Forecasting Exchange Rates Using Artificial Neural Networks

Ahmed BENLARIA*
Algerian-African Economic Integration Laboratory, Adrar University
Algeria
ahmed.benlaria@univ-adrar.edu.dz

Lahcen BOUBEKEUR
Sustainable Developments and Computing Laboratory, Adrar University
Algeria
boubekeur@univ-adrar.edu.dz

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Abstract :
This aims to forecast the exchange rates of the Algerian Dinar against the US dollar using artificial neural networks by building the optimal neural network to know the accuracy of prediction in this method and this is because of the characteristics of exchange rates time series, as they are non-linear, dynamic and random. The lagged values of the monthly data of the Algerian Dinar exchange rates against the US dollar were used as inputs for three artificial neural networks that differed in their architectures in terms of the number of neurons in their hidden layer, and they were compared in terms of prediction efficiency. The results of the study showed that the artificial neural network which contains eight hidden neurons, has outperformed the other networks in predicting accuracy.

***Key Words*:** Forecasting, Exchange rate, Algerian dinar, Artificial intelligence, Artificial Neural networks.

JEL Classification : F31, E47.

*Corresponding author: Benlaria Ahmed (*ahmed.benlaria@univ-adrar.edu.dz*)

Introduction:

It would be hard to overstate the importance of exchange rates for the world economy. They affect output and employment through real exchange rates. They affect inflation through the cost of imports and commodity prices. They affect international capital flows through the risks and returns of different assets (King, Osler, & Rime, 2012). Exchange rates are justifiably a major focus for policymakers, the public, and, of course, the media.

It is clear that the impact of the exchange markets recently in the Arab countries quickly moved to the markets for goods and services, and imposed more inflationary pressures in most countries. With the governments of the Arab region re-pricing public services and goods in the Arab region in addition to the exchange market crisis, it is expected that inflation rates in them will rise, according to the Arab World Bank Fund.

Also, several countries from the region, including Algeria, rushed to rely on global debt markets in order to bridge the financing gap, which would impose many pressures. As a total, Standard & Poor's credit rating agency expects, in light of the economic crisis in the region resulting from low oil prices, that the total sovereign debts of 13 countries in the region will reach 814 billion dollars in 2020, an increase of 116 billion dollars over the previous year.

Predicting exchange rates is a problem in the international financial sector. This is due to the state of uncertainty and fluctuations in exchange rates that hinder forecasting efforts. These fluctuations are the result of many factors affecting the foreign exchange markets, including economic, political, and even psychological. But because of the many advantages that can be benefited from by investing in this field, many researchers tried to solve the problems of forecasting exchange rates, and this led to the use of many methods for that.

Initially, primary methods of forecasting exchange rates were used, such as moving averages (Brown, 1963) and exponential touching (Trigg & Leach, 1967), after which many researchers used autoregressive integrated moving average models (ARIMA) (Box & Jenkins, 1970).Which was widely used until the early 1980s. In the mid-1980s, researchers focused on foreign exchange rate fluctuations. As a result, an Autoregressive conditional heteroscedasticity (ARCH) model was proposed to predict short-term fluctuations (Engle, 1982). Next, (Chen & Leung, 2003) developed a Vector error correction model (VECM) to predict exchange rates.

In the past decade, with the rapid advancement of computer technologies and the increasing demand for artificial intelligence (AI), researchers have become more capable of financial forecasting by relying on Artificial Neural Networks (ANNs). The neural network method is characterized by its high ability to model non-linear relationships, and it can overcome cases of data loss and incompleteness and discover hidden relationships between variables through the available data. This method does not need to suggest or use any hypothetical prior models, that is, we do not need to define any prior hypotheses about these relationships, and if there is a mathematical relationship between the dependent variable and the independent variables, then the neural networks method will determine this relationship through a special training and learning process. In contrast to the traditional statistical methods that oblige the researcher to study the problem theoretically in order to identify the relationship between the studied variables and define them before starting to build statistical models for them, and that also requires determining the probability distributions of the variables and determining the hypotheses for building these models.

