Short-Term Load Forecasting of Ontario Electricity Market by Considering the Effect of Temperature

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***Abstract*—Short-term load forecasting is an essential instrument in power system planning, operation, and control. Many operating decisions are based on load forecasts, such as dispatch scheduling of generating capacity, reliability analysis, and maintenance planning for the generators. This paper discusses significant role of artificial intelligence (AI) in short-term load forecasting (STLF), that is, the day-ahead hourly forecast of the power system load. A new artificial neural network (ANN) has been designed to compute the forecasted load. The data used in the modeling of ANN are hourly historical data of the temperature and electricity load. The ANN model is trained on hourly data from Ontario Electricity Market from 2007 to 2011 and tested on out-of-sample data from 2012. Simulation results obtained have shown that day-ahead hourly forecasts of load using proposed ANN is very accurate with very less error. However load forecast considering the effect of temperature is better than without taking it as input parameter.**

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

I. INTRODUCTION

With an introduction of deregulation in power industry, many challenges have been faced by the participants of the electricity market. Forecasting electricity parameters such as load and energy price have become a major issue in power systems [1]. The fundamental objective of electric power industry deregulation is to maximize efficient generation and consumption of electricity, and reduction in energy prices. To achieve these goals, accurate and efficient electricity load forecasting is becoming more and more important [2]-[3].

Load forecasting is categorized as short-term, medium-term, and long-term forecasts, depending on the time scale. The forecasting of hourly-integrated load carried out for one day to week ahead is usually referred to as short-term load forecasting. Short-term load forecasting plays an important role in power systems since the improvement of forecasting accuracy results in the reduction of operating costs and the reliable power system operations [4].

The load at a given hour is dependent not only on previous loads but also on much important weather related variables. Effective integration of various factors into the forecasting model may provide accurate load forecasts for modern power industries.

Various techniques have been developed for electricity demand forecasting during the past few years. Several research works have been carried out on the application of artificial intelligence (AI) techniques to the load forecasting problem as AI tools have performed better than conventional methods in short-term load forecasting. Various AI techniques reported in literatures are expert systems, fuzzy inference, fuzzy-neural models, neural network (NN). Among the different techniques on load forecasting, application of NN technology for load forecasting in power system has received much attention in recent years [5]-[12]. The main reason of NN becoming so popular lies in its ability to learn complex and nonlinear relationships that are difficult to model with conventional techniques [9].

This paper discusses significant role of artificial intelligence in day-ahead load forecasting, that is, the hourly forecast of the power system load over day, week & month. In this paper, artificial neural network designed using MATLAB R13 has been used to compute the day-ahead hourly load forecast in Ontario Electricity Market. Both the hourly temperature and hourly electricity load historical data have been used in forecasting. The temperature variable is included in forecasting of load because temperature has a high degree of correlation with electricity load. The neural network models are trained on hourly data from 2007 to 2011 and tested on out-of-sample data from 2012. The simulation results obtained have shown that artificial neural network (ANN) is able to make very accurate short-term load forecast with average errors around 1%-3.80%.

This 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 day-ahead forecast. Results of simulation are presented and discussed in Section IV. Section V discusses the conclusion and future work.

II. ARTIFICIAL NEURAL NETWORK FOR LOAD FORECASTING

Neural networks are composed of simple elements called neuron, operating in parallel. A neuron is an information

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processing unit that is fundamental to the operation of a neural network. The three basic elements of the neuron model are (i) set of weights, (ii) an adder for summing the input signals and (iii) activation function for limiting the amplitude of the output of a neuron [13]. A neural network can be trained to perform a particular function by adjusting the values of the connections (weights) between elements. In loads forecasting, typically, many input/ target pairs are needed to train a neural network. Neural network is mapped between data set of numeric inputs and a set of numeric targets. The neural network consists of two-layer feed-forward network with sigmoid hidden neurons and linear output neurons. It can fit multi-dimensional mapping problems arbitrarily well, given consistent data and enough neurons in its hidden layer. The neural network is trained with Levenberg-marquardt back propagation algorithm [14].

