Performance Evaluation of New and Advanced Neural Networks for Short Term Load Forecasting

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Abstract— **Electric power systems are huge real time energy networks where accurate short term load forecasting (STLF) plays an essential role. This paper is an effort to comprehensively investigate new and advanced neural network (NN) architectures to perform STLF. Two hybrid and two 3-layered NN architectures are introduced. Each network is individually tested to generate weekday and weekend forecasts using data of Nova Scotia, Canada. Overall findings suggest that 3-layered cascaded NN have outperformed almost all others for weekday forecasts. For weekend forecasts 3-layered feed forward NN produced most accurate results. Recurrent and hybrid networks performed well during peak hours but due to occurrence of constant high error spikes were not able to achieve high accuracy.**

Keywords—Short term load forecast; artificial neural networks; Cascaded neural networks; Recurrent Neural Networks; Hybrid architecture

I. INTRODUCTION

Short term load forecasting is one of the most crucial functions of a utility power system. With negligible storage of energy in the system, the operation of an electric power system becomes a challenging task. All the involved entities in a power system perform load forecasting on a continuous basis in order to operate efficiently in today's deregulated market. Both increment and reduction in forecasting accuracy result in uneconomic operation. Hodge in [1] studied the implications of both positive and negative load forecasting error and concluded that errors on either side may result in high operating costs. Moreover, Hobbs in [2] quantified the relationship between forecasting error and operating costs by showing that a 1% reduction in forecasting error of 10 GW utility results in an annual savings of US $ 1.6 million.

STLF methods are classified into two main types; conventional or classical and computational or artificial intelligence techniques. The standalone classical methods are insufficient to fulfill the needs of efficient economic operation in today's deregulated market. Among artificial intelligence methods ANNs has been researched for almost the last three decades [3]. The Cascaded NN (CNN) and Recurrent NN (RNN) have not been given much attention recently. Though some studies do test these networks in [4 – 9] but a thorough model does not appear to have been developed to take advantage of all benefits that might be achieved as a result of using these advanced architectures.

This paper presents the results of work to comprehensively investigate CNNs and RNNs to perform STLF and explore their advantages and disadvantages Hybrid network architectures combining CNN and RNN are introduced. In this architecture inputs are cascaded in each layer as well as local and global feedback loops are also used. Furthermore, two 3-layered versions of FFNN and CNN are also demonstrated to produce good forecasts. A total of eight architectures are individually tested and their results are compared with each other. Case study data of Nova Scotia, Canada is used to test the performance of networks under study on real data.

Following this introduction, an overview of the ANN architectures used in this paper is presented in section II. In section III the implementation of ANN architectures to perform STLF is discussed. Section IV contains results and discussion followed by conclusions in section V.

II. OVERVIEW OF ANN ARCHITECTURES

There are eight ANN architectures used to perform STLF in this paper. The most commonly used Feed Forward NN (FFNN) is shown in Fig. 1. It contains one hidden and one output layer. The Cascaded NN (CNN) is shown in Fig. 2 which has the same basic architecture as FFNN with the input cascaded to the output layer. Two recurrent networks, the recurrent NN with local feedback (RNNL) shown in Fig. 3 and recurrent NN with global feedback (RNNG) is shown in Fig. 4. Both recurrent network architectures also have the same network parameters as that of FFNN, the RNNL has a feedback path from hidden layer to the input layer, whereas the RNNG has a feedback path from output layer to input layer.