Exchange rate time series are usually non-linear, dynamic, random and nonparametric (Zhang & Wu, 2009). Hence, traditional statistical methods are not sufficient to predict such chains, and therefore more modern methods have been used. Neural networks are one of the methods that have been used in many different studies, and they can be used to predict the exchange rates of the Algerian Dinar, due to the lack of a suitable statistical model to accurately predict future values of exchange rates.

On this basis, this topic will address the following main problem: How can neural networks be used to predict the exchange rates of the Algerian Dinar?

I. Exchange rates in Algeria:

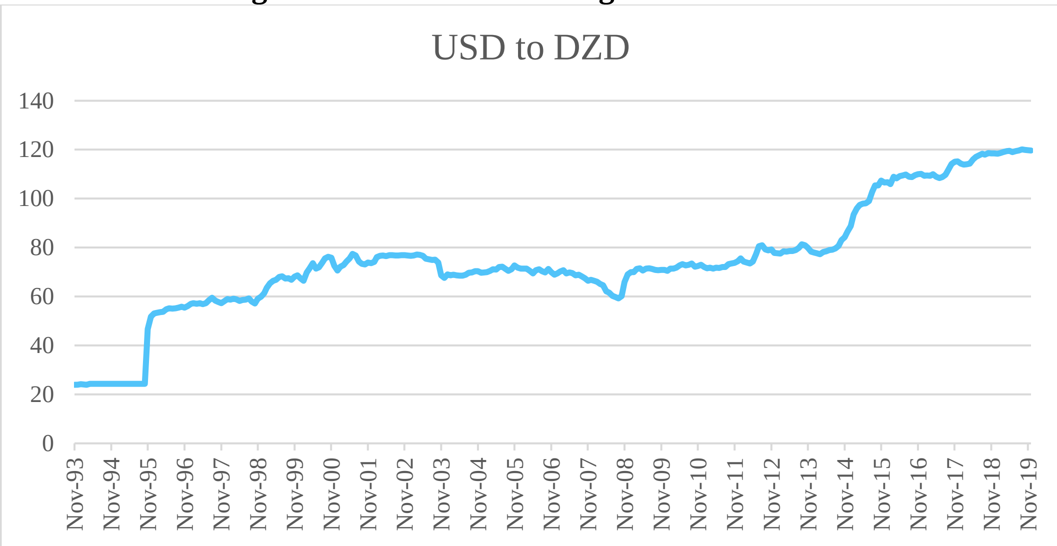
In September 1991, the Monetary and Loan Board decided to reduce the exchange rate of the Algerian Dinar by 22%, according to an agreement with the International Monetary Fund within the framework of credit preparedness, bringing the exchange rate to 22 Dinars against the US dollar. This situation continued until March 1994. After Algeria had concluded the reform and structural adjustment program with the International Monetary Fund on April 10, 1994, the Monetary and Loan Board decided to reduce the Dinar in March 1994 by 7.3% and 40.17% in April of the same year, i.e., by 47.47% in two months. The exchange rate of the Dinar reached 36 Dinars against one dollar in 1994.

At the end of 1994 the system of pegging to a basket of currencies was replaced with fixing sessions, and this method represents one of the techniques for pricing by public auction to determine the exchange rate of the Algerian Dinar from the last third of the year 1994 until the end of 1995, and this method depends on daily sessions held in the headquarters of the Central Bank and the gathering of representatives of commercial banks headed by the representative of the Central Bank. This new method was able to determine a quasi-real exchange rate that is subject to the law of supply and demand from one side without disturbances and in line with the objectives related to exchange reserves and monetary policy.

At the beginning of 1996, the Algerian Dinar entered the float phase, as it became determined udaccording to the law of supply and demand in the monetary market, which incles, in addition to the Bank of Algeria, commercial banks in Algeria, with the possibility of the Bank of Algeria's intervention in this market in order to maintain the balance and stability of the Algerian Dinar. The balance of payments also rebounded at this stage as a result of the increase in oil prices, which enabled Algeria to build a large exchange reserve. This improvement contributed to strengthening the application of an exchange rate policy, which was relatively stable, as well as the low inflation rates compared to those prevailing in the major trading partners.

