2010 Second International Conference on Advances in Computing, Control, and Telecommunication Technologies

Forecasting Sunspot Numbers with Recurrent Neural Networks (RNN) using 'Sunspot Neural Forecaster' System

Reza Ezuan Samin
Faculty of Electrical and Electronics Engineering
Universiti Malaysia Pahang
Kuantan, Pahang, Malaysia
reza@ump.edu.my

Ruhaila Md. Kasmani
Faculty of Science, Arts and Heritage
Universiti Tun Hussein Onn Malaysia
Batu Pahat, Johor, Malaysia
ruhaila@uthm.edu.my

Azme Khamis
Faculty of Science, Arts and Heritage
Universiti Tun Hussein Onn Malaysia
Batu Pahat, Johor, Malaysia
azme@uthm.edu.my

Syahirbanun Isa
Faculty of Science, Arts and Heritage
Universiti Tun Hussein Onn Malaysia
Batu Pahat, Johor, Malaysia
syahir@uthm.edu.my

***Abstract*—This paper presents the investigations of forecasting performance of different type of Recurrent Neural Networks (RNN) in forecasting the sunspot numbers. Recurrent Neural Network will be used in this investigation by using different learning algorithms, sunspot data models and RNN transfer functions. Simulations are done using Matlab 7 where customized Graphic User Interface (GUI) called 'Sunspot Neural Forecaster' have been developed for analysis. A complete analysis for different learning algorithms, sunspot data models and RNN transfer functions are examined in terms of Mean Square Error (MSE) and correlation analysis. Finally, the best optimized RNN parameters will be used to forecast the sunspot numbers.**

***Keywords*— Sunspot numbers, Recurrent Neural Networks (RNN), Mean Square Error (MSE)**

I. INTRODUCTION

Solar activity forecasting becomes one of the main interests in the scientific field due to the emission of solar particles and electromagnetic radiations affects. The affects include in telecommunication systems, electric power transmission lines, space activities concerning operations of low-Earth orbiting satellites and long term climate variations, weather and other ionosphere parameters. Therefore it is very important to know in advance the future behavior of solar activity, which is strongly related to the number of dark spots observed on the sun. For this reason, the yearly sunspot numbers are used in order to model the behavior of the solar activity. The sunspot numbers was obtained from the ftp server of National Geophysical Data Center (NGDC) and the data ranging from 1700 until 2008.

In the past, researchers had been using different method such as neural network, fuzzy logic neural network and time series in order to forecast the sunspot numbers. Reference [1], [2], [3] and [4] have applied Neural Network (NN) as predictor tools. De-rectification processes before the normalization of the data have been implemented in [1]. Then, the data are trained by Elman network with only one input, a recurrent hidden layer and one output using a back propagation algorithm. The result is better than most of the existing solar activity forecasting methods. Instead of using one input and one output as in [1], 12 inputs and 12 outputs that are fed into Recurrent Neural Network (RNN) system [2]. They employed method of optimization and selection of training, testing and examination sets of neural network input data sets. The results and reliability of neural network forecasting are presented for period 1999-2000 only

Meanwhile [3] forecast the sunspot numbers using three types of neural networks namely Feedforward Neural Network (FNN), Modular Neural Network and RNN. For all three types of networks, [3] worked on cross validation to select the number of nodes in each layer and finally compared in term of the Average Relative Error. In [4], a combination of Artificial Neural Network(ANN) and Genetic Evolutionary Algorithm (GEAs) is proposed where the *GEA's* searching engine will be used to evolve candidate ANN topologies, enhancing forecasting models that show good generalization capabilities. Then a comparison was performed with bio-inspired methods and time series methods which revealed better forecasting performances.

Reference [5] applied new method called Time-delay Added Evolutionary Forecasting (TAEF) method for time series prediction of the sunspot numbers which performs an evolutionary search of the minimum necessary number of dimensions embedded in the problem for determining the characteristic phase space of the time series.

978-0-7695-4269-0/10 $26.00 © 2010 IEEE
DOI 10.1109/ACT.2010.50

Meanwhile, [6] have applied nonlinear dynamics approach in forecasting the sunspot numbers. The model is based on a local hypothesis of the behavior on embedding space, utilizing an optimal number of neighbor vectors to predict the future evolution. The performance of this method for the current 23rd sunspot cycle suggests its valuable insertion in the set of the so-called non precursor statistical numerical prediction techniques.

