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ORIGINAL ARTICLE

Artificial Neural Network for Modeling the Economic Performance: A New Perspective

Ahmed Ramzy Mohamed[1]

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Abstract
This paper discusses a new representation for the efficiency frontier method through a proposed algorithm for augmented feed forward back propagation neural network models, in order to estimate the economic performance, and the effectiveness of macroeconomic policies in Egyptian economy, by using a quarter time series data from 1990Q1 to 2019Q2. In this study I developed artificial neural network models—ANN—corresponding with the conditions of the Egyptian economy, by building an optimal efficiency frontier and then comparing the actual performance of the Egyptian economy with that limit, which includes the lowest possible variations for both inflation and output. As for the new contribution of this study, it is designated to calculate the optimal inflation rate and the optimal output level in the Egyptian economy through a model, which combines the higher predictive power of feed forward neural network models and the high explanatory power of a stationary or random walk stochastic models, in order to obtain the fitted values of the optimal output level, in addition to the optimal inflation rate. It is clear from the results of the study, the extent of the essential congruence between the actual Egyptian economic performance during the study period and the economic performance index that was built via the new contribution of this study.

Keywords Artificial Neural Network Models · Efficiency Frontier Method · New Loss Function · Economic Performance Index

Introduction

Improving the level of economic performance is no longer just a goal that economic policies seek to achieve. Rather, it has been transformed from being that into an indicator, through which the effectiveness of economic policies can be judged.

✉ Ahmed Ramzy Mohamed
drahmed_ramzy@hotmail.com

[1] Department of Economics, Modern Academy for Computer Science and Management Technology, Cairo, Egypt

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Whether the economic performance is a goal or an indicator, it is important to reach a quantitative measure by which this performance can be translated into numbers that are easy to judge. The economic authorities continuously strive for adopting economic policies in response to what is happening in the variables surrounding the environment in which the economy operates, therefore, it is found that recent studies in this field seek to use the policy reaction function, through which it is possible to identify the size of change required in economic policy tools in order to reach the planned level of the ultimate goals of this policy. The applied studies (Cecchetti and Krause 2002; Cecchetti et al. 2006); also, used the efficiency frontier method in order to judge the economic performance accurately and clearly, as well as, assess the effectiveness of the economic policies in terms of their ability to improve the level of economic performance or not.

Measurability is one of the important criteria that must be taken into account by the economic authorities. When deciding to achieve a specific goal, the target must subject to accurate measurement, through quantifying the amount of this goal in a quantitative manner, in addition to the amount of change required to achieve in this goal, as it is considered the signal by which it becomes clear the direction of economic policies in achieving the final goal, enabling economic authorities to monitor and evaluate the performance, and the path of economic policies. The efficiency of selecting and directing economic policy tools is considered insufficient to ensure the success of achieving policy objectives, when making economic policy decisions. The presence of quantitative measures is vital to complete the elements of success in achieving the goals set by economic authorities (Rzhevskyy et al. 2018).

It became clear by 2016 the inconsistency between the ways in which macroeconomic policies are applied within the Egyptian economy and the method of managing the exchange rate. This resulted in an unstable economic environment, within which the fluctuations in the real exchange rate increased in light of the different exchange rate regimes applied in the Egyptian economy. The effectiveness of the monetary policy decreased and the levels of financial deficit increased. This matter led to an increase in transaction costs, weak competitiveness of national industries reflected in the form of a depletion of the level of net international reserves held by monetary authorities, and decreased Economic growth rates, investment, employment, and output. This has led to high inflation rates and accumulation of gross domestic debt levels to rates that are difficult for the Egyptian economy to continue bearing. Therefore, it was logical that the Executive Board of the International Monetary Fund agreed in November 2016 to provide financial assistance to Egypt through an agreement to benefit from "Extended Fund Facility"—EFF—with a value of 8.59 billion SDR, about 12 billion USD. The program achieved its key objective regarding the macroeconomic stability, which is considered a precondition for attracting investment, raising growth, and creating jobs. Current account deficits have fallen and foreign exchange reserves are at all–time high levels. Growth has recovered from around 4 to 5.5% now, and it is expected to reach 6% by next year, while unemployment has fallen below 9% to its lowest level in over a decade. Public debt has begun to decline and inflation has fallen steadily on track to reach single digits by next year. This sets the stage for broader reforms, such as improving the business climate, which can lead to higher private sector–led investment and job creation.