III. DATA INPUTS AND ANN MODEL

The models are trained on hourly data of Ontario Electricity Market from 2007 to 2011 and tested on out-of-sample data from 2012. The data used in the ANN model are both the temperature and electricity load hourly historical data. The temperature variable is included because temperature has a close relationship with electricity load. The relationship between demand and average temperature is shown in Fig. 1, where a nonlinear relationship between load and temperature can be observed. For the load forecast, the input parameters include

- Dry bulb temperature
- Dew point temperature
- Hour of day
- Day of the week
- Holiday/weekend indicator (0 or 1)
- Previous 24-hr average load
- 24-hr lagged load
- 168-hr (previous week) lagged load

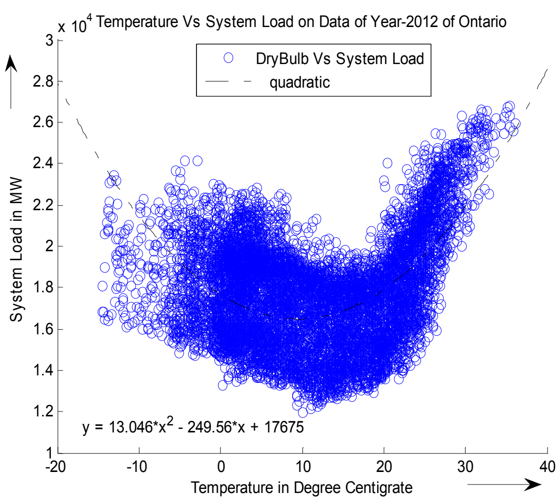

Fig. 1. Scatter plot of system load vs. temperature with fitting equation.

IV. SIMULATION AND RESULTS

In this paper hourly day-ahead load forecasting has been done for sample of each day, week & month of data of year 2012 using neural network tool box of MATLAB R13a. The ANNs are trained with data from 2007 to 2011 and tested on out-of-sample data from 2012. 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 day ahead hourly actual and forecasted load for every weeks for the year 2012 are also generated. Simulation results of Ontario Electricity Market are discussed below.

A. For Ontario Electricity Market Without Considering Temperature Effect

The ANN model used in the forecasting has input, output and one hidden layers. Hidden layer has 60 neurons. Inputs to the input layer are as listed above for load forecast without considering temperature data. After simulation the MAPE obtained is 2.91% for load forecasting for the year 2012.

Multiple series plots between actual load & forecasted load from 06-12 May, 2012 & from 05-11 August, 2012 and also plots of MAPE with maximum error (4.87%) and minimum error (1.68%) for day ahead hourly weekly forecast in year 2012 have been shown in Fig. 2 and Fig. 3. The simulation results show that the highest & least error occurred with MAPE of 9.98% & 1.09% for day-ahead forecast of 06 August & 23 October, 2012 respectively.

The box-plot of the error distribution of forecasted load as a function of hour of the day is presented in Fig. 4. It shows the percentage error statistics of hour of the day in year 2012. It is also evident that the maximum error is for the 6th hour of the day and minimum error for 21st hour of the day in year 2012. The box-plot of the error distribution of forecasted load as a function of day of the week is evaluated in Fig. 5 which shows the percentage error statistics of day of the week in year 2012. The maximum error is for the Monday and minimum error for Friday in year 2012.

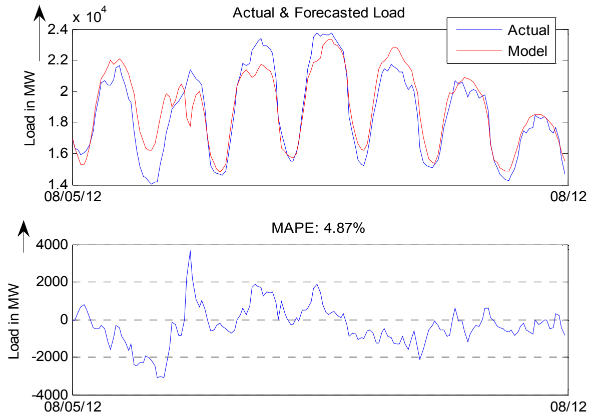

Fig. 2. MAPE is maximum (4.87 %) for the forecast of 05-11 August, 2012 for day ahead hourly weekly forecast.

