Predicting the exchange rate of the Egyptian pound using neural networks

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Abstract

The analysis of the volatility in the exchange rate has long been a vital challenges and important topic in international finance. Because it is influenced by many factors and forces, while linear models are not able to capture nonlinear

techniques and methods have been evolved in the last few decades for exchange rate prediction to overcome the limitations of the linear methods as well as the development of artificial intelligence, which has led to the development of alternative solutions utilizing non-linear modelling.

This paper aims to use Artificial Neural Networks (ANN) to predict the value of the Egyptian pound in terms of US dollars, by depending on fundamental economic variables. The study concluded that the mean absolute percentage error (MAPE) is 2.8%. This result indicates that neural networks is accurate by 97.2% in forecasting exchange rate depends on the macroeconomic variables.

Keywords:
Exchange Rate; Forecasting; Egyptian pound; Artificial Neural Networks.

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1. Introduction

After the collapsed of the Bretton Woods System in the 1970s, the fluctuations in the exchange rates in different exchange market become a more volatile than ever. The problem of foreign exchange rate misalignment one of the substantial problems facing economists, and it reflects to some extent incomplete knowledge of the behavior of exchange rate and their determinants. Especially with the trend of the exchange rate inconsistent with the economic fundamentals, in addition to the difficulty of explaining the reasons for this disruption if it results from market failure, failure of models, or failure of economic policies.

Despite the significant progress in econometric methods in the study and analysis of the exchange rate, the empirical studies of many theories and models of the exchange rate proved their inability to predict the exchange rate, especially in the short term. Frankel (1986), and Froot and Rogoff (1995) While the study of Frankel (1993) criticized monetary models in estimating the exchange rate, Branson, Halttunen and Masson (1977) and Frenkel (1984) criticized the study of the theory of financial assets in determining the exchange rate, especially in the long term.

In the same context, Meese and Rogoff (1983) found that none of the forecasting models of the exchange rate established by economic theory has a better ability to forecast, over a period lower than 12 months, rather than the forward rate models or random walk, emphasizing the paradox that the variations of exchange rates are completely random. Pacelli, Bevilacqua, & Azzollini (2011).

On the other hand, many studies approve the role of fundamental economic factors in determining the value and

behavior of the exchange rate in long-term period use econometrics model to determine equilibrium exchange rate such as behavior equilibrium exchange rate (BEER) of Clark and MacDonald (1999) and fundamental equilibrium exchange rate (FEER) of Williamson (1983)

2. The problem of the study

According to the disability of traditional models to get accurate model for predict the behavior of exchange rates due to its non-linearity relationship with other factors this study uses a neural network which unlike most of the traditional model-based forecasting techniques, The Selection of the ANN approach for exchange rates forecasting is because of ANNs' unique features and powerful pattern recognition capability.

3. The Aim of The Study

This paper aims to study the determinants of exchange rate of Egyptian pound and measure the accuracy of neural network to predicting exchange rate of Egyptian pound from fundamental economic variables.

4. Hypothesis of the study

The use of neural networks in forecasting can develop ahigh accurate model to predict the real exchange of Egyptian pound depends on economic forces.

5. Literature Review

With the transfer from fixed exchange rate to floating exchange rate system, where the value of exchange rate is determined by the forces of demand and supply. However, it is difficult to measure the behavior of trends in exchange market as they

relate to the minute-by-minute actions of prices within the real market. Currencies determined by the following factors: Nasution, Arvin. (2000)

• Real business
• News releases
• Economic indicators (fundamental analysis)
• Chart theory (technical analysis)

The predictability of the exchange rate depends on three main ideas:

- First one is efficient-market hypothesis (EMH) (Fama,1970, 1991), which states that financial markets are "informationally efficient". There are no profit opportunities that could arise from forecasting the exchange rate market and no models could outperform random walk (RW) model.
- The other two approaches disagree with above argument, claiming that the market is not always efficient and that by using the fundamental variables (fundamental analysis) or chartist approaches (technical analysis) researchers can outperform the RW model.

