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Study dynamic system behavior of Time series using Artificial Neural Networks application to sunspot data

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Abstract

In this work the ability of artificial neural network to mimic a function is used to find artificial neural network system that can grasp the behavior of sunspots which can be used to forecast future observations.

The model constructed using artificial neural network gives a better result in the predication of the sunspot observations especially in the case of time delay neural network, because time delay neural network unlike recurrent neural network, has a simple structure. A method of identifying a dynamic system was presented, which depends on using multi-dimensional Taylor series by analyzing the resulted output of artificial neural network system.

Keywords: artificial neural network, dynamic system ,sunspot and multi-dimensional Taylor series.

1 Introduction

Time series forecasting is a common problem. Different statistical methods were used to predict the future trend of the time series by extracting information about the data behavior, some of the time series data can be modeled easily by using one method, but is difficult to do with another . It is also proper to suppose that the observed time series data results from a dynamic system with unknown parameters. Some of these parameters may be random variables. Dynamic systems can be represented by a set of differential equations (or their discrete counterpart, difference equations)[12].

Most of the recent literature has focused on using statistical models to determine the parameters of their neural network structure, see[1, 4, 15]. Or they compare the forecasting abilities of ANN with traditional statistical model like [5].

More recently, artificial neural networks (ANN)[10, 13] can provide an alternative approach for forecasting of time series data by training ANN using collected examples; ANN used to predict time series in different area , Moseley, N.[11] used the monthly totals inventories and sales. While Al-hidi, H. and Al-Hasan, Z. [2] chosen the weekly stock of seven different Saudi companies, Karatasou, S. *et.al*. [9] dealing with the hourly consumption of energy in building, Xin Xie, J *et.al.* [18] conducted on the sunspots prediction problem using ANN.

The data set used in this work is sunspots average of years1700 through 2007, All data used in this work were extracted from [19]; the important of chosen sunspots is that it can help predict conditions of short-wave radio propagation or communications. It is also thought that it has a detrimental effect on power lines transmission.

In the following subsequent sections of this work reviews the relation between dynamic system and neural network and then shows how ANN can be used to time series predict. In section 2 we give a brief review of the training manner for ANN and the algorithm, which is used. The subsequent sections present the training results, in section 3 we give the forecasting experiment results. We present the equivalent dynamic system in section 4. The last section presents our conclusion

1.1 Neural Networks and Dynamic Systems

Any real-world processes can be represented as dynamical systems (systems that evolve in time). Dynamic systems are described by means of differential equations which, can be solved by many analytical or numerical methods such as Euler method or Rang_kutta method [12].

ANN can be used to model dynamic systems, the structure of such a system is modified to meet the requirements of external or/and internal information that flows through the network [7, 13].

Recurrent neural networks (RNN) and Time delay neural network (TDNN) can be used to approximate the behavior of the dynamic systems; both (RNN, TDNN) are nonlinear or linear dynamic systems where the states evolve according to certain nonlinear state equations; and it is applied to many problems involving modeling and processing of temporal signals, such as adaptive control, forecasting, system identification, and speech recognition [3, 6].

In neural networks, specially feed forward and Hopfield network (special class of recurrent neural network) exhibit as fixed point behavior. But for the case of recurrent neural network it is found that such ANN can exhibit all of the three possible asymptotic behaviors. Training the ANN modifies its internal structure to give the structure that models the dynamic system (see Figure 1.1a) and the process is represented by an equation shown in Figure 1.1b

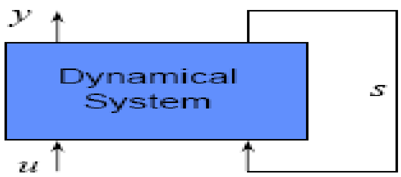
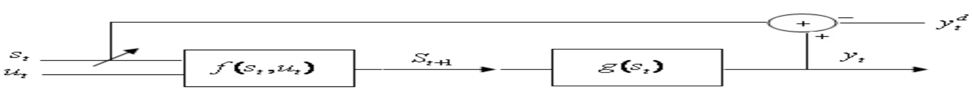


Figure 1.1a: The general structure of dynamical system.



$$S_{t+1} = f(s_t, u_t) \qquad (1.1)$$
$$y_t = g(s_t)$$
$$\sum_{t=1}^{T} (y_t - y_t^d)^2 \rightarrow \min_{f,g}$$

Figure 1.1b: The equations that represent a dynamical system.