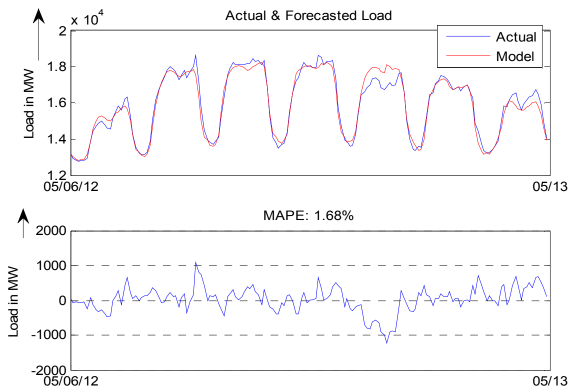

Fig. 3. MAPE is minimum (1.68%) for the forecast of 06-12 May, 2012 for day ahead hourly weekly forecast in the year 2012.

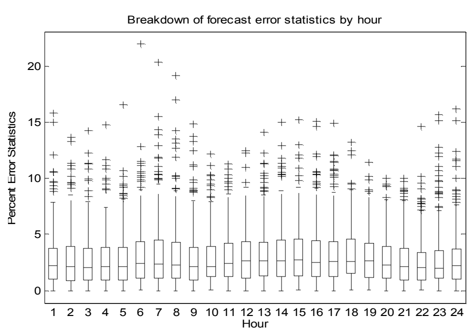

Fig. 4. Error distribution of forecasted load as a function of hour of the day in year-2012 for Ontario electricity market without temperature data as input.

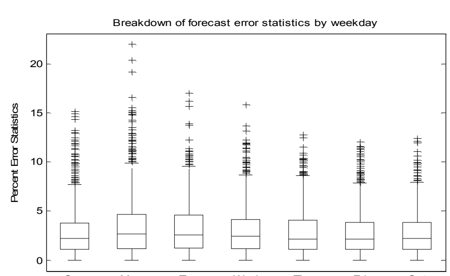

Fig. 5. Error distribution for the forecasted load as a function of day of the week in year-2012 for Ontario market without temperature data as input.

B. For Ontario Electricity Market With Considering Temperature Effect

The ANN model used in the forecasting has input, output and one hidden layers. Hidden layer has 60 neurons. Inputs to the input layer as listed above for load forecast by taking temperature data as input variable. After simulation the MAPE obtained is 2.38% for load forecasting of year-2012 as shown in Fig. 6.

Multiple series plots between actual load & forecasted load from 06-12 May, 2012 & from 05-11 August, 2012 and also plots of MAPE with maximum error (3.83%) and minimum error (1.54%) for day ahead hourly weekly forecast in year 2012 have been shown in Fig. 7 and Fig. 8. It has been observed that the maximum & minimum error occurred with MAPE of 8.16% & 0.85% for day-ahead forecast of 06 August & 03 February, 2012 respectively. Multiple series plots between actual load & forecasted load for 03 February, 2012 and also plots of MAPE with minimum error (0.85%) for day-ahead forecast in year 2012 have been shown in Fig. 9.

The box-plot of the error distribution of forecasted load as a function of hour of the day is presented in Fig. 10. It shows the percentage error statistics of hour of the day in year 2012. It is also evident that the maximum error is for the 6^{th} hour of the day and minimum error for 19^{th} hour of the day in year 2012. The box-plot of the error distribution of forecasted load as a function of day of the week is evaluated in Fig. 11 which shows the percentage error statistics of day of the week in year 2012. The maximum error is for the Monday and minimum error for Friday in year 2012.

