Journal of Multidisciplinary Engineering Science and Technology (JMEST)
ISSN: 2458-9403
Vol. 5 Issue 10, October - 2018

Recurrent Neural Networks in Time Series Prediction

Dezdemona Gjylapi
Department of Computer Science,
University "Ismail Qemali",
Vlore, Albania
dezdemona.gjylapi@univlora.edu.al

Eljona Proko
Department of Computer Science,
University "Ismail Qemali",
Vlore, Albania
eljona.proko@univlora.edu.al

Alketa Hyso
Department of Computer Science,
University "Ismail Qemali",
Vlore, Albania
alketa.hyso@univlora.edu.al

***Abstract* — Time series forecasting is the use of a model to predict future values based on previously observed values. Time series forecasting has some important applications in real life, and also these kind of problems are a difficult type of predictive modeling problem. This paper studies the ability of the recurrent neural networks (RNN) to perform time-series forecasting. In RNNs, the signals passing through recurrent connections constitute an effective memory for the network, which it can then use the information in memory to better predict future time series values. In this paper we use a recurrent dynamic network, the Non-linear Auto-Regressive with eXogeneous inputs (NARX) model, to forecast time series like EURO/ALL exchange rate, USD/ALL exchange rate, Consumer Price Index (CPI) and Interest Rate for credits in Euro. The conclusion is that the RNN model achieves a high accuracy on the time series forecasting.**

Keywords — neural network; prediction; time series; RNN; NARX

I. INTRODUCTION

The artificial neural networks can be used in many real-life problems and because of their nonlinear model, they can be used in many business problems, such as the time series prediction.

Forecasting time series has some important applications, because most of the time it is required to calculate some metric indices, which may be related to economy, politics, technology, etc. Also, because it is mandatory to measure the possible risks around future events, to prevent adverse events by forecasting the event, identifying the circumstances preceding the event, as well as taking corrective measures to avoid the event.

Another application is forecasting the adverse, but still inevitably events, to lessen their impact in advance.

Finally, many people would like to benefit from the prediction of time series, because most of the businesses and projects require certain planning, which most of the time is performed with an uncertainty knowledge of the future conditions. There are many products that can be subject to financial forecasting [1].

A time series is a signal that is measured in regular time steps. The estimation of future values in a time series is commonly done using past values of the same time series. The time step of a series may be of any length, for example: seconds, hours, days, months, years, etc. [2].

Our time series contain monthly data.

Time series prediction tools are divided in two main categories: linear modes and non-linear models.

Before the '80, the time series prediction used linear parametric autoregressive (AR), moving-average (MA) or autoregressive moving-average (ARMA) models introduced by Box and Jenkins [3].

In the nonlinear prediction category some models to be mentioned are: neural networks, Support vector machines, Fuzzy systems, Bayesian estimators etc.

The advantage of the artificial neural network approach is that this model can capture the relationship of nonlinear data, especially if the economy is very volatile, and it is superior when it comes to forecasting chaotic data [4].

Neural networks can be divided into static and dynamic networks. The static networks have no feedback elements and no delays. The output is calculated directly from the current inputs [5].

The dynamic networks are more powerful compared to static networks, though they may be difficult to train. They can be trained to learn sequential or time-varying patterns, precisely because they contain feedback elements or delays. This makes these networks the main choice in different applications such as financial forecasting, classification, word recognition, error detection, etc.

In this paper we use recurrent dynamic networks as we are interested in the time series prediction.

The rest of the paper is organized as follows: Section 2 presents a brief description of the RNN and the NARX model, Section 3 explains the results of the NARX model in time series prediction, and finally, Section 4 presents our conclusions.

II. Recurrent Neural Networks

The human brain is a recurrent neural network: a special type of network of neurons with recurring connections.

It can learn many behaviors, sequence processing tasks, algorithms, programs that are not learnable by traditional machine learning methods. This explains the rapidly growing interest in artificial RNNs. Some recent applications of these networks include adaptive robotics and control, handwriting recognition, speech recognition, keyword spotting, music composition, stock market prediction, time series forecasting etc. [6].

A backpropagation network may have recurrent connections so that a unit (node) can turn its activation as an input back to itself, or to other units at the same or lower levels.

In some cases, this type of neural network may have links that reverse the result from the output layer nodes in the input layer, and some input layer nodes return their activation back to themselves.

In general, recurring nets are used for pattern processing that can have variable lengths that will be treated as sequences, divided into pieces and displayed on the network at a different time step [7].