Based on the foregoing, we do not only need to achieve stability in the Egyptian economy, but, at the same time we need more independence and effectiveness of monetary policy, and armament with a set of efficient macroeconomic policies to counter what may occur in economic changes in the Egyptian economy. On the other hand, there is a need for clear measures to monitor the Egyptian economic performance and measure the effectiveness of macroeconomic policies. In this study I developed a new representation for Efficiency Frontier Method through a proposed algorithm for artificial neural network models—ANN—corresponding with the conditions of the Egyptian economy to measure the economic performance and the effectiveness of macroeconomic policies in Egypt, by building an optimal efficiency frontier and then comparing the actual performance of the Egyptian economy with that limit, that includes the lowest possible fluctuations for both inflation and output.

Efficiency Frontier Method and Policy Reaction Function

Whereas, the economic literature suffered from the limited studies that attempted to measure the economic performance and effectiveness of monetary policy, Taylor presented the idea of this measurement based on the Efficiency Frontier Method theory in his famous article that carried the title of " Estimation And Control Of A Macroeconomic Model With Rational Expectations" in 1979. The idea did not see the light in a quantitative or practical manner except at the hands of both (Cecchetti and Krause 2001) in their study presented in 2001, and it aimed at measuring and determining the responsibility of monetary policy in achieving gains and losses of economic performance, and stabilizing macroeconomic conditions.

This study has used time series data for a cross–sectional sector that includes 24 countries in the period from 1980 to 1990, by building the Optimal Efficiency Frontier, then, comparing the actual performance of the economy to that extent that includes the lowest possible fluctuation for inflation and output, which represents actual performance with the lowest possible fluctuations representing the optimal performance, and then measuring the effectiveness of macroeconomics policies. In order to measure economic performance, the study depends on the newly loss function used in policy analysis by central banks, that aims at minimizing the losses of the economy represented by fluctuations in output levels and inflation rates. The loss function can be expressed through the following functional form:

$$MP_i = \lambda var(\pi_i) + (1-\lambda)var(y_i), 0 \le \lambda \le 1, i = 1,2,3,\ldots,\infty \tag{1}$$

where MP_i is the macroeconomic performance, $var(\pi_i)$ and $var(y_i)$ are the variability of inflation and output in period i, λ is the coefficient of the policymaker's preferences, which depends on the policymaker's reaction to the fluctuations in the economy and its goal for output gap stabilization relative to inflation stabilization. This coefficient takes a value ranging from zero to one. If the goal of the policymaker is

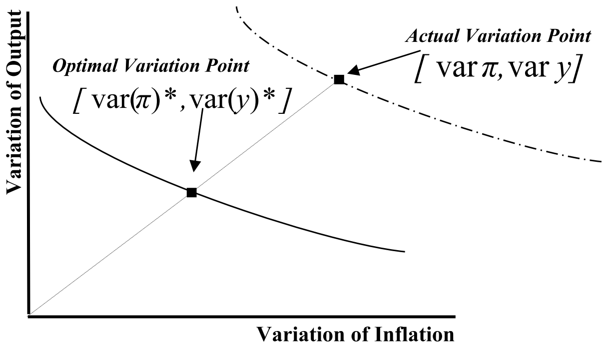


Fig. 1 Derivation of the Optimal Variances; Source: Cecchetti, S., and Krause, S., "Central Bank Structure Policy Efficiency, and Macroeconomic Performance: Exploring Empirical Relationships", The Federal Reserve Bank of St. Louis, 2002, P49

the stabilization of inflation, the zero equality for λ will be the optimal choice for policymaker. If his goal is to output gap stabilization, λ will be chosen equal one. The value of this parameter is obtained according to the available information on the conditions and structure of the economy (Taylor 2017).

