0.64	0.58	0.45	0.64
30	0.6	0.72	0.71	0.75	0.6	0.81	0.64	0.83
31	0.56	-----	0.63	0.88	0.55	----	0.62	0.67
Avg.	**0.68**	**0.63**	**0.68**	**0.67**	**0.66**	**0.62**	**0.69**	**0.62**

TABLE III

RESULTS FOR OUT-OF-SAMPLE DAILY TEST FROM SEPTEMBER TO DECEMBER IN YEAR 2014

Day	MAPE (%) for Each Day of the Month in Year 2014 During One Hour-Ahead Load Forecast for Toronto, Canada Using Different ANN Algorithms							
	Levenberg-Marquardt				Bayesian Regularization			
	Sep.	**Oct.**	**Nov.**	**Dec.**	**Sep.**	**Oct.**	**Nov.**	**Dec.**
1	0.94	0.58	0.54	0.51	1.16	0.62	0.44	0.57
2	1.01	0.7	0.4	0.6	0.91	0.68	0.48	0.58
3	0.64	0.72	0.79	0.61	0.61	0.63	0.76	0.57
4	0.75	0.61	0.64	0.58	0.73	0.62	0.58	0.46
5	0.82	0.51	0.8	0.63	1.03	0.51	0.79	0.59
6	0.82	0.67	0.57	0.52	1	0.55	0.59	0.43
7	0.91	0.57	0.45	0.48	0.85	0.52	0.49	0.5
8	0.6	0.63	0.44	0.62	0.67	0.56	0.46	0.57
9	0.67	0.63	0.53	0.43	0.67	0.57	0.54	0.42
10	0.69	0.6	0.7	0.51	0.7	0.58	0.58	0.5
11	0.96	0.36	0.67	0.59	0.95	0.4	0.7	0.6
12	0.67	0.71	0.66	0.38	0.7	0.62	0.71	0.48
13	0.58	0.98	0.43	0.53	0.58	1	0.43	0.45
14	0.56	0.85	0.55	0.37	0.52	0.74	0.57	0.43
15	0.61	0.59	0.57	0.41	0.64	0.58	0.61	0.44
16	0.54	**1.83**	0.42	0.51	0.54	**1.94**	0.42	0.49
17	0.5	0.8	0.51	0.6	0.53	0.76	0.5	0.59

18	0.66	0.49	0.46	0.53	0.65	0.52	0.41	0.44
19	0.59	0.46	0.45	0.41	0.57	0.5	0.41	0.34
20	0.71	0.58	0.33	0.36	0.74	0.48	0.34	0.35
21	0.69	0.49	0.44	0.56	0.77	0.48	0.45	0.54
22	0.72	0.69	0.53	0.46	0.77	0.64	0.55	0.52
23	0.69	0.6	0.68	0.54	0.58	0.53	0.69	0.51
24	0.75	0.68	0.69	1.43	0.71	0.56	0.66	1.5
25	0.62	0.76	0.61	1.08	0.59	0.71	0.61	1.09
26	0.71	0.51	0.38	1.27	0.63	0.57	0.44	0.9
27	0.79	0.7	0.89	0.79	0.7	0.72	0.75	0.84
28	0.83	0.78	0.67	0.55	0.69	0.64	0.6	0.49
29	0.75	0.72	0.61	0.73	0.75	0.74	0.66	0.58
30	0.7	0.61	0.49	0.42	0.61	0.57	0.47	0.49
31	---	0.64	------	0.93	-----	0.63	-----	0.95
Avg.	**0.72**	**0.68**	**0.56**	**0.61**	**0.72**	**0.65**	**0.56**	**0.59**

V. CONCLUSION AND FUTURE WORK

This paper presents the short term load forecasting of electricity of Toronto, Canada. Here ANN algorithms (Levenberg Marquardt back propagation & Bayesian Regularization) are used for this purpose and to have a highly efficient, accurate and reliable forecast. The average MAPE during testing by Levenberg Marquardt back propagation, Bayesian Regularization & Scaled Conjugate Gradient were 0.63%, 0.62% & 96.77% respectively. The MAPE found was much lesser than expected when used by Levenberg Marquardt back propagation & Bayesian Regularization algorithms but a high error was occurred when Scaled Conjugate Gradient algorithm was used. So, it must not be used for STLF. In future, effects of weather parameters like humidity, precipitation, and wind velocity on short-term load forecasting may be worked out. Also a hybrid ANN model must made for enhancing the forecasting capabilities.

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