This paper presents a forecasting methodology for sunspot numbers by exploiting RNN as forecasting tools. Customized forecasting system called 'Sunspot Neural Forecaster' for predicting the solar activity using MATLAB software are developed. Instead of using the ordinary and less user friendly command window in MATLAB, more user friendly graphic user interface (GUI) is used. The combination of this work with RNN has allowed a simple and very user friendly prediction system for sunspot-related time series to determine the optimum neural networks parameters in order to forecast the sunspot numbers.

II. SUNSPOT DATA

In terms of solar activity forecasting, one of the main topics that researchers always look into is the sunspot numbers forecasting. The mysterious cycles in sunspot numbers have intrigued many investigators including geologist, astronomers, climatologist, economist, historians and statisticians. The sunspot numbers have major effects on various terrestrial phenomena such as long range weather prediction. Sun-weather relationship in the stratosphere is well understood and sunspot numbers have to be taken into account in electrical system, telecommunications and interplanetary flight [7].

Solar activity is frequently monitored by many world observatories. They provide the relative number of dark spots observed on the sun day after day. The international sunspot number, R_i is an index characterizing the level of solar activity and it is regularly given by the Solar Influences Data Analysis Centre (formerly the Sunspot Index Data Centre) (SIDC). These data are recorded to give the so-called sunspot related time series. In this work, we employ the Yearly Sunspot Number that was obtained from the National Geophysical Data Centre (NGDC) through the ftp server: ftp://ftp.ngdc.noaa.gov/STP/SOLAR_DATA/SUNSPOT_NUMBERS/. Fig. 1 indicates the time series plot for sunspot numbers from 1700 until 2008.

III. METHODOLOGY

In this section, Recurrent Neural Networks (RNN) is used to forecast the data of sunspot numbers. By using different type of learning algorithms, different type of model and different transfer function, analysis are done in terms of Mean Square Error (MSE) and correlation analysis for the best optimized parameters of the RNN. This optimized RNN will then be used to foreca(1)st the sunspot data from 2008 to 2012.

RNN, also known as Elman network [8] exploited positive feedback by inserting recurrent connections in order to build memory as depicted in Fig. 2. These structures are Multi Layer Perceptron (MLP) with the difference that the input layer is constituted by input neurons and context units, which store

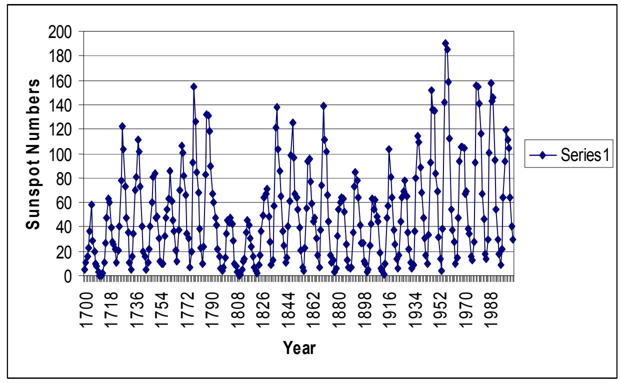

Figure 1. The yearly Sunspot numbers

delayed hidden layer neurons values from the previous time step to present them to the network as additional input inputs in the current time step. The outputs of the network are not fed back to the inputs and each hidden neuron has a context unit, so RNN includes as many context units as hidden neurons.

For the analysis, it will be divided into three parts. The first part involves analysis for different learning algorithm. In the second part, the analysis is done for different models NN1, NN2, NN3 and NN4. Finally, the analysis will be on different transfer function on hidden layer and output layer of the RNN. By doing all these analyses, the best optimized RNN parameters can be obtained that will then be used to forecast the sunspot number from year 2009 until 2015. The detail explanations for each analysis are:

A. *Different Learning Algorithms Analysis*

In terms of learning algorithms analysis, three algorithms are used which are Levernberg-Marquardt (trainlm), Resilient Backpropagation (trainrp) and BFGS Quasi-Newton (trainbfg). Analyses are done by using these training algorithms while using the same model (NN1) and the hidden nodes ranging from 1-50.