The Mean Absolute Percentage Error (MAPE) & Mean Absolute Error (MAE) between the forecasted and actual loads for each week & month has been calculated and presented in the Table I & Table II respectively for the year 2012. Result for daily MAPE for day ahead hourly forecast from January-December, 2012 is discussed in Table III,IV & V. From the results in Table I-V it is observed that MAPE with temperature data is much better than MAPE without considering temperature as input. This indicates that temperature data is a very important parameter for load forecasting using ANN. From the results obtained from Table II, it is clear that maximum MAPE (3.83%) is for July, 2012 and minimum MAPE (2.23%) is for November, 2012 without considering the effect of temperature for Ontario electricity market. Also, it is clear that maximum MAPE (2.78%) is for July, 2012 and minimum MAPE (2.05%) is for February, 2012 for Ontario market with temperature data as input variable.

Simulation result of day-ahead load forecast of 26 January, 2012 with temperature data as input variable to ANN is shown in Fig. 12 & the MAPE is 1.20%.

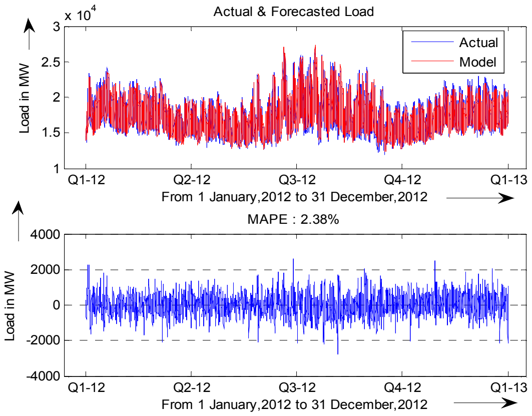

Fig. 6. Multiple series plot between actual load & forecasted load by ANN in year 2012 with temperature as input for Ontario electricity market.

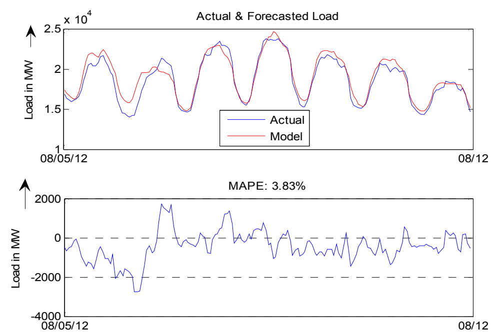

Fig. 7. MAPE is maximum (3.83 %) for the forecast of 05-11 August, 2012 for day ahead hourly weekly forecast.

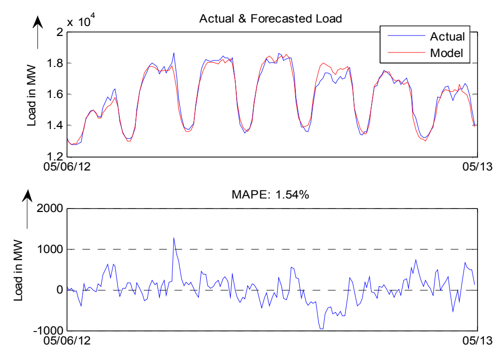

Fig. 8. MAPE is minimum (1.54%) for the forecast of 06-12 May, 2012 for day ahead hourly weekly forecast in the year 2012.

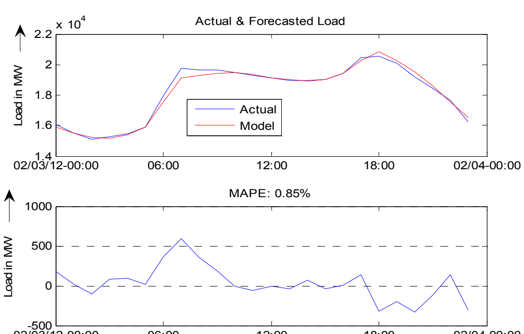

Fig. 9. MAPE is minimum (0.85%) for the forecast of 03 February, 2012 for day ahead hourly forecast in the year 2012.

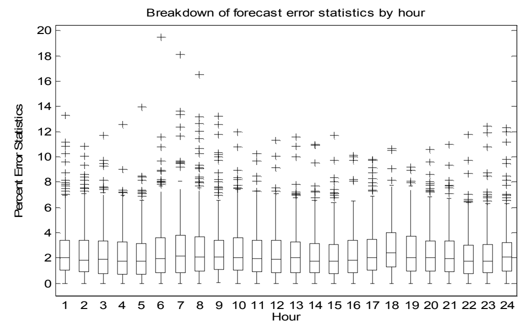

Fig. 10. Error distribution of forecasted load as a function of hour of the day in year-2012 of Ontario market with temperature data as input to ANN.