1.2 Time Series Prediction using Neural Nets

To analyze time series, we need some steps, which are considered very important for this purpose. They include modeling, identification of the model and parameter estimation. According to [1, 5, 17] There are a few specific structures of neural networks, which are used to predict time series such as time delay neural network (TDNN) and recurrent neural network (RNN). In TDNN, the network is a multi-layer perceptron, where the time series data depends on the present input as well as some previous inputs [1].see (equation 1.21).

$$Y_{k+1} = NN(Y_K) \qquad OR \qquad Y_{k+1} = NN(Y_K, Y_{k-1}, \ldots\ldots, Y_{K-L}) \qquad (1.21)$$

In general, this method is called the sliding window technique and can be described analytically by the next equations below:

$$x(t) = [x(t), x(t-k), \ldots\ldots\ldots, x(t-(M-1)K)] \qquad (1.22)$$

$$x_1(t+k) = f(x(t)) \qquad (2.23)$$

Where M is past values or M-tuples as inputs and one output is time step (t); time series observation, $x_1(t+k)$ is a multi step ahead predication.

In RNN used in time series forecasting, there are two classes that can be specific outputs of network they are: the feed back into an input layer or a hidden layer. For a recurrent neural network the forecasting function may be written as:

$$\hat{x}_t = f_2(w_{bo} + \sum_h w_{ho} * f_1(w_{bh} + \sum_i w_{ih} * x_{t-j} + \sum_j w_{ch} * h_{j,t-1})) \qquad (2.24)$$

Where w_{bo} , w_{bh} the weight of bias for the output & input layer, it's equal to 1

w_{ho} = the weight from the input layer to the output layer.

w_{ih} = the weight from the input to the process unit in input layer.

w_{ch} = the weight for a context layer.

x_{t-j} = the past time series observations.

$h_{j,t-1}$ Represent the feedback-value.

2 Testing / Experimental Results

In this section, we have chosen the BP for training TDNN, RNN. generally for back propagation learning algorithm[14], it is better to transform the raw time series data into indicators that represent the underlying information[16]; more explicitly, the data must be normalized to the period [0, 1]. The optimal values of learning rate, number of process elements (neurons) in input layer and number of past observation that are used as inputs for ANN are determined empirically using trail by error. The activation function of the first layer is a non-linear logarithmic sigmoid function and a linear function in the second layer. The training initial weights used in this case has ones in diagonal of the first square part of weight matrix, The output layer contain 1 process element because we using one step ahead forecasting.

FFNN and RNN both will be applied on the same data set ,then we used the best to construct a dynamic model used to predict these sunspots number using unseen data set and compare the accuracy of model to assessing the results.

2.1 TDNN Results

Training process requiring to determine the optimal values of learning rate, number of process elements (neurons) in input layer and number of past observation that are used as inputs to the system.

In this test the number of iteration(epoch) is kept fixed to 50000 iteration, the number of process elements in the first layer is kept fixed to 40 process elements, the number of lag input is kept fixed to 10.

it is seen that 0.000013 learning rate leads to better results in testing both the training set and the test set. this value was used to find the optimal number of neuron in input layer ,it found that 13process unit is considered as the best choice, the past experiments are used to getting the best number of lags , the error rate in the best one was on 11 past observations (lag).

The prepared pattern of the input and output are divided into two sets which one of them for training and the other for testing; after choosing the optimal value of lag observation, the training data set is taken from year 1711 to 1907 and the rest 100 points from the year 1908 to 2007 is taken as testing set

The resulted curve obtained after training phase is shown in Figure 2.1a will be compared to actual time series curve. It is noted that as the number of iteration increased the obtained curve becomes better and better using all two measured (RMSE and MRSE).