In Fundamental analysis, which focuses on the economic forces of supply and demand that causes price movement, although it has disadvantages, as most fundamental variables are available in a monthly or annual basis, they are mainly applicable to long-term forecasting instead of short-term forecasting. The fundamental analysis is essential to not only to predict the exchange rate but also to know the variables which have significant influence on the exchange rate, and determine the suitable police to ensure stable of exchange rate, or target a specific value of exchange rate.

Technical analysis, which is the analysis of a financial market using historical patterns and focusing on price movement, charts, trends, trading volume, have shown that issuing buy and sell signals which are generated by technical indicators can outperform the out of sample performance of the RW model (Brock et al.,1992; Gencay, 1996).

Despite the success of technical analysis, these models are not possessing a reliable statistical background. This inefficiency led the economists to use other statistical models such as the Box and Jenkins modelling approach (ARIMA model) (Box et al., 1994), Due to the high volatility of the market, researchers established more advanced statistical methods in order to capture the market's volatility by designing models that can predicting the conditional variance of the series like GARCH model (Bollerslev, 1986; Engle, 1982).

Hsieh (1989) collect both AR and GARCH models by firstly estimating an AR model and then applying a GARCH model on the residuals. This model was able to outperform the Random Walk model. However, diagnostics tests shown that there was still nonlinear relation in the residuals.

Hu, Zhang, Jiang, and Patuwo (1998) propose that, the not success of those models isn't only due to their linear structure, as nonlinear statistical approaches like GARCH models also did not outperform the RW model; but a prior assumption of the model's structure. Yao and Tan (2000) have also argued that the features of monetary data which have high volatility, complexity, noisy environments, etc. can't be described by simple linear structural models, autoregressive and moving average processes, or maybe simple noise processes.

With the development of data science based on artificial intelligence and use neural networks, which are described as

data driven nonparametric modelling approaches that not require a priori assumption and considered more appropriate for the approximation of the nonlinear and sophisticated functions special for the financial analysis. (Zhang et al., 1998).

G. P. Zhang, B. E. Patuwo and M. Y. Hu (1998) presents an evaluate the neural networks for nonlinear time series forecasting. Results show that ANN are valued method for modelling and forecasting nonlinear time series while traditional linear methods are not as capable for this task. Bellgard and Goldschmidt (1999) use different forecasting techniques including exponential smoothing, random walk, ARMA models and artificial Neural Networks. Their study was based on the exchange rate of Australian Dollar/ US Dollar and they concluded that exchange rate shows non-linear patterns which is better to explained by neural network models. Also, Dunis and Williams (2002) showed that Neural Network models can add value to the forecasting process, with applied a neural network for the EUR/USD exchange rate prediction; concluded that Neural Network models outperform the more traditional modeling techniques.

Chen, J. C., & Narala, N. H. R. (2017) used Feedforward Backpropagation Neural Network model i for forecasting exchange rates between Indian rupee and US dollar, based on economic data as inputs (inflation, real interest rates, gross domestic product (GDP), current account balances, government budget balances and debts of both countries) from 2001 to 2014. the study found that, the most effective model was Feedforward Backpropagation Neural Network (FBNN), and its accuracy by use the least Mean average percentage error (MAPE) valued by 1.32% and is considered to be most impressive model.