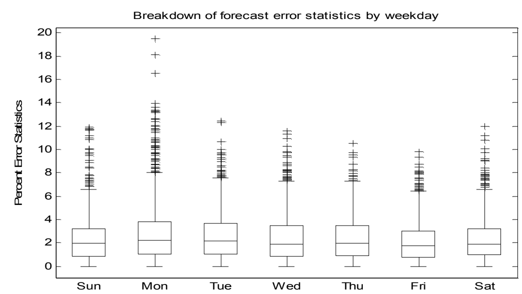

Fig. 11. Error distribution for forecasted load as a function of day of the week in year-2012 for Ontario market with temperature data as input to ANN.

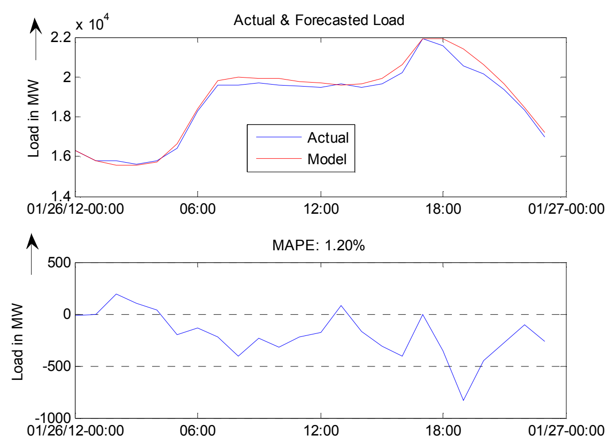

Fig. 12. Day-ahead hourly load forecast of 26 January, 2012 with temperature parameter as input.

TABLE I
RESULTS FOR OUT-OF-SAMPLE TEST FOR YEAR 2012

S. N.	Duration (Year 2012) mm/dd - mm/dd	Without Temperature data		With Temperature data	
		MAPE (%)	MAE (MW)	MAPE (%)	MAE (MW)
1	01/01-01/07	3.97	733.84	2.96	540.2
2	01/08-01/14	2.48	466.22	1.8	342.26
3	01/15-01/21	2.83	553.77	2.1	411.57
4	01/22-01/28	2.04	375.7	1.75	316.5
5	01/29-02/04	2.44	439.09	1.87	328.37