Recurrent neural network architectures can have many different forms. One common type consists of a standard Multi-Layer Perceptron (MLP) plus added loops. Others can be fully connected, i.e. every neuron connected to the others in a uniform structure as shown in Fig. 1.

During the last decade, several methods for supervised training of RNNs have been explored. There are several types of training algorithms known, but there is no best algorithm known. Standard training techniques for RNNs are Backpropagation revisited and Backpropagation through time. This suites more for simple architectures and deterministic activation functions, while when the activations are stochastic, simulated annealing approaches may be more appropriate [8].

The RNNs are very powerful, because they combine the two following properties:

– Distributed hidden state that allows them to store a lot of information about the past efficiently.
– Nonlinear dynamics that allows them to update their hidden state in complicated ways.

With enough neurons and sufficient time, RNNs can compute anything that can be computed by computer.

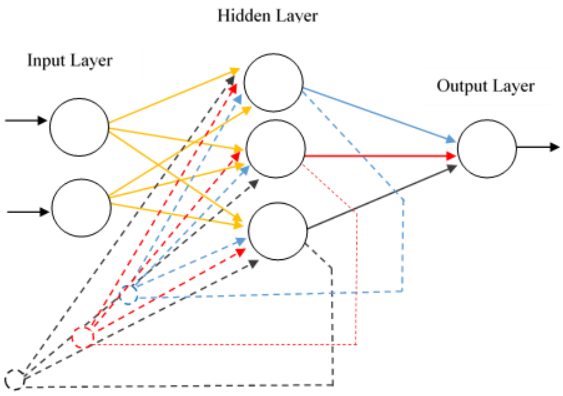

Fig. 1 *The structure of a RNN*

A. *The NARX model*

An alternative RNN formulation has a single input and a single output, with a delay line on the inputs, and the outputs fed back to the input by another delay line.

This is known as the Non-linear Auto-Regressive with eXogeneous inputs (NARX) model.

The nonlinear autoregressive network with exogenous inputs (NARX) is a recurrent dynamic network, with feedback connections enclosing several layers of the network.

The NARX model is based on the linear ARX model, which is commonly used in time-series modeling.

The defining equation for the NARX model is (1):

$$y(t)=f(y(t-1),y(t-2),\ldots,y(t-ny),x(t-1),x(t-2),\ldots,x(t-nu)) \quad (1)$$

where the next value of the dependent output signal y(t) is regressed on previous values of the output signal and previous values of an independent (exogenous) input signal [5].

The standard NARX network uses a sigmoid transfer function in the hidden layer and a linear transfer function in the output layer.

In this paper we use the MATLAB NARX model with the number of neurons in the hidden layer and the number of delays varying on the time series to predict.

Also, the training method depends on the time series to predict. The training continued until the validation error failed to decrease for six iterations.

III. Testing and Results

A. *The data used for neural network*

The series used to train and test the network are: CPI data series, Exchange rate Euro/ALL, USD/ALL and the Interest Rate in Euro time series. These time series are chaotic in nature.

Journal of Multidisciplinary Engineering Science and Technology (JMEST)
ISSN: 2458-9403
Vol. 5 Issue 10, October - 2018

The data used are monthly data: CPI time series data from Dec 1989- May 2017; Euro/All and USD/ALL time series data from Jan 2002- May 2017; Interest Rate in Euro time series data from Jan 2002- May 2016. These data was stored in a .xls file and served as input to the neural network models. In general, ANN models require large amounts of data. These data is provided from the official sites of INSTAT[1] and the Bank of Albania.

B. *Interest Rate in Euro time series*

For the interest rate in Euro time series prediction we have used the NARX network with eight neurons in the hidden layer and four delays as shown in Fig. 2. The training algorithm used is Levenberg-Marquadt.
The correlation error is presented in Fig. 3.

As can be seen by the figure there is only one nonzero correlation error occurred in zero lag, so we can say that the model is adequate and the prediction is very good. The mean square error for this time series is 0.25. Regression R Value is 0.8462 as shown in Fig. 4.