6. OVERVIEW OF NEURAL NETWORKS

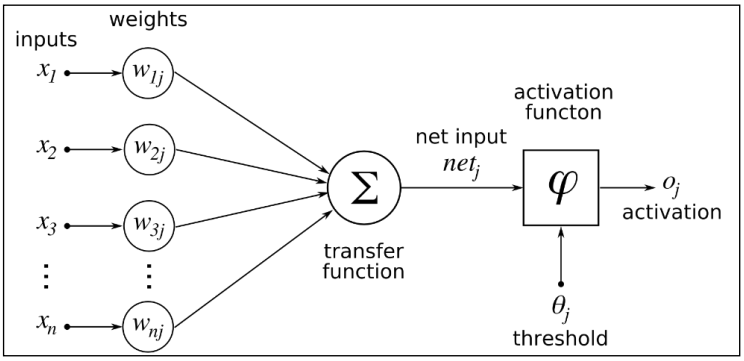
6.1 What are a Neural Networks?

Neural network; also cited to as Artificial Neural network; acts to some extent like to neurons in human mind. It gains knowledge through learning process; just like human mind learn through past events. It's a function of predictor variables (independent input vectors) that minimize the prediction error of target variable (dependent output variable).

A neural network can define also as a massively parallel distributed processor that contains a natural propensity for storing experiential knowledge and making it available to be used. Haykin, S., (2004).

Figure (1)

Artificial Neuron



SOURCE: http://uc-r.github.io/ann_fundamentals

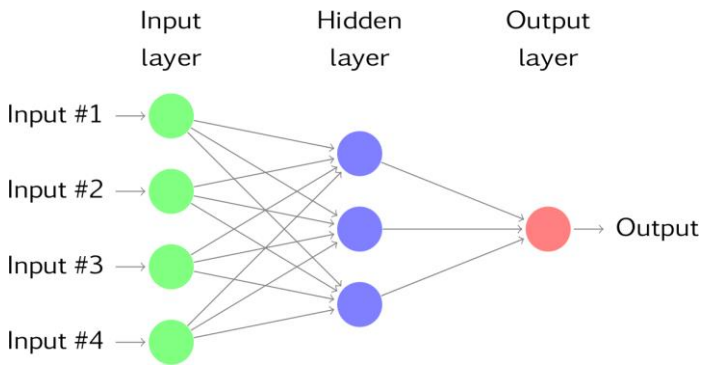
In ANN, "Each neuron implements a simple task of data processing by converting received inputs into processed outputs." (Zhang, Peter, 2003*)* Through the connections

between these neurons, knowledge can be achieved and stored. A neuron may be divided into three parts. First, the input connections, second the summing and activation functions and lastly, the output connections see figure (1).

- **Input layer:** The neural network receives its data within the input layer. The number of nodes (neurons) in this layer depends on the number of inputs to a model and each input requires one neuron.
- **Hidden layer**: The hidden layer lies between the input and output layers and there can be many hidden layers. This permits the network to learn, adjust, and generalize from the previously learned facts to the new input. As each input output set is presented to the network, the internal mapping is recorded in the hidden layer.
- **Output layer:** Having been trained, the network responds to new input by producing an output that represents a forecast. During training, the network collects the in-sample output values within the output layer.

Figure (2)

A typical feedforward neural network (MLP) with four inputs and one hidden layer with three hidden neurons.



6.2 Learning and adapting

Neural networks develop an inner structure to unravel problems. within the training process, connection weights rearrange their values and expose a data pattern. Thus, the basic feature of NN is that they're trained, not programmed. There are two distinct learning modes: supervised and unsupervised.

- The supervised learning mode presents input-output data combinations to the network. Consequently, the connection weights, initially randomly distributed, adjust their values to provides output that's as close as possible to the actual output.
- The unsupervised learning mode is independent of the external influences to adjust weights. There are not concrete data to correct the neural networks' pattern identification. Therefore, the unsupervised learning mode looks for the trend in inputs and adapts to the network function.

7. **An overview of the Egyptian exchange rate**

Before the Economic Reform Program in 1991 there have been many exchange rates of the Egyptian pound in different markets, as there was the formal exchange market where the exchange rate is set administratively; and there was the informal market (the black market) where the exchange rate is set by the dealers in this market.