6	02/05-02/11	2.92	552.34	1.89	359.91
7	02/12-02/18	2.79	513.81	2.25	413.02
8	02/19-02/25	3.14	570.96	2.21	399.15
9	02/26-03/03	2.57	475.49	2.18	397.25
10	03/04-03/10	3.36	610.92	2.42	441.33
11	03/11-03/17	2.72	448.39	2.75	451.5
12	03/18-03/24	2.69	426.87	2.89	467.96
13	03/25-03/31	2.49	426.55	2.11	359.75
14	04/01-04/07	2.74	468.34	2.14	361.16
15	04/08-04/14	2.26	385.52	2.22	378.52
16	04/15-04/21	2.41	400.15	2.56	434.41
17	04/22-04/28	2.49	429.58	2.36	401.09
18	04/29-05/05	2.19	345.81	2.08	330.35
19	05/06-05/12	**1.68(min.)**	271.14	**1.54(min.)**	249.12
20	05/13-05/19	2.54	426.17	2.3	381.01
21	05/20-05/26	3.09	547.48	1.96	330.22
22	05/27-06/02	3.93	692.9	3.04	532.95
23	06/03-06/09	2.41	415.03	1.93	321.4
24	06/10-06/16	4.33	795.98	3.06	551.08
25	06/17-06/23	4.07	838.2	2.19	435.4
26	06/24-06/30	3.5	675.87	2.83	542.79
27	07/01-07/07	3.57	741.41	2.55	512.19
28	07/08-07/14	3.08	592.61	2.8	552.78
29	07/15-07/21	4.45	866.46	2.9	550.01
30	07/22-07/28	4.09	813.74	2.88	561.02
31	07/29-08/04	3.45	701.21	2.53	488.58
32	08/05-08/11	**4.87 (max.)**	890.64	**3.83 (max.)**	690.72
33	08/12-08/18	3.13	569.49	2.17	385.39
34	08/19-08/25	2.82	542.74	2.02	369.53
35	08/26-09/01	3.92	740.82	2.91	534.1
36	09/02-09/08	3.5	603.63	3.11	534.05
37	09/09-09/15	4.34	691.02	3.67	560.46
38	09/16-09/22	2.22	361.39	2.05	330.51
39	09/23-09/29	2.21	354.29	2.29	370.79
40	09/30-10/06	1.89	304.71	1.9	307.52
41	10/07-10/13	2.99	482.02	2.73	437.82
42	10/14-10/20	2.14	360.67	1.83	307.51
43	10/21-10/27	1.81	299.55	1.98	329.1
44	10/28-11/03	2.38	411.03	2.27	396.97
45	11/04-11/10	2.12	394.9	2.18	407.69
46	11/11-11/17	1.94	351.72	2.22	405.67
47	11/18-11/24	2.2	394.36	2.03	364.55
48	11/25-12/01	2.82	532.86	2.3	438.33
49	12/02-12/08	2.33	425.96	2.24	408.36
50	12/09-12/15	2.69	503.46	2.12	401.76
51	12/16-12/22	2.68	497.49	2.33	431.3
52	12/23-12/29	3.9	684.51	2.83	496.91
53	**Average**	**2.91**	**526.90**	**2.38**	**424.07**

TABLE II

RESULTS FOR OUT-OF-SAMPLE MONTHLY TEST IN YEAR 2012

S. N.	Month	Without Temperature data		With Temperature data	
		MAPE (%)	MAE (MW)	MAPE (%)	MAE (MW)
1	January	2.86	536.31	2.17	402.98
2	**February**	2.76	511.52	**2.05 (min.)**	378.46
3	March	2.8	475.71	2.53	427.28
4	April	2.49	420.3	2.31	388.86
5	May	2.67	459.01	2.17	365.78
6	June	3.48	658.69	2.49	458.32
7	**July**	**3.83 (max.)**	759.45	**2.78 (max.)**	543.91
8	August	3.65	691.38	2.68	488.92
9	September	3.03	496.01	2.72	440.28
10	October	2.25	371.85	2.2	365.2
11	**November**	**2.23 (min.)**	409.26	2.11	388.85
12	December	2.99	543.41	2.48	452.62