This so–called idea of efficiency frontier method can be illustrated, thus the ability to measure the effectiveness of macroeconomic policies, and improve economic performance or not graphically, through the curve provided by Taylor "Taylor Curve", which explains the optimal fluctuations in output and inflation, which allows building the efficiency limit in Fig. 1, that depends on the reciprocal fluctuations of both output levels and inflation rates.

Thus, any point on this curve shall represent an optimal performance point for the economy, i.e. it shows the lowest possible level of fluctuations in output and inflation, while the actual variation point shall represent the actual performance point of the economy, which is far from the optimal performance point of the economy. If the level of the macroeconomic performance is optimal, then the economy will fall on this curve. Whenever, there is an improvement in the level of the overall economic performance, the actual performance point of the economy will turn to the left to approach the efficiency limit indicated on the Taylor curve (Koop et al., 2009).

Likewise, the effectiveness of macroeconomic policies can be measured by the difference between the actual variations of inflation, output, and the optimal values on the efficiency curve, i.e. how far the actual performance point of the economy is from the point of optimal variation on the Taylor curve. When the derivative curve—on which the actual performance point of the economy—downwards the efficiency curve, the effectiveness of the macroeconomic policies increases, until they become fully effective when the two curves apply. On the other hand, when the derivative curve upwards in the opposite direction from the efficiency curve, the effectiveness decreases until it becomes ineffective. Under this scenario the macroeconomic performance and Policy inefficiency can be defined as;

$$MP_i = \lambda\left[var\left(\pi_i\right) - var\left(\pi_i\right)^*\right] + (1-\lambda)\left[var\left(y_i\right) - var\left(y_i\right)^*\right], \tag{2}$$

where $var\left(\pi_i\right)^*$ and $var\left(y_i\right)^*$ are the variances of inflation and output under the optimal policy, respectively. The more efficient policymakers are at implementing the optimal policy, the closer MP_i will be to zero. The baseline assumption in several applied studies is that the inflation target Variation for all countries is 2%, other previous studies (Olson and Enders 2012) have referred to this calculation once on the basis of the lowest inflation rate, and once on the basis of the average inflation rate during the period. In my opinion, the average is more realistic, because the lowest inflation rate can be achieved under sudden or unexpected economic conditions, and therefore it is difficult to rely on. Optimal variation of output rate can be calculated, also, by the logarithmic linear trend values (Destefanis et al. 2018) elaborate the measure for the output gap as the difference in the log of real gross domestic product from its trend value computed through the Hamilton (2017) filter, while inflation is calculated as the year–to–year percentage difference of the consumer price index (all items) minus its trend value computed through the Hamilton (2017) filter, The study assume that the filter–measured trend is able to capture explicit or implicit inflation target of the countries considered. This choice is motivated by the fact that the study didn't observe an explicit target in all countries of the sample.

This is what the new contribution of this paper aims at overcoming it, and the controversy surrounding these target values through artificial neural network models. The gains and losses of economic performance can be calculated through the result of subtracting economic performance in the current period MP_i from economic performance in the previous period MP_{i-1}. It is clear from the equation by which economic performance is calculated that the result of this equation represents the amount of economic performance losses; therefore, if the result of subtracting is in a positive value, this means that the level of economic performance is improved and also the size of losses is declined in the current period from its counterpart in the lagged period. On the other hand, if the result of subtracting economic performance in the current period from economic performance in the previous period is in a negative value, this means that the level of economic performance decreases, and also the increase in the volume of losses in the current period from its counterpart in the previous period.

Artificial Neural Network Models

By following the simulated effect of this biological model of the neural network, it is possible to deduce the artificial neural networks models that act as interconnected groups of neurons grouped into layers that send information to each other. Neural networks receive information and signals through a number of cells called the Input Layer, so that each neuron in the input layer represents an independent variable that affects network outputs with different weights that reflect the relative weight of the importance of each independent variable in interpreting the behavior of the outputs (Stephenson 2010).