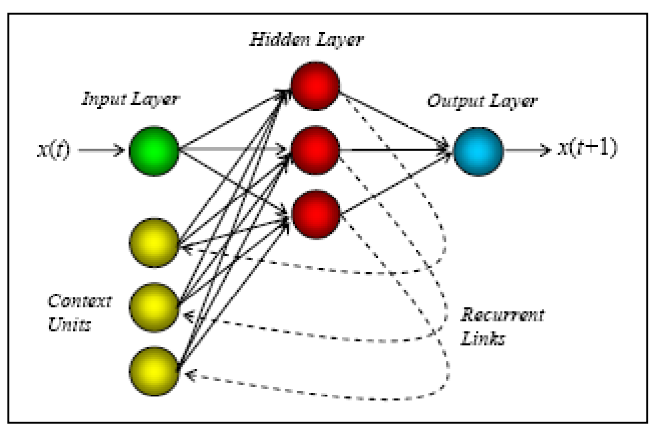

Figure 2. Structure of RNN with one input and one output.

B. Different Models Analysis

For this part, based from the first analysis of different learning algorithms, the best learning algorithms is selected for this second analysis. Analyses are done by using different model while using the same hidden nodes ranging from 1-50. The analysis for different model data will involve four models which are NN1, NN2, NN3 and NN4. NN1, NN2, NN3 and NN4 model consist of three, four, five and six inputs with one output respectively that will then be fed in the RNN system for analysis purpose.

C. Transfer Function Analysis

For this part, based from the second analysis of different model, the best model is selected for this third analysis. Analyses are done by using different transfer function while using the same hidden nodes ranging from 1-50. The transfer function that are used for these analyses are Tansig-Purelin and Logsig-Purelin for the hidden layer and output layer of the Recurrent Neural Network (RNN) respectively.

D. 'Sunspot Neural Forecaster'

In order to analyze the forecasting performance of the sunspot numbers, the 'Sunspot Neural Forecaster' was developed. This system enables the user to analyze the Sunspot data easily by incorporating the RNN parameters and analysis under one simple graphic user interface (GUI). Fig. 3 shows the main interface of the 'Sunspot Neural Forecaster'.

The GUI that have been developed will enable the user to select the two type of Neural Networks which are Feedforward Neural Network (FNN) and Recurrent Neural Network (RNN). The user can also select the sunspot model data in order to compare which model is better than the other. In terms of the analysis, the user can tune different type of Neural Network parameters such as learning algorithms, hidden nodes and epoch much more easily compared to the conventional command in Matlab command window.

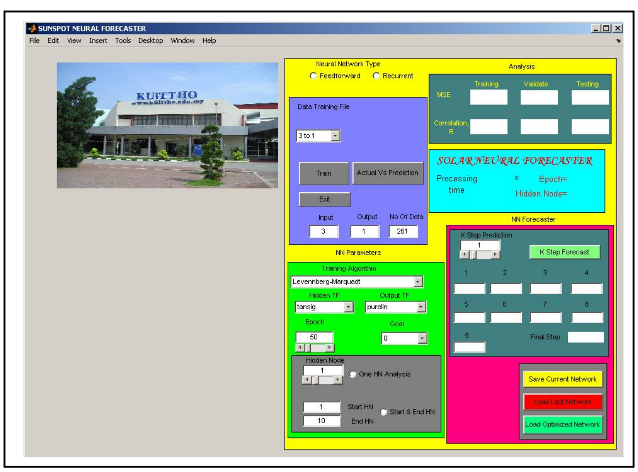

Figure 3. Graphic user interface (GUI) for "Sunspot Neural Forecaster".

IV. RESULTS AND DISCUSSIONS

In this section, the system are analyzed and tested within the simulation environment of Matlab and the corresponding results are presented. The three modes of learning algorithms of the system are considered. Two criteria are used to evaluate the performances of the system:

A. Mean Square Error (MSE)

Equation (1) is the general equation for Mean Square Error (MSE) where, y_t is the actual observation and $\hat{y}_t$ is the output of the models. *T* is number of prediction. These criteria are mean based and are frequently used performance measures in the literature.

$$\text{MSE} = \frac{\sum_{t=1}^{T}(y_t - \hat{y}_t)^2}{T}, \quad i = 1, 2, \ldots, n \qquad (1)$$

B. Correlation Analysis

Correlation is a measure of the relation between two or more variables. In this case, it is the relation between the RNN forecasted sunspot numbers value with the actual value of the sunspot numbers. Correlation coefficients can range from -1.00 to +1.00. The value of -1.00 represents a perfect negative correlation while a value of +1.00 represents a perfect positive correlation. A value of 0.00 represents a lack of correlation.