Figure 1 shows the evolution of the Algerian Dinar exchange rate against the US dollar during the period 1993-2019

Fig. 1 : Evolution of exchange rate 1993-2019



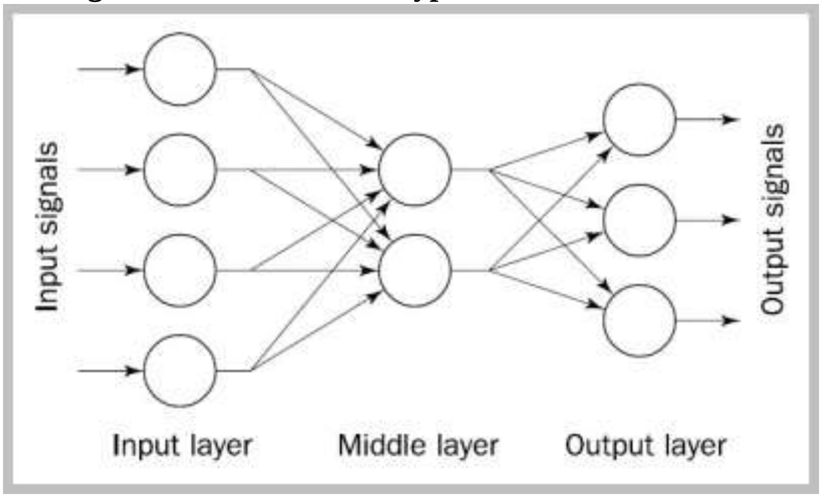
Source : Compiled by the Researchers based on IMF database and OANDA

II. Artificial Neural Network (ANN) model

A neural network can be defined as a thinking model based on the human mind. The brain is made up of a densely connected group of neurons, or basic information processing units, called neurons. The human brain includes approximately 10 billion neurons and 60 trillion connections and electrical synapses between them (Shepherd & Koch, 1990). By using many neurons simultaneously, the brain can perform its functions much faster than the fastest computers today.

The artificial neural network structures were developed from known models of biological nervous systems and the human brain itself. The computational components or processing units, called artificial neurons, are simplified models of biological neurons. These models were inspired by the analysis of how a cell membrane of a neuron generates and propagates electrical impulses (da Silva, Spatti, Flauzino, Liboni, & dos Reis Alves, 2016).

Fig. 2 : Architecture of a typical artificial neural network

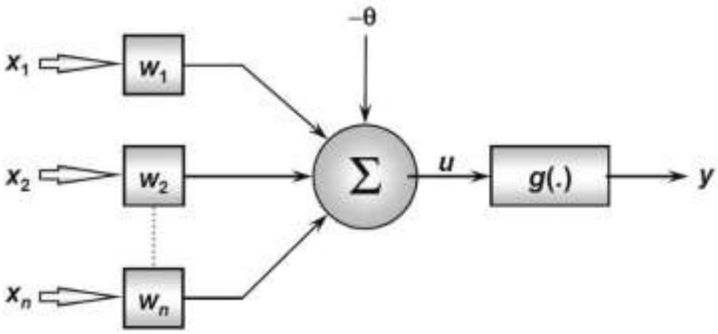


Source : (Michael N., 2005)

1. Mathematical model of Neuron:

Obviously, it is impossible to simulate factually various characters of the biological neuron in a current computer, and we must make various reasonable simplifications. In current research on the neural network, the neuron is the most essential information-processing unit of the neural network (He & Xu, 2010).

Fig. 3 : Artificial neuron model



Source : (da Silva, Spatti, Flauzino, Liboni, & dos Reis Alves, 2016)

The multiple input signals are represented by the group $\{x_1, x_2, \dots, x_n\}$ and are analogous to the external electrical impulses that the dendrites collect in a biological neuron.

All external information that reaches the neuron is weighted by executing a set of weights $\{w_1, w_2, \dots, w_n\}$ through synaptic connections on the artificial neuron, in order to calculate the importance of each x_i input from the neuronal input by multiplying it by the corresponding synaptic weight w_i.