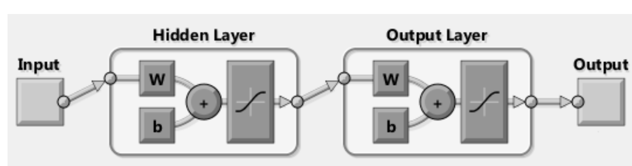

Fig. 1. Feedforward Neural Network

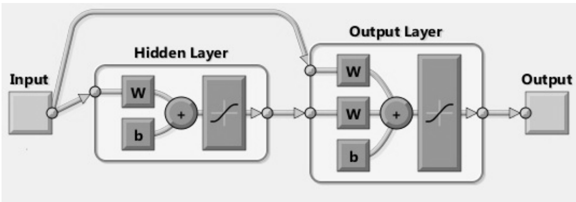

Fig. 2. Cascaded Neural Network

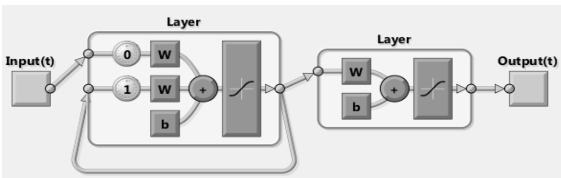

Fig. 3. Recurrent Neural Network with Local feedback

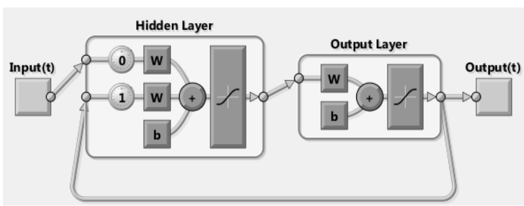

Fig. 4. Recurrent Neural Network with Global feedback

Moreover, two hybrid network architectures: Cascaded Recurrent NN with Local feedback (CRNNL) and Cascaded Recurrent NN with Global feedback (CRNNG) are shown in Fig. 5 and Fig. 6. These networks combine features from CNN and recurrent networks. Also two 3-layered versions of FFNN and CNN are also presented in Fig. 7 and Fig. 8. In the 3-layered CNN architecture the all the inputs and the outputs of each hidden layer is cascaded to the next layer.

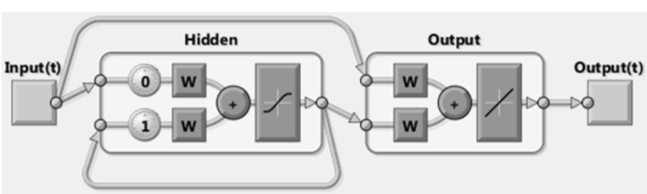

Fig. 5. Cascaded Recurrent Neural Network with Local feedback

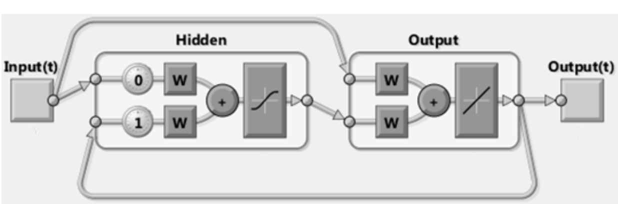

Fig. 6. Cascaded Recurrent Neural Network with Global feedback

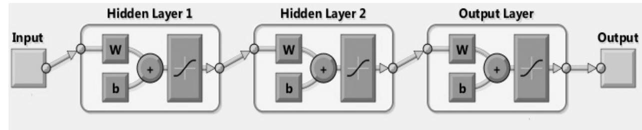

Fig. 7. 3-layered Feedforward Neural Network

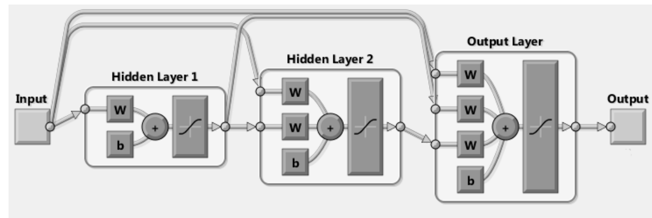

Fig. 8. 3-layered Cascaded Neural Network

III. IMPLEMENTATION OF ANN FOR STLF

To implement ANN to perform STLF, the load and temperature data of the Maritime Canadian province, Nova Scotia was taken as a case study. The load data between June 1 and August 30, 2013 was collected through utility company website, Nova Scotia Power Oasis database [10]. Temperature was selected as exogenous variable as it is the most influential of all meteorological parameters. Temperature data was downloaded from Government of Canada Climate Database [11]. After gathering all data the following procedures were followed to achieve forecasts.