TABLE III

RESULTS FOR OUT-OF-SAMPLE DAILY TEST FROM JANUARY TO APRIL IN YEAR 2012

Day	MAPE (%) In Different Months of Year 2012							
	Without Temperature data				With Temperature data			
	Jan.	Feb.	Mar.	April	Jan.	Feb.	March	April
1	2.24	1.82	1.75	3.35	2.33	1.17	1.45	2.76
2	5.47	1.8	2.57	3.48	3.39	1.45	2.14	1.46
3	8.16	1.28	2.08	1.59	4.5	**0.85**	2.15	1.6
4	2.72	1.87	2.36	3.03	1.94	2.02	1.56	2.27
5	3.85	1.41	4.52	2.78	3.58	0.94	1.91	2.48
6	2.35	2.26	2.49	2.37	2.46	1.87	1.58	1.29
7	3	3.21	5.87	2.55	2.53	2.02	5.59	3.09
8	2.89	3.69	2.71	2.29	1.9	2.67	2.03	2.52
9	1.86	3.15	2.39	2.05	1.66	2.19	2.02	2.1
10	3.43	3.12	3.16	2.41	2.46	2.11	2.28	2.8
11	1.7	3.63	5.09	2.44	1.49	1.45	5.32	1.46
12	1.48	3.52	2.13	2.83	1.4	2.15	2.04	2.51
13	2.86	4	4.98	1.95	2.38	3.12	4.01	1.96
14	3.11	3.28	1.33	1.84	1.34	3.48	1.17	2.19
15	3.09	2.88	1.54	3.04	1.93	2.46	1.21	2.55
16	4	1.86	1.42	2.39	2.89	1.95	2.48	3.53
17	3.86	2.46	2.58	2.19	2.7	1.33	3.01	2.78
18	2.67	1.56	2.12	2.12	1.37	1.26	2.42	1.85
19	3.03	2.17	3.58	1.85	2.49	1.32	3.91	1.79
20	1.77	6.04	2.32	1.58	1.58	3.67	2.07	1.83
21	1.39	2.71	3.36	3.68	1.74	2.82	3.51	3.61
22	2.73	2.58	2.35	2.58	1.66	1.71	3.17	2.26
23	2.41	1.95	3.17	2.25	2.2	1.84	2.54	2.34
24	1.86	3.87	1.91	2.47	1.5	2.94	2.61	2.12
25	2.12	2.7	2.46	3.84	1.64	1.16	2.32	3.39
26	1.55	2.85	3.17	2.66	1.2	1.64	2.02	3.08
27	2.2	2.7	2.54	1.65	2.41	2.25	2.5	1.43
28	1.39	2.38	1.73	1.97	1.65	2.04	1.35	1.87
29	3.56	3.65	2.32	3.43	1.92	3.56	2.14	2.93
30	2.91	----	2.37	2.07	2.23	-----	1.89	1.88
31	3.83	-----	2.81	-----	3.42	------	2.53	-----

TABLE IV

RESULTS FOR OUT-OF-SAMPLE DAILY TEST FROM MAY TO AUGUST IN YEAR 2012

Day	MAPE (%) In Different Months of Year 2012							
	Without Temperature data				With Temperature data			
	May	Jun.	July	Aug.	May	Jun.	July	Aug.
1	2.96	2.73	2.1	3.86	2.26	2.29	2.76	3.38
2	1.45	2.25	5.08	4.15	1.74	2.11	4.54	2.31
3	1.31	1.25	4.14	2.61	1.37	1.25	2.16	2.17
4	1.56	1.86	3.68	3.16	2.24	1.86	2.14	2.15
5	2.55	2.89	1.68	5.35	2.15	2.02	1.32	5.31
6	1.65	3.29	3.78	**9.98**	1.27	1.77	1.44	**8.16**
7	1.63	3.11	4.55	4.25	1.48	2.28	3.53	2.17
8	1.29	2.66	4.72	2.7	1.13	1.79	3.17	1.8
9	1.43	1.8	2.39	5.96	1.25	2.54	3	3.69
10	2.85	6.96	2.61	3.12	2.74	3.9	2.28	3.14
11	1.09	2.72	2.54	2.7	1.19	1.48	3.05	2.52
12	1.83	4.61	4	1.61	1.74	3.95	3.04	1.23
13	2.09	5.23	2.63	3.08	2.29	3.86	2.35	1.27
14	2.7	2.91	2.67	3.1	3.03	2.65	2.69	2.33
15	2.33	5.79	2.11	3.42	1.25	4.27	3.05	2.75
16	3.67	2.08	4.41	3.84	2.45	1.28	1.86	2.46
17	2.11	1.97	3.32	3.01	3.01	2.23	2.73	2.32
18	2.53	3.48	4.18	3.83	2.59	2.11	2.54	2.81

19	2.36	6.02	6.87	1.33	1.47	2.5	3.49	2.01
20	1.92	5.08	5.82	2.41	0.95	2.83	3.49	1.11
21	4.33	3.86	4.47	2.47	3.69	1.29	3.09	2
22	1.83	5.24	7.1	3.05	1.67	2.39	3.05	1.45
23	2.04	2.84	4.49	4.02	1.7	2	1.81	2.29
24	5.04	1.55	6.26	3.26	2.76	1.66	5.14	2.31
25	3.79	4.36	5.64	3.17	1.41	3.03	4.6	2.93
26	2.68	4.27	1.22	3.54	1.56	4.24	1.98	3.03
27	2.4	2.14	2.19	2.39	1.86	3.14	1.79	2.35
28	6.53	5.27	1.7	4.01	4.36	3.73	1.77	2.53
29	4.8	3.86	2.6	4.96	4.74	1.82	2.18	5.08
30	5.58	3.04	4.16	4.7	3.26	2.19	2.65	2.89
31	3.2	-----	3.62	4.45	2.65	-----	2.86	1.69