This mean the designed structure approximate the behavior of the sunspot relation.

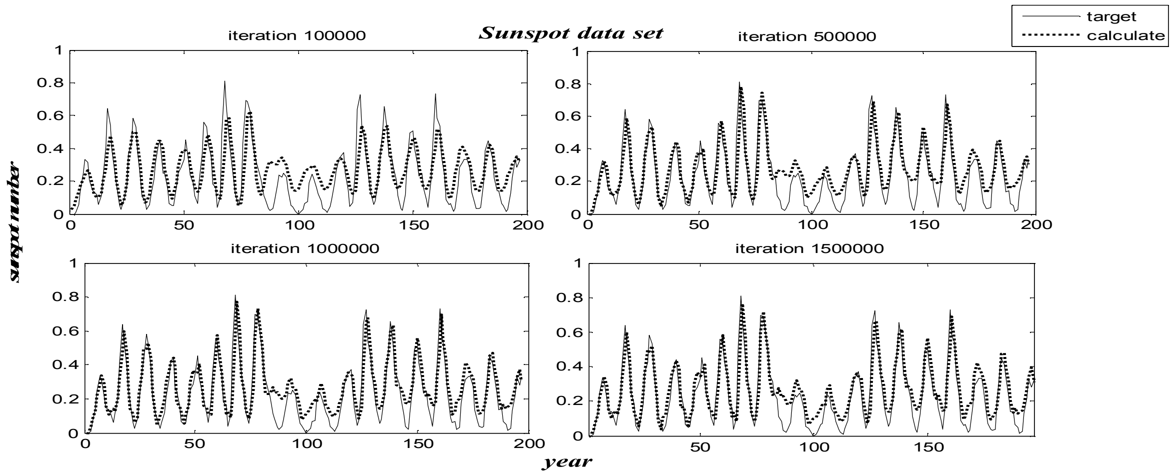


Figure 2.1a: Real values (——) and modeled values (┅┅) of time delay neural network of sunspot series during the period 1711-1907

For the testing data that is not used of training. Figure 2.1b shows the resulted curves when testing data is used compared to the actual curve, which is highly approximate to the actual data. The results curves become more and more identical to the actual curves.

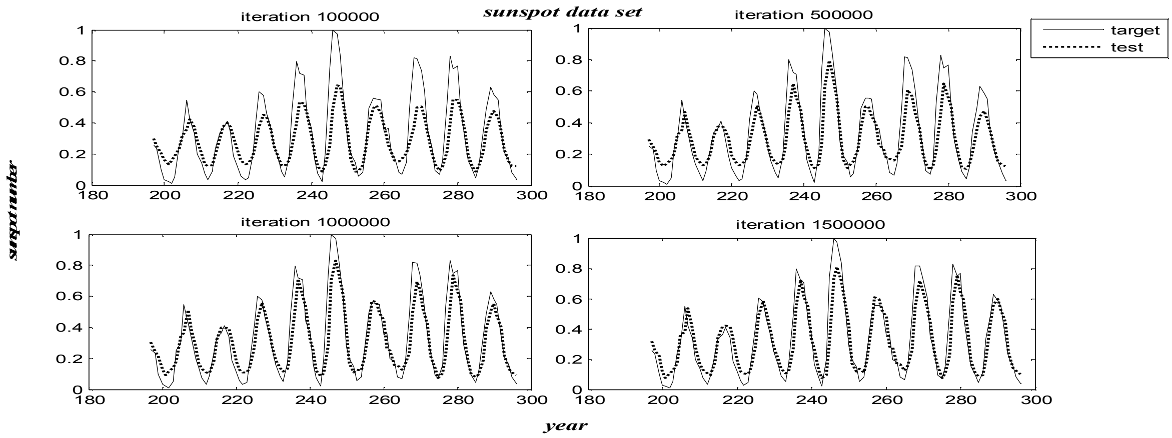


Figure 2.1b: Real values (——)and modeled values (┅┅) of time delay neural network of sunspot series during the period 1908-2007.