1) Statistical Analysis and selection of Input parameters

In order to study load response and factors affecting it a statistical analysis was performed after gathering the data. The last week of August from August 24 to 30, 2013 was selected for forecasting. The remaining data points from June 1 to August 23 were selected for training. Data of four weeks prior to the forecasting week was given preference for input selection. To study the relationship between loads of previous hours of same day and previous days in a week on current load, a graph were plotted. The week selected to plot was dated from July 30 to August 4 which is the first week of August. Load curves of each day were plotted on graph of that week to examine the relationship between load demand at any specific hour and load at previous hours and previous day same hour. The graphs containing load curves for Nova Scotia for week mentioned are shown next:

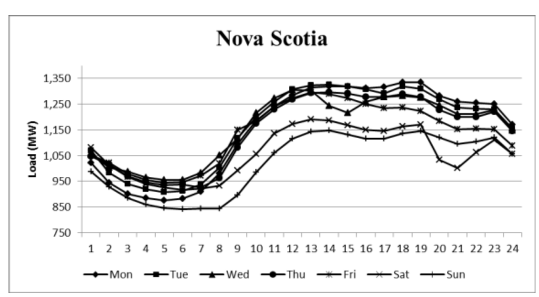

Fig. 9. Daily Load Curves

It can be seen that load values of previous hour and previous days match each other closely. The slopes almost replicate each other. Also the load behavior of weekend days Saturday and Sunday is different from other days. Hence, it was decided to forecast weekdays and weekends separately. With the help of these graphs four inputs were selected for Weekdays and one for Weekend forecast. If y(h) is considered to be the variable to represent present load then the inputs for weekdays include load for previous hour of same day – y(h-1) , same hour of previous day – y(h-24), same hour two days before – y(h-48) and same hour three days before – y(h-72). For weekend only y (h-1) was selected as their load curve generates a unique response.

Furthermore, to study the effect of the load series of previous weeks on present load a graph for each jurisdiction was produced. A sample of data was selected comprising of load data for four weeks from July 22 to August 18, 2013 with week 1 starting from July 22, week 2 starting from July 29, week 3 from August 5 and week 4 from August 12 respectively. Fig. 10 presents the load curves of four weeks stated for Nova Scotia.

It can be noted that load curves of four weeks are closely related to each other. Also, the response for weekends is more similar to each other than weekdays. Thus two inputs for weekday forecasts and three inputs for weekends were selected. The inputs selected for weekdays include the load for same hour previous week – y (h-168) and same hour two weeks before – y (h-336). For weekends the load of same hour three weeks before – y(h-504) was selected in addition of former two.

In order to study the effect of temperature on load the following set of graphs shown in Fig. 11 were plotted for each province by using data points of week 1. The first graph in the figure consists of load and temperature curves superimposed on each other depicting the relationship between both variables. The second graph plots the temperatures of each day of the week.

A close association between variations in temperature and respective change in load can be seen. Also temperatures of previous days are similar to each other. Henceforth, three temperature variables were selected for weekends which include current temperature denoted by t (h), temperature of pervious hour – t(h-1) and temperature of same hour of the previous day – t(h-24). Since the load response of each day of weekend is unique for temperature variables of the same day (t(h) and t(h-1)) were selected as inputs.

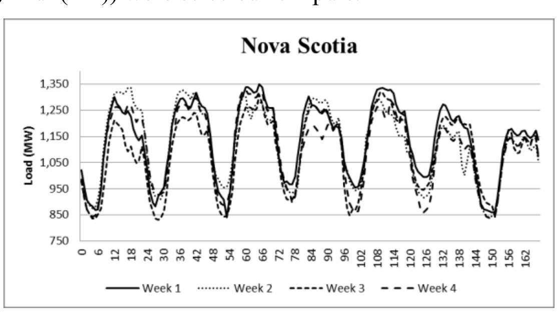

Fig. 10. Weekly Load Curves

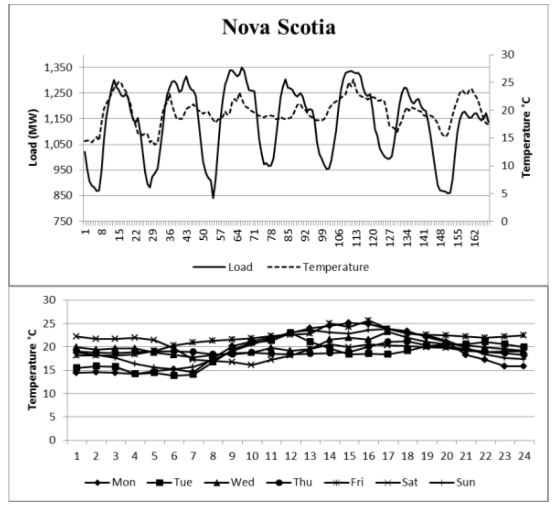

Fig. 11. Weekly load and temperature (above), Daily temperature (below)

In total, nine inputs for weekdays forecast and six inputs for weekend forecasting were selected. They are summarized in table I.