With the Economic Reform and Structural Adjustment Program, one of the primary elements of the reform included a large fiscal adjustment, an exchange rate anchor and some price

liberalization. These reforms, refocus monetary policy towards disinflation (Selim, 2011)

The Monetary police began a transition to a flexible exchange rate regime in 2000, a first attempt to a floating regime in January 2003 and the successful transition to a unified flexible exchange rate regime in late-2004. From 2000 to 2004, the Egyptian £ experienced a cumulative depreciation of 68 per cent against the US$ (Helmy, O., Fayed, M., & Hussien, K,2018).

In spite the devaluation of the Egyptian pound to about L.E7 for one U.S. dollar in 2005; however, it soon returned back to its normal average rate (L.E5.5 for one U.S. dollar) because this flexible exchange system was in place. This flexible system allows the prices of the Egyptian exports to decrease and the prices of Egyptian imports to increase; hence, the Egyptian exports to the global market increase and its imports from the global market decrease.

In December 2004, the Central Bank of Egypt began establishing the interbank foreign exchange market, which contributed to appreciate in the value of the pound by 4% during one quarter of this launch. The stability of the exchange rate and the increase in the interest rate led to an increase in the preference for domestic savings in the local currency.

The improvement in the terms of trade, rise in external demand and the increase in foreign capital inflows were reflected in the foreign exchange rate, causing the foreign exchange rate to drop from 5.7 to 5.4 during the period 2006-2007. As a result of the repercussions of the global financial crisis on the Egyptian economy in 2008, the foreign exchange rate increased from 5.3 in 2008 to 5.6 in 2009. on the other hand, the real effective

exchange rate witnessed an appreciation of around 11 percent during (2005-2008). (Hosni, R.,2015).

The repercussions of the Egyptian revolution in 2011 led to an increase in political unrest and insecurity, an increase in the degree of uncertainty, a decrease in the rate of economic growth and indicators of the Egyptian Stock Exchange, and the depletion of foreign reserves of foreign exchange. Financial fragilities have continued to build up with rising fiscal deficits, inflation and debt, also Egypt has witnessed a decrease in the sources of the foreign exchange. These sources are represented in:

- Tourism revenues.
- Foreign direct and indirect investments.
- Remittances.

as a result of decrease those sources of foreign trade, the exchange rate depreciated by 13 per cent from LE 5.80 in January 2011 to LE 7.26 in 2015 as depicted the significant decrease in foreign reserve during this period urged the reemergence of the parallel market. Nonetheless, the CBE announced a number of decisions and restrictions to combat the emergence of the parallel market. Inflation rates were highly volatile during the period 2011- 2015.

On 3 November 2016, The Central Bank of Egypt (CBE) announced the free-floating of the pound in an attempt to alleviate an ailing economy struck by a severe shortage of U.S. dollars, waning international reserves and a widening margin between black and official exchange rate markets. Earlier that day, the CBE had devalued the currency to 13 EGP per USD, which represented a weakening of 46.3% from 8.88 EGP per USD previously.

In the Egyptian economy there are many factors weaken the ability of devaluation to improve the trade balance, even in the long term. These restrictions are related to the nature of exports and imports. First, the nature of Egyptian exports, which are primarily either primary products whose demand are derived demand from the demand for other products; or the low elasticity of demand for them for changes in their prices. Second, the nature of Egyptian imports which are dominated by food and investment goods. (Ahmed Mohamed Ezzat 2018)

the Central Bank of Egypt (CBE) devalued the country's local currency in November 2016. (The dollar exchange rate had jumped to over 18 pounds a few days after the CBE decision). in July 2017, the foreign exchange rate began to stabilize at the level of 17.7 and fluctuate around this value, with a tendency towards a gradual improvement in the value of the exchange rate, table (1) in index. The price of the Egyptian pound began to gradually improve since late 2016 and with the beginning of the year 2017, until the price of the dollar (purchase) reached 17.68 against the Egyptian pound, compared to the highest point of 19.13 pounds in 2016 with an improvement rate of 7.6% and a decrease in the price of the dollar against the pound of 1.45 Egyptian pounds.