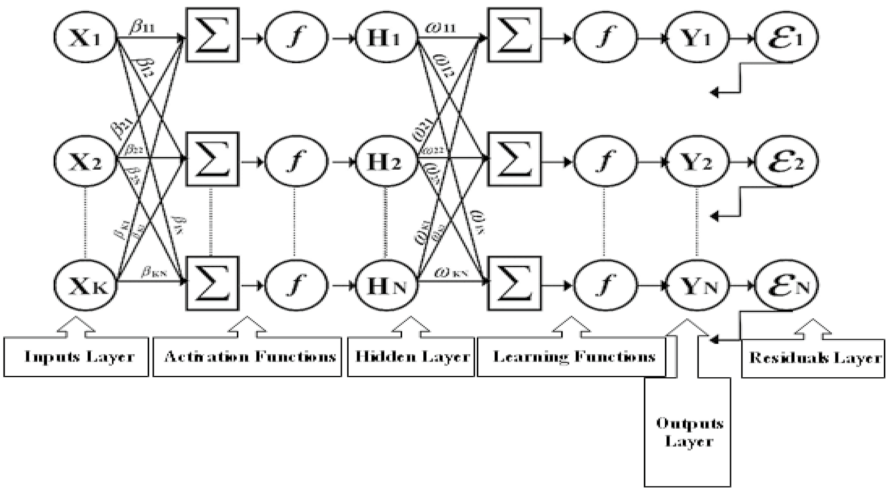


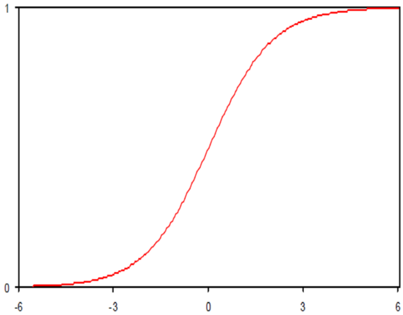
Fig. 2 Artificial Neural Network schema; Source: This figure has been prepared by the researcher

The input layer connects with a number of other neurons–called the Hidden Layer–through the communication channels. This layer matches the axon biological cell, while the nucleus matches its mechanism action, and the communication channels matches the neurotransmitters. This hidden layer is connected to another layer called the Output Layer which contains one or more cells depending on the model to be explained. (Fig. 2) shows that each set of inputs is triggered to obtain a set of outputs, as these inputs are weighted by multiplying them by the relative weights at the meeting points, and then they are grouped to determine the activation functions of the cells.

Through (Fig. 2), and before displaying the activation functions within the artificial neural network models, the following functional form of artificial neural network models can be clarified (Gonzalez 2000):

$$\begin{bmatrix} H_1 \\ H_2 \\ \vdots \\ \vdots \\ H_N \end{bmatrix} = \begin{bmatrix} \alpha_{01} \\ \alpha_{02} \\ \vdots \\ \vdots \\ \alpha_{0N} \end{bmatrix} + \begin{bmatrix} \beta_{11} \\ \beta_{12} \\ \vdots \\ \vdots \\ \beta_{1N} \end{bmatrix} X_1 + \begin{bmatrix} \beta_{21} \\ \beta_{22} \\ \vdots \\ \vdots \\ \beta_{2N} \end{bmatrix} X_2 + \cdots\cdots + \begin{bmatrix} \beta_{K1} \\ \beta_{K2} \\ \vdots \\ \vdots \\ \beta_{KN} \end{bmatrix} X_K \quad ; \quad \begin{matrix} n = 1,2,\ldots\ldots\ldots\ldots,N \\ k = 1,2,\ldots\ldots\ldots,K \end{matrix}, \tag{3}$$

This previous model illustrates the receiving process of the hidden layer $[H_1, \ldots, H_N]$ information and signals from the inputs layer $[X_1, X_2, \ldots, X_K]$, where $\left[\alpha_{01}, \alpha_{02}, \ldots, \alpha_{0k}\right]$ are the constant–Bias Terms–, $\left[\beta_{1N}, \beta_{2N}, \ldots, \beta_{kN}\right]$ are the relative weights which represents the channels of transmission and communication between inputs K and hidden layer H. The following model also shows the transfer of final outputs for artificial neural network models from the hidden layer after processing and operation to outputs layer $[Y_1, Y_2, \ldots, Y_K]$.