2) *Data Pre-Processing*

As mentioned in the previous section the data was separated into weekdays and weekends for separate forecasts. Moreover, all data points were normalized between values of 0 and 1 in order to simplify the calculations and to quantify the effect of all temperature variables. It was done by using the following formula for load and temperature:

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{1}$$

Where x_norm is the normalised data point, x is the actual data point, x_min is the minimum data point in the series, x_max is the maximum data point in the series. Data normalization was carried out in a separate MATLAB script prior to the separation into weekdays and weekends. Then the input matrices were created in same script respectively.

TABLE I. SUMMARY OF SELECTED INPUTS FOR WEEKDAYS AND WEEKEND FORECASTS

Inputs	Denoted by	Weekdays	Weekends
Previous Hour Load	y(h-1)	✓	✓
Previous Day same Hour Load	y(h-24)	✓	X
Same Hour Load 2 days before	y(h-48)	✓	X
Same Hour Load 3 days before	y(h-72)	✓	X
Previous Week same Hour Load	y(h-168)	✓	✓
Same Hour Load 2 weeks before	y(h-336)	✓	✓
Same Hour Load 3 weeks before	y(h-504)	x	✓
Current Temp	t(h)	✓	✓
Previous Hour Temp	t(h-1)	✓	✓
Previous Day Same Hour Temp	t(h-24)	✓	X

3) Network Parameters and Training

For fastest convergence equal number of neurons as number of inputs was found to be the best combination. It was also found that with no bias networks generated accurate forecasts therefore the value of bias was set to zero. As a result the numbers of neurons used in the hidden layers were equal to the number of inputs while one neuron was used in the output layer. A linear transfer function was used for the output layer. On the other hand all prior hidden layers used hyperbolic tangent sigmoid.

Moreover, the data was further separated into training and testing datasets. The training dataset consist of data points from June 1 to August 23, 2013 whereas the testing dataset includes data from August 24 to 30, 2013. The neural network architectures mentioned in the previous section were trained using the training dataset and the Levenberg-Marquardt Back Propagation (LMBP) algorithm.

4) Error Analysis and Performance Evaluation

After finding the forecasting results two parameters were used to compare the results and evaluate the advantages and disadvantages of each network. Error analysis was done on the basis of Mean Absolute Percentage Error (MAPE). Most authors in literature use this parameter as a measure of performance of a forecasting method. Another parameter calculated for error analysis is the Root Mean Squared Error (RMSE). The choice between MAPE and other error criteria depend on statistics which is system dependent. The following formulae were used to calculate error analysis parameters:

$$MAPE = \frac{100}{N} \sum_{i=1}^{N} \frac{|y_{predicted} - y_{actual}|}{y_{actual}} \tag{2}$$

$$RMSE = \sqrt{\frac{(y_{predicted} - y_{actual})^2}{N}} \tag{3}$$

IV. Results and Discussion

The load of Nova Scotia ranges from 745 MW to 1373MW during selected time period. Though weekdays and weekend data is separated but since the province's industrialized sector is less dominant, the load curves throughout the week remain consistent. Load and temperature data from June 1 to August 25, 2013 is used for training all networks tested. The 24 hours ahead and week ahead forecasts are presented next for weekdays followed by weekend's forecasts.

1) Day Ahead Forecast

Table II shows the MAPE and RMSE of each network tested for August 26, 2013. The improvement of each network over the conventional FFNN is also presented in the table. The results indicate that the 3-layered CNN gives best overall performance with 21.88% improvement over the FFNN. The performance of CNN, RNNL, RNNG, CRNNL and CRNNG with enhancements of 16.68%, 2.8%, 5.86%, 4.76% and 5.86% have proved to be more stable during peak hours than 3-layered FFNN or CNN network.