2.2 RNN Results

By using the same number of iteration which used in TDNN, we found that,the optimal number of learning rate is 0.000013,13process elements in the first layer 13 process elements is good, the optimal number of lags , was on 10 past observations (lag).

Here, the training data set is taken from year 1710 to 1907 and the rest 100 points from the year 1908 to 2007 is taken as testing set. For training data set, the obtained results depended on the increasing of the number of iteration, and the result give very good Fig 2.2a shows this results.

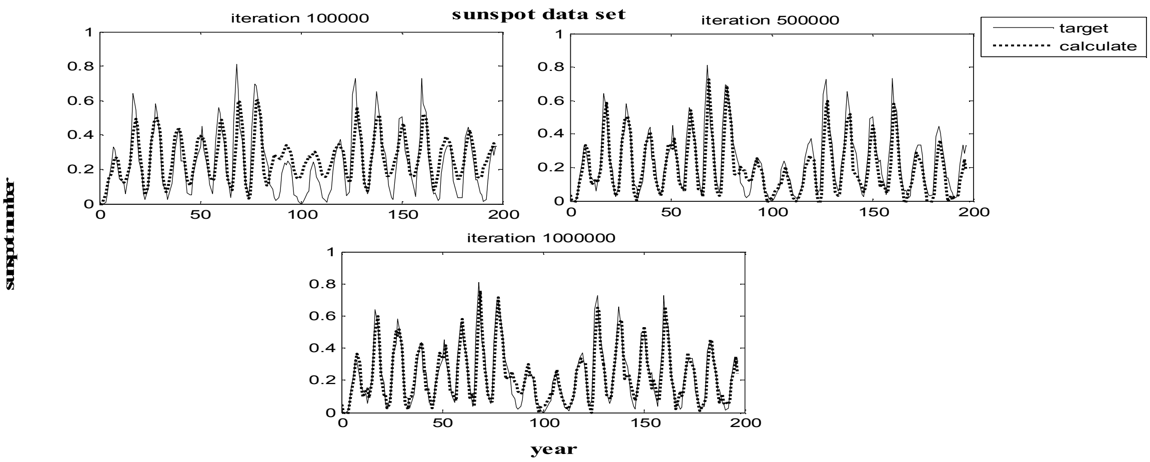


Figure 2.2a: Real values (——) and modeled values (┅┅) of recurrent neural network of sunspot series during the period 1710-1907 better result obtained with increasing of number of iteration.

The testing data is also used with the RNN training structure, the obtained results do not depended of the increasing of the number of iteration. See Fig 2.2b

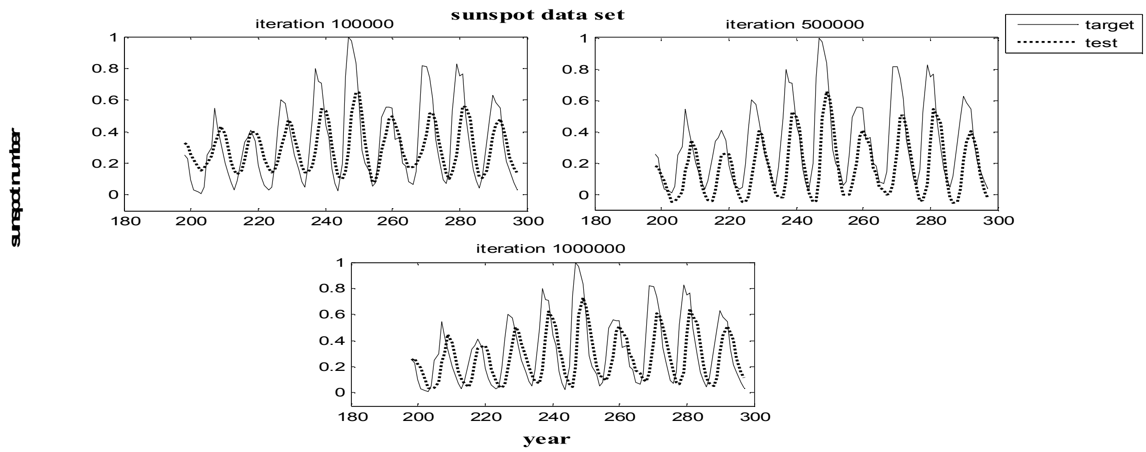


Figure 2.2b: Real values (——) and modeled values (┅┅) of recurrent neural network of sunspot series during the period 1908-2007.