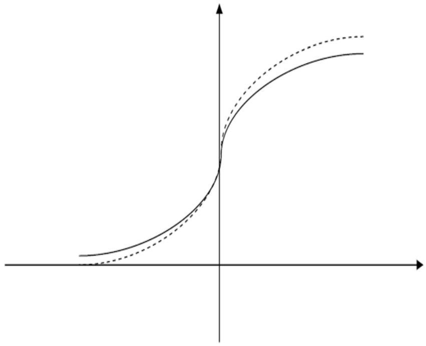


Fig. 3 Logistic cumulative distribution function; Source Gonzalez, S., "Neural Networks for Macroeconomic Forecasting: A Complementary Approach to Linear Regression Models", Bank of Canada – Department of Finance, Working paper No. 07, 2000, P 2

$$\begin{bmatrix} Y_1 \\ Y_2 \\ \vdots \\ \vdots \\ Y_K \end{bmatrix} = \begin{bmatrix} \gamma_{01} \\ \gamma_{02} \\ \vdots \\ \vdots \\ \gamma_{0K} \end{bmatrix} + \begin{bmatrix} \omega_{11} \\ \omega_{12} \\ \vdots \\ \vdots \\ \omega_{1K} \end{bmatrix} H_1 + \begin{bmatrix} \omega_{21} \\ \omega_{22} \\ \vdots \\ \vdots \\ \omega_{2K} \end{bmatrix} H_2 + \cdots\cdots + \begin{bmatrix} \omega_{N1} \\ \omega_{N2} \\ \vdots \\ \vdots \\ \omega_{NK} \end{bmatrix} H_N \quad ; \quad \begin{matrix} n = 1,2,\ldots\ldots\ldots\ldots,N \\ k = 1,2,\ldots\ldots\ldots\ldots,K \end{matrix}, \tag{4}$$

where $[\gamma_{01}, \gamma_{02}, \ldots, \gamma_{0k}]$ are bias terms, $[\omega_{1k}, \omega_{2k}, \ldots, \omega_{Nk}]$ are the relative weights which represents the channels of transmission and communication between hidden layer H, and outputs N. It has been clear from the previous discussion of biological neurons that the output of these cells is a function of the impulses intensity contained in them, and the activation, learning functions in the cell itself, to match the same outputs layer of artificial neural network models, that depend primarily on the fundamental function of activation functions in stimulating explanatory variables of the inputs layer, and the hidden layer to reach the best estimation for the artificial neural network models (Chen 2005). There are many activation functions that are used to train neural networks; however, Nonlinear activation Functions are the ones that provide an opportunity to exploit capabilities of artificial neural network models, allowing them to reach the best weighted relative weights, and the most accurate estimation results even in dealing with complex data. Figure 4 shows the logistic cumulative distribution function, which is the most common activation function in artificial neural network models (Kuan and Halbert 1994).

The Sigmoid Function is one of the most important types of non–linear logistical activation functions, and is most used to activate explanatory variables within inputs layer or units of the hidden layer in the network, as shown in (Fig. 3). This function is used to train multi–layer networks that are trained by back propagation processes[1];

[1] The back propagation operations processes take from the principle of learning on which the artificial neural network models is a clear method for them, as it is clear from (Fig. 3) how mean square errors return to the inputs layer from outputs layer to reach these errors to the lowest possible level, each error

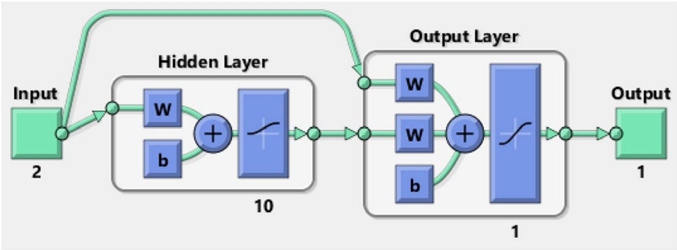


Fig. 4 The proposed algorithm for training and estimating neural network models; Source: This figure has been prepared by the researcher based on the data provided in the statistical appendix, and on the basis of the MATLAB 2018 software package