Considering Figure 3, it is possible to see that the artificial neuron is composed of seven basic elements, namely (da Silva, Spatti, Flauzino, Liboni, & dos Reis Alves, 2016):

- Input signals $\{x_1, x_2, \dots, x_n\}$ are the signals or samples coming from the external environment and representing the values assumed by the variables of a particular application. The input signals are usually normalized in order to enhance the computational efficiency of learning algorithms.
- Synaptic weights $\{w_1, w_2, \dots, w_n\}$ are the values used to weight each one of the input variables, which enables the quantification of their relevance with respect to the functionality of the neuron.
- Linear aggregator (Σ) gathers all input signals weighted by the synaptic weights to produce an activation voltage.
- Activation threshold or bias (θ) is a variable used to specify the proper threshold that the result produced by the linear aggregator should have to generate a trigger value toward the neuron output.
- Activation potential (u) is the result produced by the difference between the linear aggregator and the activation threshold. If this value is positive, i.e. if $u \geq \theta$, then the neuron produces an excitatory potential; otherwise, it will be inhibitory.
- Activation function (g) whose goal is limiting the neuron output within a reasonable range of values, assumed by its own functional image.
- Output signal (y) consists on the final value produced by the neuron given a particular set of input signals, and can also be used as input for other sequentially interconnected neurons.

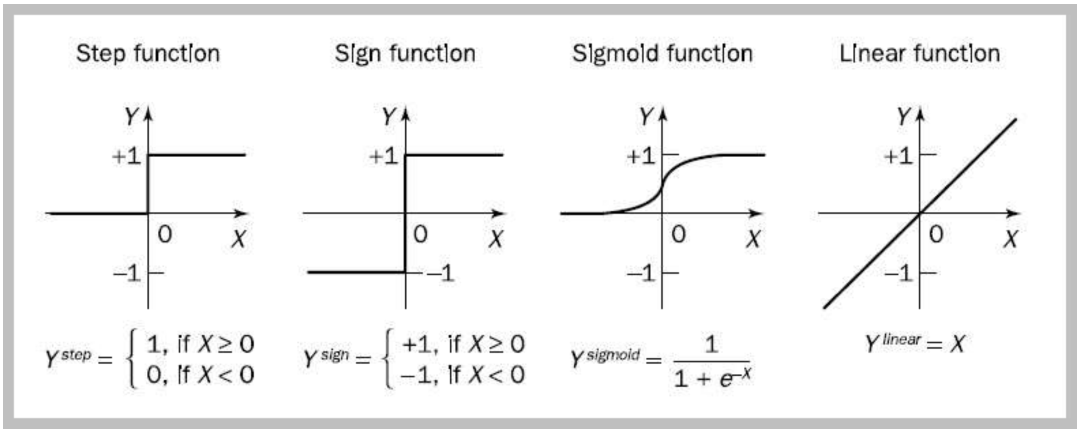
2. Activation Functions:

Each neuron contains an activation function and a threshold value. The threshold value is the minimum value that an input must have to activate the neuron. The activation function is applied and the output passed to the next neuron(s) in the network.

An activation function is designed to limit the output of the neuron, usually to values between 0 to 1, or -1 to +1. In most cases the same activation function is used for every neuron in a network (Da Costa Lewis, 2017).

Many activation functions have been tested, but only a few have found practical applications. Four common choices – the step, sign, linear and sigmoid functions – are illustrated in Figure 4.

Fig. 4 : Activation functions of a neuron



Source : (Michael N., 2005)

The step and sign activation functions, also called hard limit functions, are often used in decision-making neurons for classification and pattern recognition tasks. The sigmoid function transforms the input, which can have any value between plus and minus infinity, into a reasonable value in the range between 0 and 1. Neurons with this function are used in the back-propagation networks. The linear activation function provides an output equal to the neuron weighted input. Neurons with the linear function are often used for linear approximation (Michael N., 2005).

3. Training Processes and Properties of Learning

One of the most relevant features of artificial neural networks is their ability to learn from samples, which express the behavior of a system. Hence, after the network learns the relationship between input and output, it can generalize solutions, which means that the network can produce output close to the expected (or desired) output for any given input values.