3 Future forecasting results

From previous sections, the TDNN trained structure is selected to be used for one of the purposes of this work which future forecasting based on training process to make the designed ANN structure to get the behavior of the system that produce the sunspots. The TDNN trained structure is selected to be used for future forecasting 2008-2020.

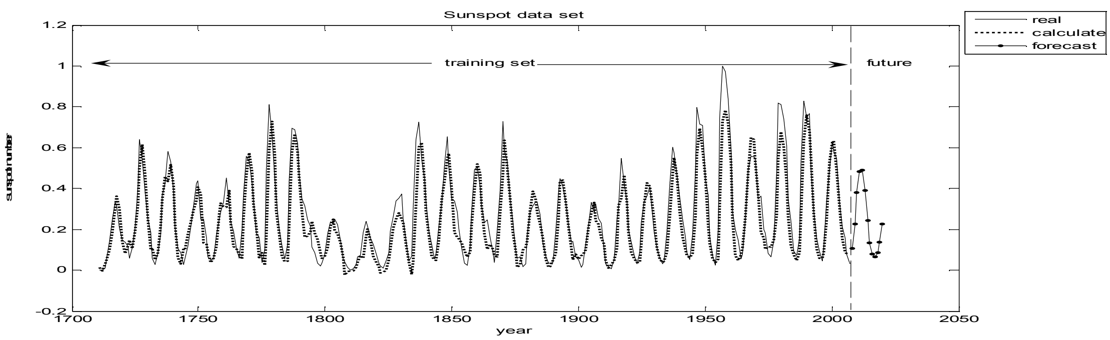


Figure 3: Real values (——)and modeled values (┅┅) of sunspot series during the period1711-2007 and values (—•—) of forecasting sunspot series during the period 2008-2020

4 Equivalent dynamic system

- It requires analyzing the output that resulted from neural network using multi-dimensional Taylor series [8]. $$y_2 = g(w2 * f_1(w1 * x1))$$

After the obtained result of the first order is computed, it found that the first order is not exactly as the ANN result when this result is compared with result that can be calculated by adding some parts of second order. It found that the change is done toward to get the result of ANN structure, this change has a linear relation which can be correct by remove this linear relation, see Fig 4a

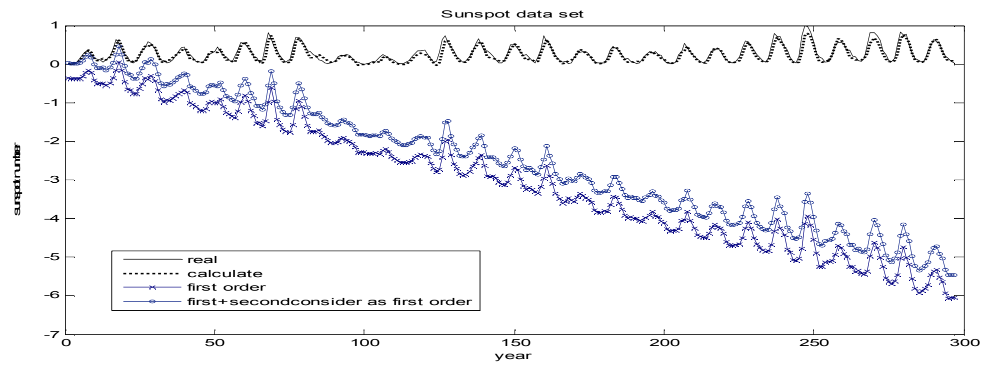


Figure 4a: Real data ( ) and modeled data( ) and first order( ) and ( ) of first order plus some terms of second order for data set of 1711-2007

This can be done by finding the best line passes through the first order curve, which mean computing the slope and intersection of this line, then adding to the curve the mirror image of computed line curved x-axis which will eliminate the slope effect by terms, fig 4b appear the best line and the mirror image.