The year 2018 witnessed relative stability of the exchange rate of the pound against the US dollar, with a slight relative increase, so that the price of the dollar against the Egyptian pound at the end of 2018 reached 17.86 Egyptian pounds, an increase of 18 piasters and a rate of about 1.5%

The recovery phase began in (2019), as it witnessed the start of the recovery of the Egyptian economy and the real transformation towards growth, as the Egyptian economy achieved a primary surplus for the first time, reaching 2% of

GDP in the year 2018/2019, and an initial surplus in the fiscal year 2019/2020. The performance of the Egyptian pound against the dollar improved by 10.5%, at a value of 1.88 pounds, to reach the price of the US dollar at the end of 2019 at 15.99 Egyptian pounds for purchase.

The performance of the Egyptian pound against the US dollar continued to improve during the first two months, to complete the stage of reaping the fruits of the economic reform program, with an improvement rate of 3%, at a value of 45 piasters, bringing the price of the dollar for purchase to 15.54 Egyptian pounds, and with the start of the spread of the Corona virus crisis in March 2020, which hit Emerging currency markets deteriorated sharply, with the expectation of a state of stagnation for the global economy by the International Monetary Fund. However, the performance of the Egyptian pound was affected by a very slight percentage, as the price of the dollar rose against the pound by 15 piasters, or by less than 1%.

The study indicated that with the start of implementing the precautionary measures from the Central Bank on March 15, 2020, the price of the dollar (for purchase) stabilized for two whole months at 15.69 Egyptian pounds, then witnessed a state of rise and fall at an average of 15 piasters during the period from May 15 until now, bringing the price of the dollar The US dollar was 15.65 Egyptian pounds, back down again from the rate in effect before the implementation of the precautionary measures from the Central Bank of Egypt on March 15, which was 15.69 Egyptian pounds at the time.

8. RESEARCH METHODOLOGY

the study aims to predicting exchange rate depending on the fundamental economic data of Egyptian economy from (2001-2019) and will achieve this goal by create an artificial neural network and use it to forecasting exchange rate till 2023.

Quarterly data was relied on for the most prominent macroeconomic variables, which were determined according to economic theories and econometric studies of the determinants of the exchange rate.

1- The nominal exchange rate
2- growth rate of GDP
3- The interest rate on treasury bills is 91 days
4- The interest rate on deposits is 3 months
5- percentage OF Foreign direct investments to the GDP
6- percentage of net trade balance to GDP
7- Ratio of total liquidity to GDP
8- The ratio of dollar deposits to total deposits
9- percentage OF total deficit of the budget to GDP
10- Ratio of external debt to GDP
11- Ratio of total domestic debt to GDP
12- The value of exports to the value of imports
13- The ratio of current proceeds to current payments
14- the inflation rate.

This data was collected through the Central Bank of Egypt monthly bulletins during the period 2001-2019. The number of observations for each variable represented 76 observations and were divided into two groups; The training set aims to train and prepare the model, and the test group to verify the validity of the models, and to know the efficiency of this technique in analyzing time series.

the ANN model based on The Levenberg-Marquardt back-propagation algorithm this algorithm is used widely to build

and train the network and has proved to be worthy in combining technical and economic indicators to perform the prediction.
In this study the forecasting performance of the ANN model is evaluated by used statistical metrics, namely, Mean Squared Error (MSE)**,** Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE).