TABLE II. Day Ahead Forecast for Nova Scotia

Architecture	MAPE	RMSE	Improvement
FFNN	2.32	32.66	0.00%
CNN	1.93	26.28	16.68%
RNNL	2.26	30.29	2.80%
RNNG	2.18	31.23	5.86%
CRNNL	2.21	30.92	4.76%
CRNNG	2.18	31.20	5.86%
FFNN (3L)	1.99	26.48	14.42%
CNN (3L)	1.81	26.23	21.88%

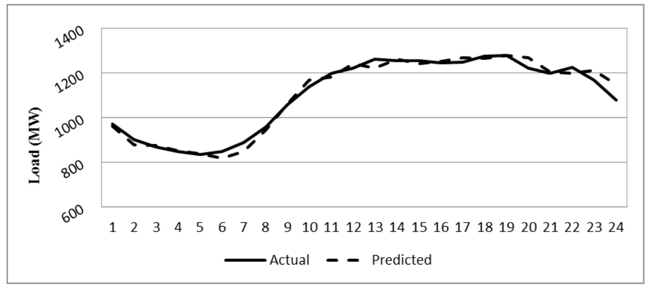

Fig. 12. Day Ahead forecasting results for 3-layered CNN

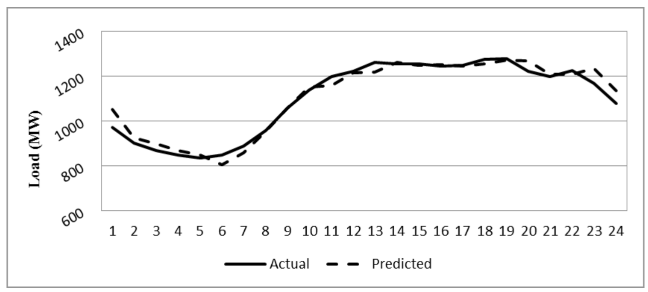

Fig. 13. Day Ahead Forecasting results for FFNN

On the basis of consistency if the forecasting errors during starting and ending hours are acceptable to a utility company then CNN can be the best choice among all. Also networks with recurrent paths takes longer time to converge but gives better error response and closely matches the load curve during peak hours. Fig. 12 and 13 show the forecasts produced by the best and worst performing networks (3-layered CNN and FFNN).

2) Week Ahead Forecast

The forecast performance of all the networks for week ahead forecast for the week starting from August 26 to August 30, 2013 is presented in Table III. The forecast generated by FFNN has the highest forecasting error and the improvement of other networks is compared with it.

The cascaded networks CNN and 3-layered CNN have proven to be better than other networks with improvements of 8.26% and 10.04% respectively. The other networks have also shown improvement specially the RNNG network (5.83%). The prediction of 3-layered FFNN (1.76% improvement) is much like FFNN but the overall error curve is found to be consistent. Also, all recurrent networks perform better during peak hours. The hybrid networks CRNNL (4.81%) and CRNNG (4.15%) also proved to be better than the FFNN and produced lower error during the starting and ending hours during the days of selected week. The forecasts generated by 3-layered CNN with lowest MAPE and FFNN with highest error are demonstrated in Fig. 14 and 15.

3) Weekend Forecast

The weekend forecasts for August 24 and 25, 2013 were generated. The resulting MAPE for all the networks are presented in table IV. RNNG has given the worst performance among all other architectures. The comparison of performances with respect to FFNN is also shown in table IV. 3-layered FFNN has produced the best results with 20.48% improvement over FFNN. CRNNG and CNN with performance enhancements of 18.07% and 14.19% are also worth mentioning. Specifically the CRNNG gives the best performance during peak hours. The remaining networks; 3-layered CNN (10.22%), CRNNL (3.61%) and RNNL (3.08%) have also shown better performance for weekends as they did for weekdays. Overall the performances of all networks for weekends have forecasted better results than weekdays. Fig. 16 and 17 give the forecasting results of 3-layered FFNN and RNNG which gave the best and worst accurate forecasts.

1) Summary of Load forecast results for Nova Scotia

Table V summarizes all the forecasting results achieved for Nova Scotia followed by a graphical presentation in Fig. 18.

V. CONCLUSION

The ANN designs examined in this paper start from the most commonly used feed forward neural network (FFNN). FFNN served as a base to compare the performances of remaining ANNs. Three advanced architectures tested were cascaded neural network (CNN), recurrent neural network with local feedback (RNNL) and recurrent neural network with global feedback (RNNG). Also, four new architectures for the application of STLF were also introduced. These include two hybrid and two modified architectures. The hybrid models proposed were the combination of CNN and the two recurrent networks first was the cascaded – recurrent neural network with local feedback (CRNNL) and the other one was cascaded – recurrent neural network with global feedback (CRNNG). Modified architectures consisted of 3-layered FFNN and 3-layered CNN. In order to explore the applicability of these designs real data from Canadian province; Nova Scotia (NS) was used to experiment each individual network.