The responses of the forecasting system with the different learning algorithms are shown in Fig. 4. The overall result demonstrates that, the Levernberg-Marquardt algorithm can give the best performance compared to the other learning algorithms in terms of MSE and correlation analysis. Hence, the training algorithm was chosen as the training algorithm for the next analysis.

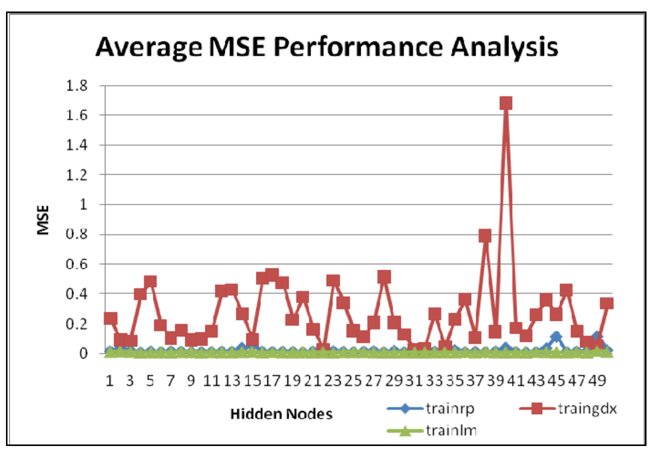

Figure 4. Average MSE performance for different learning algorithms.

Fig. 5 shows the system responses of the forecasting system under different model analysis. The result shows that the NN1 model achieved the lowest MSE with the value of 0.0069 as compared to 0.009,0.0125 and 0.0115 for the NN2, NN3 and NN4 models respectively. Table 1 indicates the MSE best performance for each model and based from that, NN1 is the best model compared to the others. Hence, the NN1 model was chosen as the best model for the next analysis.

For the last analysis, the responses of the forecasting system for NN1 model with the different transfer functions are shown in Fig. 6. The overall result demonstrates that, the Tansig-Purelin transfer function can give the best performance compared to the Logsig-Purelin in terms of MSE and correlation analysis. Therefore, this transfer function will be used for the forecasting of the sunspot data.

All the three analyses that have been done were meant to get the best RNN parameters that can be used for the next stage which is the forecasting of the sunspot numbers. Hence, we can conclude that the optimized RNN parameters for the Sunspot Numbers forecasting system are:

- Training algorithm = Levenberg Marquardt.
- NN model = NN1.
- Transfer function = Tansig/Purelin.
- Hidden nodes = 7.

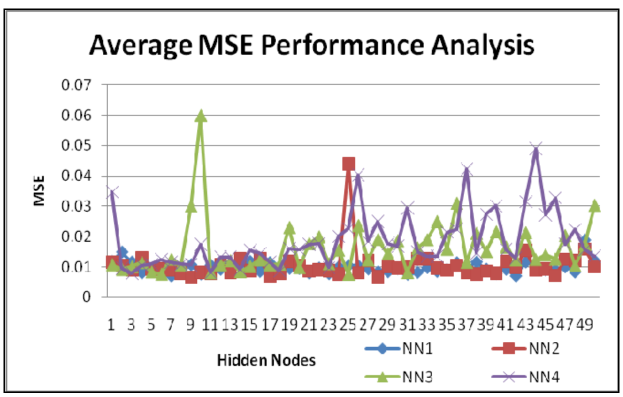

Figure 5. Average MSE performance for different models.

TABLE I. PERFORMANCE ANALYSIS FOR DIFFERENT MODEL

Analysis	Model			
	NN1	*NN2*	*NN3*	*NN4*
Average MSE	0.0069	0.009	0.0125	0.0115
	Correlation			
Training	0.9231	0.9333	0.9315	0.9258
Validation	0.9524	0.9374	0.9280	0.8930
Testing	0.9349	0.9430	0.9322	0.9127

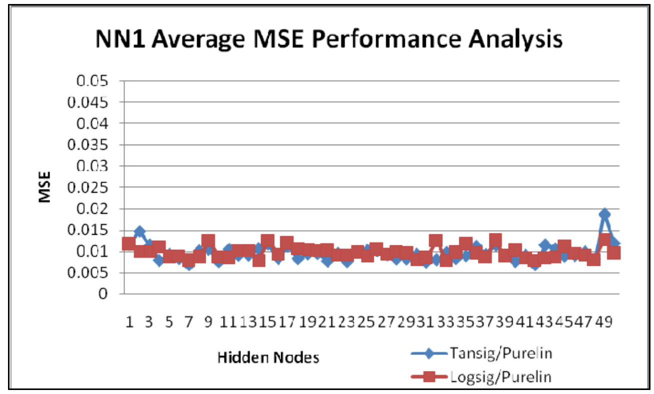

Figure 6. NN1 model average MSE performance analysis

By using the optimized RNN parameters, the forecasting part can then be executed in order to forecast the sunspot numbers from year 2008 until 2015. Fig. 7 indicate the performance between the actual output and NN prediction using the optimized NN parameters as above.