- **Mean Squared Error (MSE):** This is the mean over all patterns of the square of the actual value minus the predicted value, i.e., the mean of (actual minus predicted) squared.

$$MSE = \frac{1}{N}\sum_{K=1}^{N}(|A_K - P_K|)^2 \quad \ldots\ldots\ldots\ldots (1)$$

- **Root Mean Square Error (RMSE):** it returns root mean squared errors between actual and predicted values and can be written as

$$RMSE = \sqrt{\frac{1}{N}\sum_{K=1}^{N}(|A_K - P_K|)^2} \quad \ldots\ldots\ldots\ldots (2)$$

- **Mean Absolute Error (MAE):** it gives the average absolute error between actual and predicted values,

$$MAE = \frac{1}{N}\sum_{K=1}^{N}|A_K - P_K| \quad \ldots\ldots\ldots\ldots\ldots (3)$$

- **MAPE**: mean absolute percentage error between actual and predicted values is calculated as

$$MAPE = \frac{1}{N}\sum_{K=1}^{N}\left|\frac{A_K - P_K}{A_K}\right| \times 100 \quad \ldots\ldots\ldots\ldots (4)$$

Where Ak is the actual value, Pk is the predicted value and N is the amount of data.

9. Empirical Findings

The result of ANN differs according to its structure, with different number of layer and neurons at each layer, the three are different degree of accuracy. The following table shows the different result from different architecture of ANN and different number layers and neurons.

Table (1)

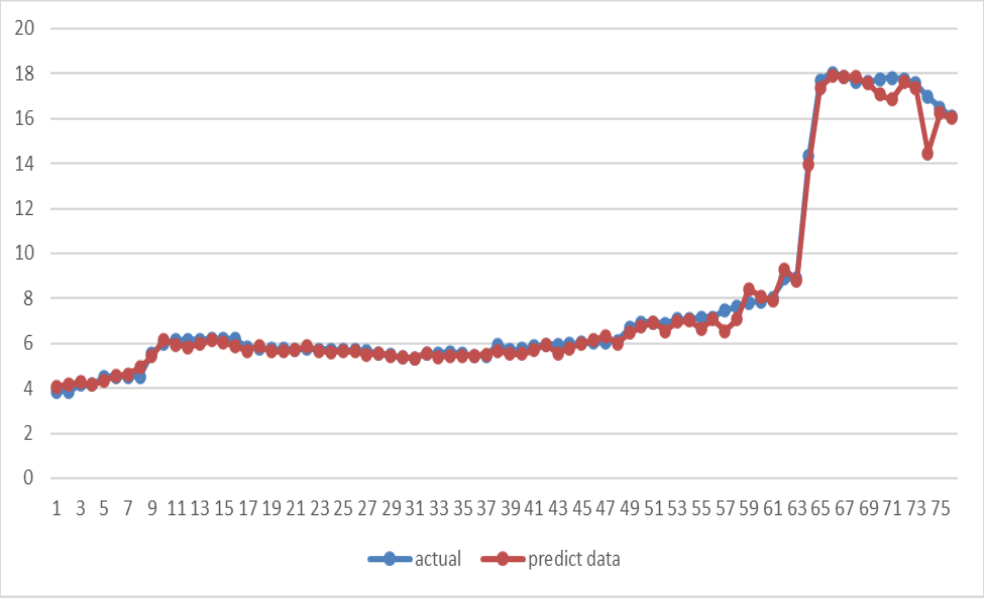
MSE for feed-forward backpropagation in the Different Epoch

Number of layers	Number of neurons in first hidden layer	mse
2	6	1.8505
2	7	37.7567
2	8	0.15452
2	9	0.44828
2	10	4.887
1	6	0.45372
1	7	0.22768
1	8	0.19014
1	9	0.34035
1	10	4.2368

the table (1) show that best Ann model when it consists of 2 layer and 8 neurons in first hidden layer, the t mean squared errors of this ANN equals to 0.15 and it predict value can be illustrated in the following figure (3)

Figure (3)