A statistical analysis of load demand of each province indicated that weekends possessed different load response than weekdays, hence weekdays and weekends were forecasted separately. The performances were evaluated on the basis of mean absolute percentage error (MAPE). Each network produced three forecasts for each province. Two out of three forecasts were day or 24 hours ahead forecast and week ahead forecast for weekdays and the third one forecasted weekend load. After concluding the forecasting results for all the cases a comparative analysis was made.

For day ahead weekdays forecasts 3-layered CNN produced the most accurate results as compared to other networks with 1.81% MAPE. For week ahead weekdays forecasts 3-layered CNN again generated the most accurate forecasts with MAPE of 1.99%. For weekend forecast 3-layered FFNN with MAPE 1.71% outperformed all networks. Hybrid and recurrent networks performed better during peak hours but didn't produce satisfactory results. Furthermore, CNN and 3-layered architectures offered big improvements. With fast convergence they produced superior results than any of recurrent networks for most cases stated. Finally, the economic worth of forecasting error depends on the operating zone of the system (Unit commitment).

TABLE III. WEEK AHEAD FORECAST FOR NOVA SCOTIA

Architecture	MAPE	RMSE	Improvement
FFNN	2.21	31.45	0.00%
CNN	2.03	28.69	8.26%
RNNL	2.16	30.80	2.32%
RNNG	2.08	29.32	5.83%
CRNNL	2.10	30.24	4.81%
CRNNG	2.12	29.93	4.15%
FFNN (3L)	2.17	31.72	1.76%
CNN (3L)	1.99	29.08	10.04%

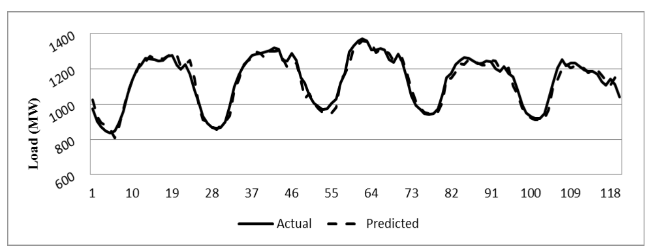

Fig. 14. Week Ahead Forecasting results for 3-layered CNN

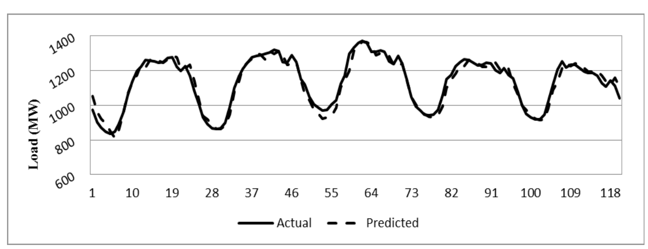

Fig. 15. Week Ahead Forecasting results for FFNN

TABLE IV. WEEKEND FORECAST FOR NOVA SCOTIA

Architecture	MAPE	RMSE	Improvement
FFNN	2.1666	29.44	0.00%
CNN	1.8481	25.80	14.19%
RNNL	2.0974	30.92	3.08%
RNNG	2.2442	32.69	-3.46%
CRNNL	2.0856	28.74	3.61%
CRNNG	1.761	28.77	18.07%
FFNN (3L)	1.7071	24.84	20.48%
CNN (3L)	1.9373	28.68	10.22%