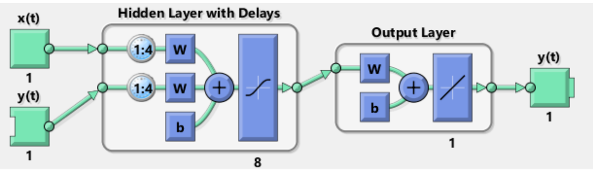

Fig. 2 *The NARX model used for Interest Rate in Euro*

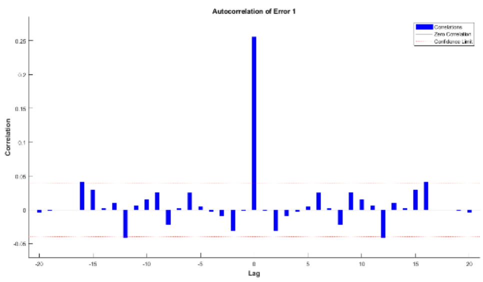

Fig. 3 *Correlation Error for Interest Rate in Euro*

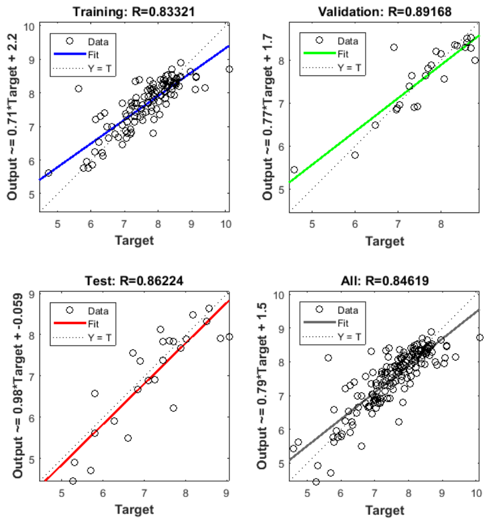

Fig. 4 *Regression R values for Interest Rate in Euro*

Fig. 5 *Interest Rate in Euro vs NARX model outputs*

C. CPI time series

For the CPI time series forecasting we have used the NARX network with ten neurons in the hidden layer and three delays as shown in Fig. 6. The training algorithm used is the Levenberg-Marquadt algorithm.
The correlation error is presented in Fig. 7

As can be seen by the figure there is only one nonzero correlation error occurred in zero lag, so we can say that the model is adequate and the prediction is very good. The mean square error for this time series is MSE=7. Regression R Value is R=0.9994 as shown in Fig. 8.

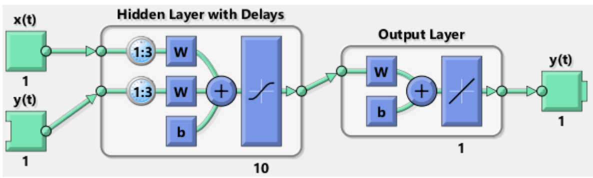

Fig. 6 *The NARX model used for CPI prediction*

[1] INSTAT - The Institute of Statistics of Albania

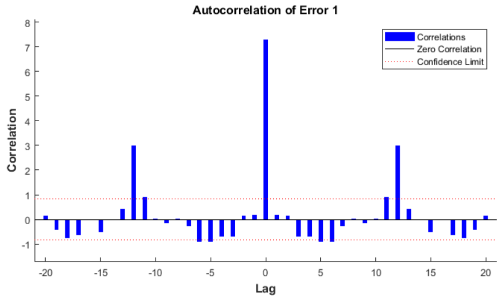

Fig. 7 *Correlation Error for CPI*

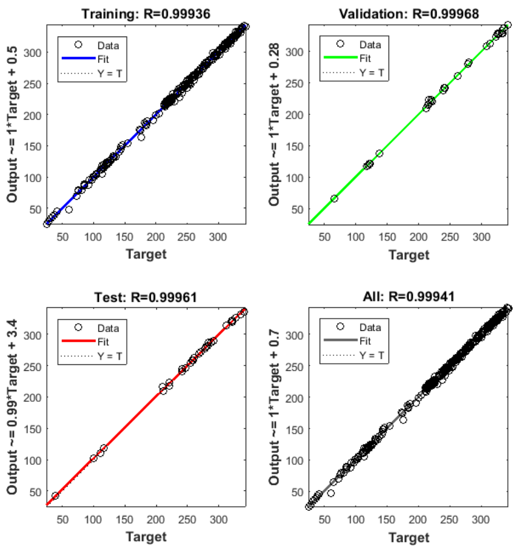

Fig. 8 *Regression R values for CPI*

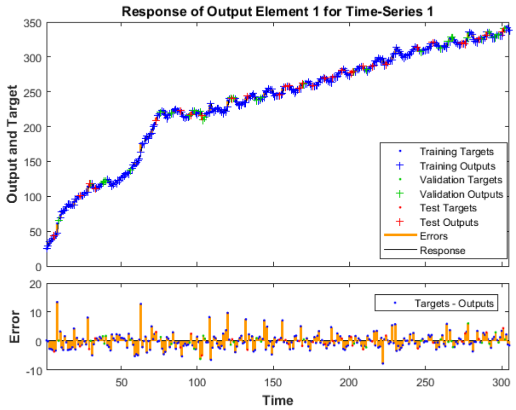

Fig. 9 *CPI time series vs NARX model outputs*

D. EURO/ALL time series

For the EURO/ALL time series prediction we have used the NARX network with ten neurons in the hidden layer and five delays as shown in Fig. 10**Error! Reference source not found.**. The training algorithms is Bayesian Regulation.