Based from Fig. 7, we can see that the NN prediction can manage to follow the pattern of the data. The difference or error between the actual output and NN output is quite small. By using the optimized RNN parameter, the forecasting of the sunspot numbers from year 2009 untill 2015 can be done. The sunspot numbers that have been forecasted using this system are 14.95, 45.70, 87.92, 110.38, 104.32, 92.58 and 76.13 from year 2009 until 2015 respectively.

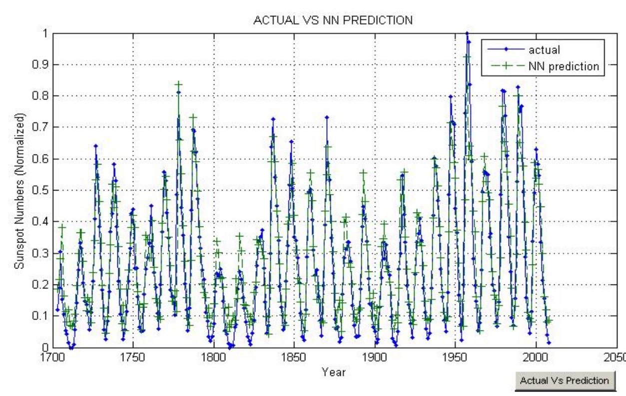

Figure 7. Actual versus NN prediction for optimized NN parameters.

V. CONCLUSION

Analyses of RNN with different parameters in order to forecast the sunspot numbers have been presented. Performances of the forecasting system are examined in terms of MSE and correlation analysis. The results demonstrated that by analyzing different type of learning algorithms, models and transfer functions of the RNN, the best optimized RNN parameters can be obtained. This optimized RNN with Levenberg Marquardt learning algorithm, NN2 model data, Tansig/Purelin transfer function with 19 hidden nodes will then be used to forecast the Sunspot Numbers from year 2009 until 2015 with the value of 14.95, 45.70, 87.92, 110.38, 104.32, 92.58 and 76.13 from year 2009 until 2015 respectively.

In the optimized NN performance analysis, the comparison between actual and NN prediction was done. In the comparison, the NN prediction can well follow the pattern of the sunspot data and therefore, we can say that the NN model can be used to forecast the sunspot data for the coming years. The result obtained on the modeling of the sunspot numbers is very good and we can say that this model can actually be used for the forecasting of the sunspot numbers for the coming years.

ACKNOWLEDGMENT

The authors would like to thank the Ministry of Higher Education, Malaysia for supporting this research under the Fundamental Research Grant Scheme (FRGS).

REFERENCES

[1] M. Salvatore and C. Francesco, " A New Technique for Solar Activity Forecasting using Recurrent Elman Networks", *International Journal of Computational Intelligence,* vol. 3, pp. 8 – 13, 2006.

[2] Dmitriev A.V. et. al, "Solar Activity Forecasting on 1999-2000 by Mean of Artificial Neural Network", *EGS XXIV General Assembly*, The Hague, Netherlands, 1999.

[3] Fessant F. et al, "On the Prediction of Solar Activity Using Different Neural Network Models", *France Telecom CNET*, 2000.

[4] Cortez et al, "Evolving Time Series Forecasting Neural Network Models", *Foundation of Science & Technology*, 1997.

[5] Ferreira A. E. et. Al, "A New Evolutuionary Method for Time Series Forecasting", Proceedings of Genetic and Evolutionary Computing Conference (GECCO), pp 2221-2221,2005.

[6] Sello S. "Solar Cycle Forecasting: A Nonlinear Dynamics Approach",Journal of Astronomy and Astrophysics, 312-320.

[7] L. Ming et.al, "Sunspot Numbers Forecasting using Neural Networks", IEEE Transactions, pp 524-529, 1990.

[8] J. L. Elman, "Finding Structure in Time", *Cognitive Science*, vol 14, pp. 179 – 221, 1990.