Compare between ANN Results with Actual Data of Exchange Rate



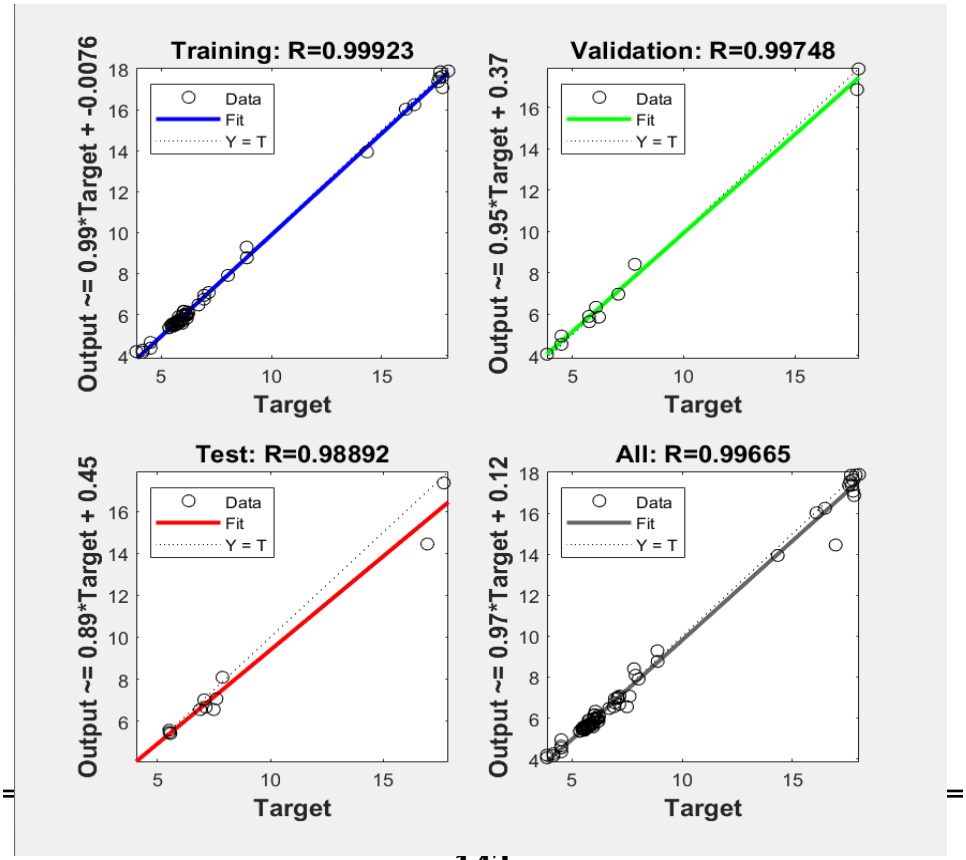
Source : Prepared by researchers depends on Microsoft excel 2016

The regression of training data, validation and all model are 0.99923, 0.99748 and 0.99665 respectively. The previous results indicate the ability of the neural network model to

predict, where the closer regression coefficient to 1, indicates the efficiency and fit of the model

FIGURE (4)

The Result of Regression of ANN Model



Source: Prepared by researchers depends on matlap v.18.

10. Evaluation of forecasting performance

performance of the ANN model is evaluated by used statistical metrics, namely, Mean Squared Error (MSE)**,** Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE).[4]

Table (2)

Results of forecasting performance by ANN

MSE	RMSE	MAE	MAPE
0.15	0.393	0.222	2.8%

This result indicates that neural networks is accurate by 97.2% in forecasting exchange rate depends on the macroeconomic variables.