There are two different learning modes: supervised and unsupervised. The supervised learning mode presents input-output data combinations to the network. Consequently, the connection weights and node biases, initially randomly distributed, adjust their values to produce output that is as close as possible to the actual output, i.e., the learning method (recursive algorithm) tries to minimize the current errors of all processing elements. With each subsequent cycle the overall network error between the desired and the actual output will be lower. Eventually, the result is a minimized error between the network and actual output (or desired network accuracy), as well as the internal network structure, which represents the general input-output dependence (Gradojevic, 2002).

Different from supervised learning, the application of an algorithm based on unsupervised learning does not require any knowledge of the respective desired outputs. Thus, the network needs to organize itself when there are existing particularities between the elements that compose the entire sample set, identifying subsets (or clusters) presenting similarities. The learning algorithm adjusts the synaptic weights and thresholds of the network in order to reflect these clusters within the network itself. Alternatively, the network designer can specify (a priori) the maximum quantity of these possible clusters, using his/her knowledge about the problem (da Silva, Spatti, Flauzino, Liboni, & dos Reis Alves, 2016).

III. Data Description:

In this research paper, the monthly data of the Algerian Dinar exchange rate against the US dollar for the period (November 1993 - December 2019) were used with a total of 314 views. The data set was obtained from IMF database and Online Forex Trading & Forex Broker (OANDA).

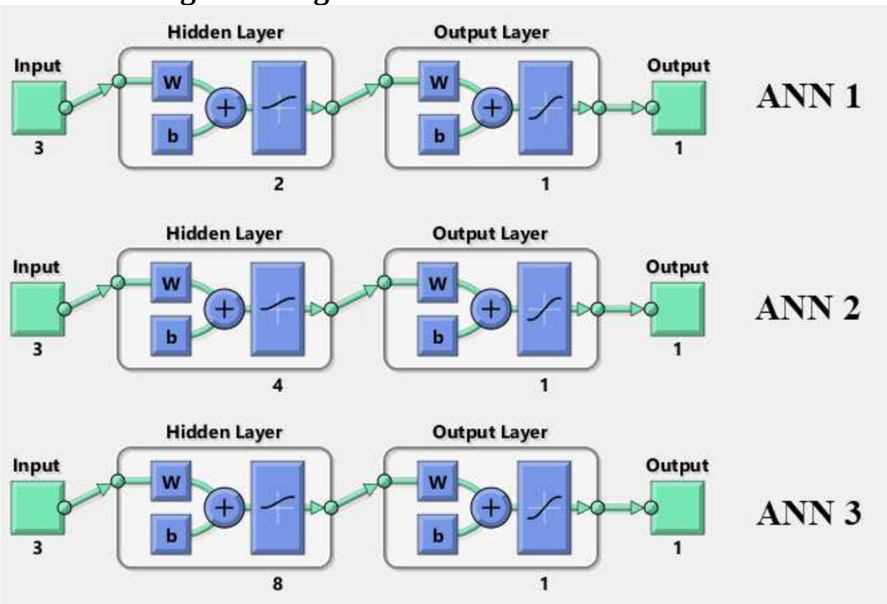
IV. Model selection

In this section, we discuss procedures for selecting an appropriate neural network model for prediction. The number of inputs and hidden units is chosen through experimentation. Data were divided into two parts: 70% for training and 30% of the remaining observations were preserved for test. A hidden single-layer feed forward neural network is used for training where the sigmoid function is used in the hidden layer and the linear transfer function is used in the output layer.

The input layer in the neural network contains three variables which are the lagged values of Algerian Dinar exchange rate time series for one month, six months and twelve months. The output layer contains one variable, which is the exchange rate.

Three neural networks are designed with the same inputs and output, and the difference between them is the number of neurons in the hidden layer. The first, second and third network contain two neurons, four neurons and eight neurons, respectively as shown in Figure 5.