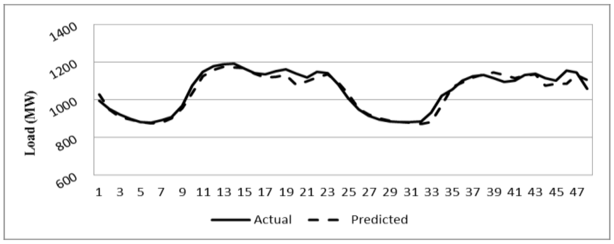

Fig. 16. Weekend Forecasting results for 3-layered FFNN

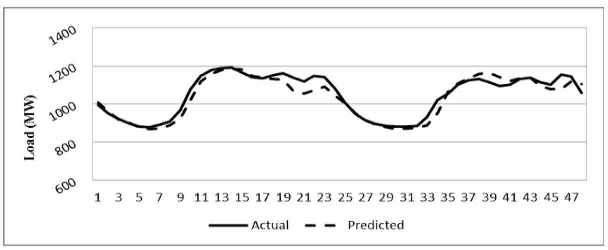

Fig. 17. Weekend Forecasting results for RNNG

TABLE V. WEEKEND FORECAST FOR NOVA SCOTIA

Architecture	Day ahead	Week ahead	Weekend
FFNN	2.32	2.21	2.17
CNN	1.93	2.03	1.85
RNNL	2.26	2.16	2.10
RNNG	2.18	2.08	2.24
CRNNL	2.21	2.10	2.09
CRNNG	2.18	2.12	1.76
FFNN (3L)	1.99	2.17	1.71
CNN (3L)	1.81	1.99	1.94

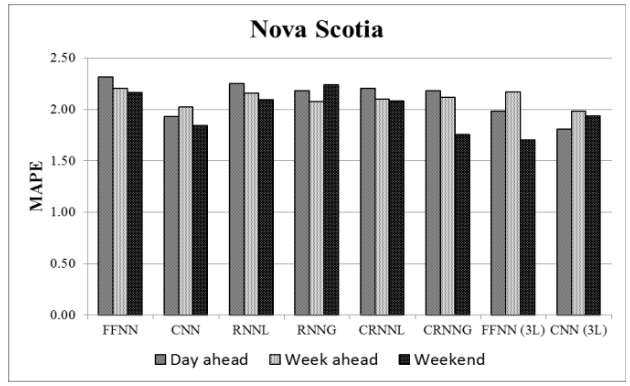

Fig. 18. Graphical presentation of load forecast results for Nova Scotia

REFERENCES

[1] Feinberg, Eugene A., and Dora Genethliou. "Load forecasting" *Applied mathematics for restructured electric power systems*, pp. 269-285, Springer US, 2005.

[2] Turkay, B.E., and Demren, D., "Electrical load forecasting using support vector machines," *Electrical and Electronics Engineering (ELECO), 2011 7th International Conference on*, pp. I-49 – I-53, 1-4 Dec. 2011.

[3] Peng, T. M.; Hubele, N.F.; Karady, G.G., "Advancement in the application of neural networks for short-term load forecasting," *Power Systems, IEEE Transactions on* , vol.7, no.1, pp.250,257, Feb 1992

[4] AlFuhaid, A.S.; El-Sayed, M.A.; Mahmoud, M. S., "Cascaded artificial neural networks for short-term load forecasting," *Power Systems, IEEE Transactions on* , vol.12, no.4, pp.1524,1529, Nov 1997

[5] Dong-Chul Park; Dong-Min Woo; Seung-Soo Han, "Electric Load Forecasting Using Adaptive Multiresolution-Based Bilinear Recurrent Neural Network," *Image and Signal Processing, 2008. CISP '08. Congress on* , vol.4, no., pp.393,397, 27-30 May 2008.

[6] Lee, K.Y.; Choi, T.I.; Ku, C.C.; Park, J.H., "Short-term load forecasting using diagonal recurrent neural network," *Neural Networks to Power Systems, 1993. ANNPS '93., Proceedings of the Second International Forum on Applications of* , vol., no., pp.227,232, 1993

[7] S. H. Shin and D. C. Park, "Short-term load forecasting using bilinear recurrent neural network," in *Proc. 4th Int. Symp. Neural Netw.*, vol. 3. pp. 111–116, 2007.

[8] Changhao Xia; Zhonghua Yang; Hongjie Li, "Electric load forecasting using virtual instrument based on dynamic recurrent Elman neural network," *Power Engineering and Automation Conference (PEAM), 2012 IEEE* , vol., no., pp.1,4, 18-20 Sept. 2012

[9] Feng Zhao; Hongsheng Su, "Short-Term Load Forecasting Using Kalman Filter and Elman Neural Network," *Industrial Electronics and Applications, 2007. ICIEA 2007. 2nd IEEE Conference on* , vol., no., pp.1043,1047, 23-25 May 2007

[10] Nova Scotia Power, Oasis Database URL:http://oasis.nspower.ca/en/home/oasis/default.aspx

[11] Government of Canada, Climate Database URL:http://climate.weather.gc.ca/data_index_e.html