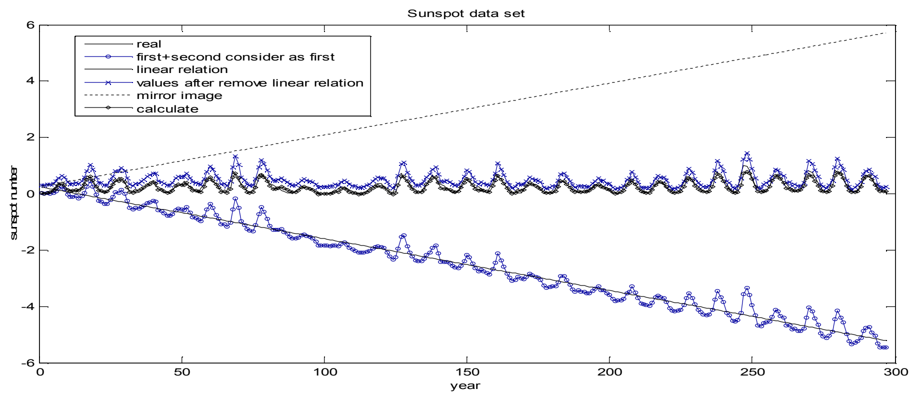


Figure 4b: Real data(–) and modelled data( ) and( ) of first order plus terms of second order with direction ( ) of values after remove linear relation.

In previous figure, It is found that the resulted curve( ) has same difference of ANN curve. To correct (or reduce) the error and give more accurate result we using the linear transformation of the scale. See fig 4c

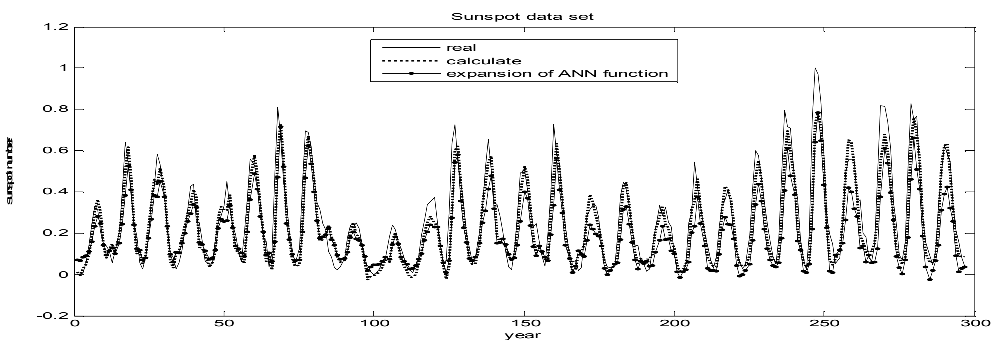


Figure 4c: Real data( ) and modeled data ( ) and( ) first and some terms of second order degree after remove linear relation and data scaled.

By equating the two Taylor series (Neural Network & Dynamic system) it is becomes easy to identify the dynamic system with coefficients as a function to weights of ANN.

5 Conclusion

It is found that feed forward NN structure with back propagation algorithm can be trained and implemented with proper lag argument of input and output results. So time delay neural network is better than recurrent neural network structure.

To find equivalent dynamic system that can produce the sunspots, Taylor series expansion is used to analyze the results obtained by ANN. The coefficients of Taylor series are function of neural network weights, so their values depend on the accuracy of training process. After the obtained result of the first order is computed, it is found that by adding some second order terms while gives the same pattern of ANN but with a negative slope.

Future work:

Future work on this work would include the using of other types of ANN topology or with higher degree inputs can be tested to get better result than the one obtained in this work.

Also, more work can be done on variables learning rate and moment term which is not properly test with this work, testing of such things may give other direction in work.

Annual sunspots average were used in this work but if monthly, weekly or daily sunspot is used may be will give different and better results.

Using of higher degree terms of Taylor series will reduce the error results in computation.

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