TABLE V

RESULTS FOR OUT-OF-SAMPLE DAILY TEST FROM SEPTEMBER TO DECEMBER IN YEAR 2012

Day	MAPE (%) In Different Months of Year 2012							
	Without Temperature data				With Temperature data			
	Sep.	Oct.	Nov.	Dec.	Sep.	Oct.	Nov.	Dec.
1	3.38	2.36	2.77	3.86	2.79	2.25	2.2	3.28
2	3.66	2.43	1.74	1.48	3.14	2.34	1.49	1.51
3	4.93	1.92	2.41	2.78	4.39	1.61	1.82	2.64
4	2.85	1.47	1.12	1.71	2.52	2.37	1.59	2.13
5	3.27	1.78	2.95	3.33	2.02	1.79	3.29	2.74
6	2.01	1.61	2.32	2.45	2.76	1.76	2.85	1.9
7	3.63	2.21	2.94	2.17	3.38	1.86	2.11	2.91
8	4.18	4.95	1.87	2.44	3.58	4.55	1.51	1.88
9	5.79	3.25	1.65	3.25	4.99	3.04	2.18	2.53
10	2.75	2.72	1.97	3.21	2.71	2.24	1.7	2.88
11	4.19	1.53	1.92	2.89	4.11	1.66	2.93	1.93
12	4.8	2.19	1.79	2.48	3.27	1.83	2.81	1.86
13	4.1	4.06	2.17	3.13	3.18	3.87	2.24	2.64
14	3.8	2.11	1.61	2.05	2.73	1.75	1.87	1.86
15	4.94	4.43	2.39	1.82	4.69	3.28	1.99	1.17
16	2.92	1.74	1.5	1.84	2.22	1.46	1.76	1.64
17	2.63	1.4	2.19	3.66	2.24	1.46	1.95	4.22
18	2.04	1.52	1.39	2.68	1.68	1.55	1.48	2.23
19	2.01	2.06	1.7	3.03	1.94	1.87	1.54	2.5
20	1.82	1.73	2.04	2.05	2.03	1.41	1.75	2.18
21	2.15	2.68	2.47	2.48	1.63	2.59	2.08	1.55
22	1.96	1.36	1.48	3	2.59	1.56	1.81	1.96
23	2.56	**1.09**	2.51	2.59	1.86	1.51	2.39	1.88
24	1.56	1.97	3.82	6.62	1.54	1.83	3.19	6.99
25	3.63	1.57	1.95	4.78	3.96	2	1.54	1.87
26	1.55	2.11	2.33	4.37	1.76	2.1	1.83	3.29
27	2.44	1.9	2.6	3.8	3.18	2.25	2.47	2.74
28	1.56	2.96	2.24	2.33	1.66	2.78	1.64	1.56
29	2.17	2.99	2.73	2.78	2.03	3.68	2.22	1.5
30	1.64	2.52	4.02	2.23	1.22	2.58	3.14	2.02
31	-----	1.29	-----	5.32	-----	1.32	-----	4.76

V. CONCLUSION AND FUTURE WORK

This paper presents an ANN model for day-ahead short-term electricity loads forecasting in Ontario Electricity market with & without considering temperature effect. Its forecasting reliabilities were evaluated by computing the MAPE between the exact and predicted electricity load values. We were able to obtain an MAPE 2.91% without temperature data & MAPE 2.38% with temperature data in the testing year-2012. The results suggest that ANN model with the developed structure can perform well in day ahead load forecasting with least possible error. It has been observed that temperature plays an important role in electricity load forecasting. In future effect of other weather parameters like humidity, precipitation, and wind velocity on short-term load forecasting may be worked out.

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