Fig. 5 : Designed artificial neural networks

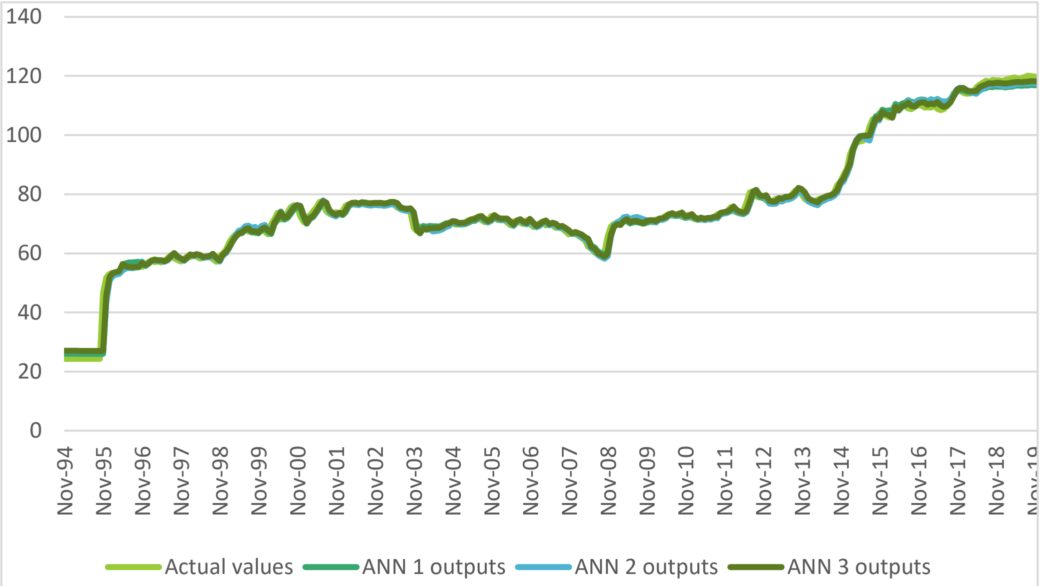


Source : Prepared by the researchers based on MATLAB software

V. Empirical findings

The predicted values of the three neural networks were close to the actual values of exchange rates as shown in Figure 6.

Fig. 6 : Actual values of exchange rates and ANNs outputs



Source : Prepared by the researchers based on MATLAB software

After training and testing the three neural networks, a comparison was made between the efficiency of the three networks based on the root mean square error (RMSE), which is calculated as follows:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} {e_i}^2}{n}}$$

The results of the comparison are summarized in the following table:

Table 1 : RMSE for the three neural networks

ANNs	Neurons in hidden layer	Sum of Squares Errors	RMSE
ANN1	2	1072.82	1.88
ANN2	4	1108.20	1.91
ANN3	8	917.05	1.74

Source : Computed by the Researchers using MATLAB and Excel software.

It is shown in Table 1 that the neural network (ANN3) that includes eight neurons in its hidden layer was the lowest in the RMSE value (1.74). This indicates that this network was the most efficient in predicting the actual values of exchange rates compared to the two other neural networks (ANN1 and ANN2) with two and four neurons in their hidden layers respectively.

The exchange rate is affected by several variables and economic factors such as money supply, interest rates, consumer price index, balance of payments and so on, as well as other non-economic factors such as political stability and rumors. But the previous results show that the exchange rate of the Algerian dinar is directly affected by previous values, and this indicates the continuous decline in its value. Also it is determined on the basis of purely monetary and financial considerations that do not take into account the real economy.

Conclusion:

In the previous section, we presented the prediction results of the neural networks model by dividing the available data into two groups: the first one for building and training the neural network, and the second for testing the network efficiency after learning. The neural network can be trained again whenever data are available on other variables that affect the exchange rate to obtain high predictive power.

The results of this study showed the high efficiency of the neural networks model in predicting the exchange rates of the Algerian Dinar. This method does not require many conditions and restrictions, which make it difficult to find the appropriate statistical models for the used data.

Moreover, this study has a univariate series of the exchange rate of the Algerian Dinar against the US dollar was used to predict future exchange rates using neural networks. Thus, the exchange rate is directly affected by previous values, and this is due to the continued decline in its value, and it is determined on the basis of purely monetary and financial considerations that do not take into account the real economy of country.

Accordingly, the following suggestions can be made:

- Neural network models can be used on univariate data, using other training methods and different architectures.
- Other inputs about the exchange rate of the Algerian Dinar can be included as inputs to build a multivariate neural network to increase the efficiency of the forecasting process.
- Major currency exchange rates can also be included as input into the neural network.

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