[4] Calculation of RMSE, MAE, MAPE use by the following website: <https://agrimetsoft.com/calculators/Mean%20Absolute%20Error>

11. Forecasting of exchange rate till 2023

In the light of the IMF prediction of different economic indicators of Egyptian economy which includes economic growth, inflation rates, external and total debits, net public budget as a percent to GDP, and net balance of trade as a percent to GDP. And with the trends of monetary policy of central bank in Egypt as follow [5]:

- Annual headline inflation of Egypt's external environment continued its acceleration path in 2021 Q2, with an annual inflation rate of 2.8%, compared to 1.6% and 0.9% in 2021 Q1 and 2020 Q4 respectively.
- The overall balance of payments registered a surplus of USD 0.3 billion in 2021 Q1 compared to a deficit of USD 5.5 billion during the corresponding period last year.
- Additionally, the increase in the current account deficit was due to the narrowing of the net services surplus as well as the widening of the non-hydrocarbon trade deficit. The net services surplus narrowed by 40% in 2021 Q1 on an annual basis, registering USD 1.3 billion compared to USD 2.1 billion in 2020 Q1. This is due to the decline in tourism revenues and transport receipts, both of which were impacted by the COVID-19 pandemic. Tourism and transportation receipts recorded USD 3.2 billion in 2021 Q1 compared to USD 4.2 billion in 2020 Q1, decreasing by 25% on an annual basis. Likewise, the non-hydrocarbon trade deficit recorded USD 11.6 billion in 2021 Q1 compared to USD 9.3 billion, widening by 25% on annual

[5] Central Bank of Egypt (2021) : "Monetary Policy Report II"
Website : <https://www.cbe.org.eg/en/Pages/HighlightsPages/Monetary-Policy-Report-2021-II.aspx>

basis. However, the increase in the current account deficit was partially mitigated by the improvement in the hydrocarbon trade balance. The hydrocarbon trade balance reversed trend to register a surplus of USD 0.2 billion in 2021 Q1 compared to a marginal deficit of USD 0.04 billion in 2020 Q1. The registered surplus was primarily due to a decrease in oil imports.

- Meanwhile, the surplus recorded on the capital and financial account was also supported by an improvement in net foreign direct investments in Egypt, which increased by 47% in 2021 Q1 compared to the corresponding period last year. The overall balance of payments surplus was reflected on the gradual accumulation of net international reserves, which rose to USD 40.3 billion in March 2021 compared to USD 40.1 billion and USD 36.0 billion in March 2020 and May 2020 respectively.
- Real GDP growth at market prices recorded a preliminary figure of 7.7% in 2021 Q2, reflecting a strong positive base effect compared to the corresponding quarter's shrunken base during the peak of the pandemic last year. Meanwhile, actual data showed that growth inched up to 2.9% in 2021 Q1 compared to 2.0% in the previous quarter, implying that growth for FY 2020/21 recorded 3.3% on average.
- The negative contribution of net exports towards overall GDP growth in 2021 Q1 was aggravated by an increase in real imports for the first time since 2018 Q1 and a sustained decrease in real exports on annual terms. Thus, both contributed negatively to GDP growth.

The result of the ANN model for the expected foreign exchange rate:

year	2020	2021	2022	2023
Exchange rates	16.4	16.6	16.8	16.7

Source: Prepared by MATLAP v.18.

12. Conclusions

Models predicting the financial phenomena, developed by economic theory over the years, can be classified into two main categories: structural prediction models or linear ones, such as econometric models as Autoregressive Conditional Heteroscedasticity (ARCH), Generalized Autoregressive Conditional Heteroscedasticity (GARCH), State Space, which are based on the general view that every action of traders can be explained by a model of behavior and thus by a definite, explicit function that can bind variables determinants of the phenomenon to be foreseen; black box forecasting models or non-linear ones, such as neural networks, genetic algorithms, expert systems or fuzzy models, which, through the learning of the problem analyzed, attempting to identify and predict the nonrandom and non-linear dynamics of prices, but without explicit ties and logical functions that bind the variables analyzed.

this paper has presented neural network models to forecasting foreign exchange using fundamental economic data

of Egyptian economy. as a result of this methods; it has been observed a remarkable perform of Ann in forecasting the exchange rate with the macrocosmic variables. on this accomplishment, a well-designed network structure acts as great role and with a minimum error.

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