We can say that the model is adequate and the prediction is very good. The mean square error for this time series is MSE=0.83. Regression R Value is R=0.99083 as shown in Fig. 12.

The correlation error is presented in Fig. 11.

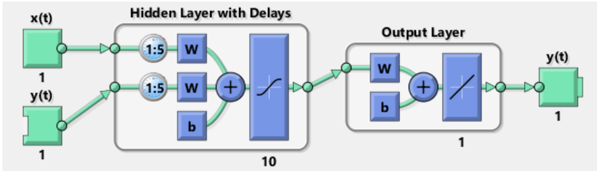

Fig. 10 *The NARX model used for EURO/ALL prediction*

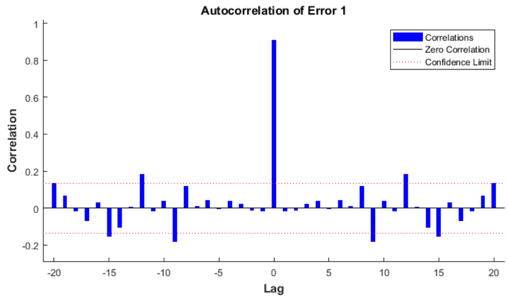

Fig. 11 *Correlation Error for Euro/ALL*

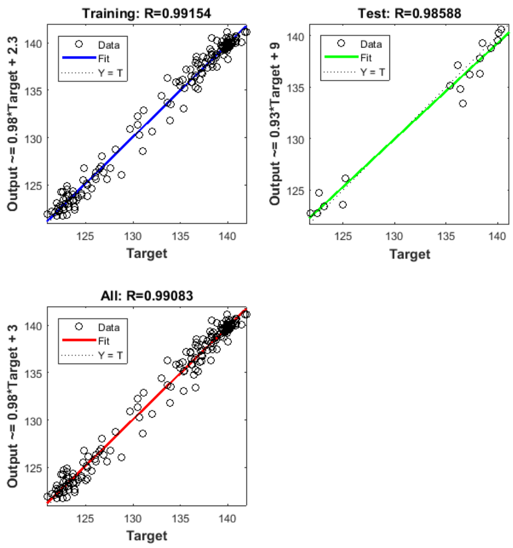

Fig. 12 *Regression R values for EURO/ALL time series*

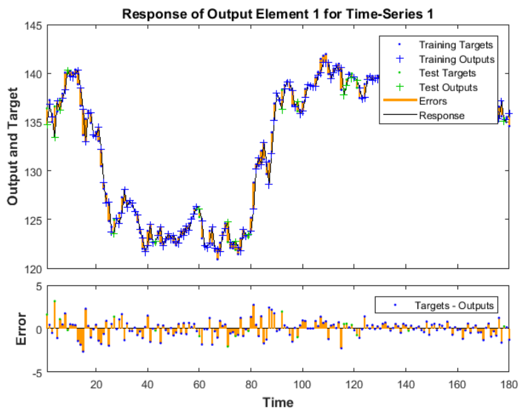

Fig. 13 *Euro/ALL time series vs NARX model outputs*

E. USD/ALL time series

For the USD/ALL time series prediction we have used the NARX network with eighteen neurons in the hidden layer and six delays as shown in Fig. 14. The training algorithms is Bayesian Regulation.
The correlation error is presented in Fig. 15.
The model is adequate and the prediction is very good. The mean square error for this time series is MSE=5.
Regression R Value is R=0.9869 as shown in Fig. 16.

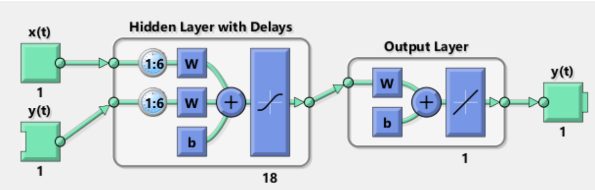

Fig. 14 *The NARX model used for USD/ALL prediction*

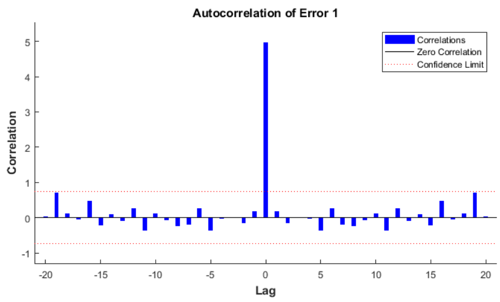

Fig. 15 *Correlation Error for USD/ALL*

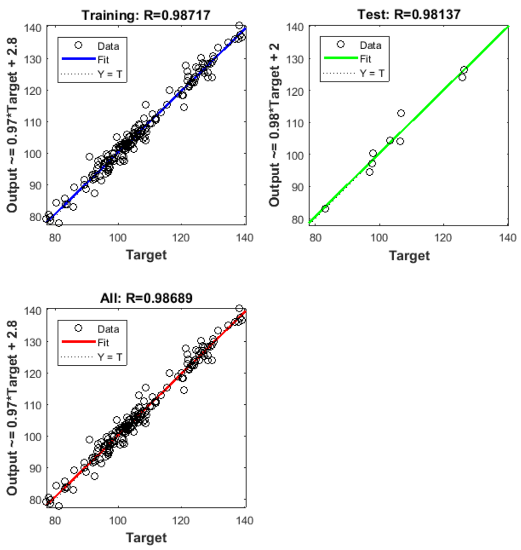

Fig. 16 *Regression R values for USD/ALL time series*

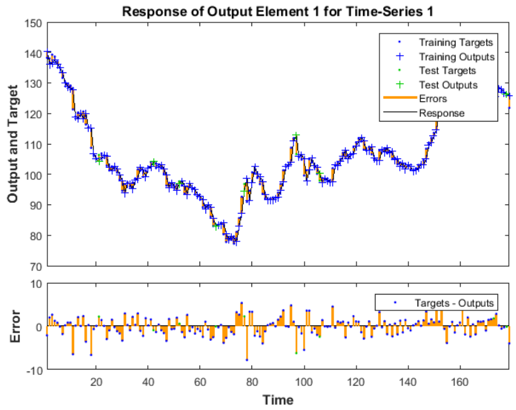

Fig. 17 *USD/ALL vs NARX model outputs*

IV. Conclusion

In this paper we presented an approach to forecast time series like CPI, Euro/ALL, USD/ALL and also Interest Rate using the recurrent neural networks.

One of the advantages of RNN is that it requires minimal preprocessing of the series data and no pre-assumption of the model underlying the data.

In the absence of strong general nonlinear theory offering suggestions on which technique is better in what situation, experimentation and heuristics are relied upon to guide the choice of the methodology, architecture and size of the neural networks in this work.

For the EURO/ALL and USD/ALL exchange rate the Bayesian Regulation algorithms fits best, while for the two other series, the Levenberg-Marquadt algorithm is the best fit.

References

[1] E. A. Plummer, "TIME SERIES FORECASTING WITH FEED-FORWARD NEURAL NETWORKS: GUIDELINES AND LIMITATIONS," 2000.

[2] P. Gómez-Gil, J. C. G. Hernandez, R. F. Delgado, M. Ramírez-Cortés and V. Alarcón-Aquino, *On the use of 'Long-Short Term Memory'neural networks for time series prediction*, IEEE CIS Mexico Chapter, 2014.

[3] E. Diaconescu, "The use of NARX Neural Networks to predict Chaotic Time Series," *WSEAS TRANSACTIONS on COMPUTER RESEARCH*, vol. 3, no. 3, pp. 182-191, March 2008.

[4] M. H. Imansyah, Suryani, Nurhidayat and Muzdalifah, "GDP Estimation and Slow Down Signal Model for Indonesia:An Artificial Neural Network Approach," *Finance and Banking Journal*, vol. 13, no. 1, pp. 77-94, 2011.

[5] MathWorks, "MathWorks," 2017. [Online]. Available: https://www.mathworks.com/help/nnet/ug/introduction-to-dynamic-neural-networks.html.

[6] J. Schaffer, L.D.Whitley and L. Eshelman, "Combinations of genetic algorithms and neural networks: A survey of the state of the art," in

Proceedings of the Third International Workshop on Combinations Genetic Algorithms Neural Networks - COGANN 92, Los Almatos, CA, IEEE Computer Society Press, 1992, pp. 1-37.

[7] D. Gjylapi, "Algoritmat gjenetik ne trajnimin e rrjetave neurale," Universiteti i Tiranes, Tirane, 2016.