this function also considered a continuous function. It may take the form of a Hyperbolic Function, which is a continuous function over the period [− 1, 1], i.e. It is a differential function and takes the following functional form:

$$F(x) = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}}, \tag{5}$$

The sigmoid function may take the form of the sigmoid binary function, which is a continuous function over the period [0, 1], i.e. it is a differential function, and if the period of this function closes to the one, this means that the signals, information, and impulses that have reached the neuron have led to the maximum level of activation. Also if this period is closed to zero, this means that there is no reaction or response on the part of the neurons towards the information reached to them. According to Eq. 3, the sigmoid binary function takes the following form (Aaron and Thomas 2017):

$$\begin{bmatrix} H_1 \\ H_2 \\ \vdots \\ \vdots \\ H_N \end{bmatrix} = \begin{bmatrix} \frac{1}{1 + e^{-(\alpha_{01} + \beta_{11}X_1 + \beta_{21}X_2 + \cdots\cdots + \beta_{K1}X_K)}} \\ \frac{1}{1 + e^{-(\alpha_{02} + \beta_{12}X_1 + \beta_{22}X_2 + \cdots\cdots + \beta_{K2}X_K)}} \\ \vdots \\ \vdots \\ \frac{1}{1 + e^{-(\alpha_{0N} + \beta_{1N}X_1 + \beta_{2N}X_2 + \cdots\cdots + \beta_{KN}X_K)}} \end{bmatrix}, \tag{6}$$

By replacing Eq. 6 in Eq. 4, the basic function of a feed forward neural network models can be derived as follows:

Footnote 1 (continued)
comes out from the neural network models enters it again until an error is lower than the previous residual was reached to it.

$$\begin{bmatrix} Y_1 \\ Y_2 \\ \vdots \\ \vdots \\ Y_K \end{bmatrix} = \begin{bmatrix} \gamma_{01} \\ \gamma_{02} \\ \vdots \\ \vdots \\ \gamma_{0K} \end{bmatrix} + \begin{bmatrix} \frac{\omega_{11}}{1+e^{-(\alpha_{01}+\beta_{11}X_1+\beta_{21}X_2+\beta_{K1}X_K)}} \\ \frac{\omega_{12}}{1+e^{-(\alpha_{01}+\beta_{11}X_1+\beta_{21}X_2+\beta_{K1}X_K)}} \\ \vdots \\ \vdots \\ \frac{\omega_{1K}}{1+e^{-(\alpha_{01}+\beta_{11}X_1+\beta_{21}X_2+\beta_{K1}X_K)}} \end{bmatrix} + \begin{bmatrix} \frac{\omega_{21}}{1+e^{-(\alpha_{02}+\beta_{12}X_1+\beta_{22}X_2+\beta_{K2}X_K)}} \\ \frac{\omega_{22}}{1+e^{-(\alpha_{02}+\beta_{12}X_1+\beta_{22}X_2+\beta_{K2}X_K)}} \\ \vdots \\ \vdots \\ \frac{\omega_{2K}}{1+e^{-(\alpha_{02}+\beta_{12}X_1+\beta_{22}X_2+\beta_{K2}X_K)}} \end{bmatrix}$$
$$+ \cdots\cdots + \begin{bmatrix} \frac{\omega_{N1}}{1+e^{-(\alpha_{0N}+\beta_{1N}X_1+\beta_{2N}X_2+\beta_{KN}X_K)}} \\ \frac{\omega_{N2}}{1+e^{-(\alpha_{0N}+\beta_{1N}X_1+\beta_{2N}X_2+\beta_{KN}X_K)}} \\ \vdots \\ \vdots \\ \frac{\omega_{NK}}{1+e^{-(\alpha_{0N}+\beta_{1N}X_1+\beta_{2N}X_2+\beta_{KN}X_K)}} \end{bmatrix}, \tag{7}$$

Neural network models have many advantages, perhaps the most important of them: that these models deal with nonlinear models that often occur in reality, and neural network models deal with complex, non stationary, fuzzy, noisy, and incomplete data. In addition, their ability to address a large number of variables and imaging a group of external relationships that do not have a fixed shape, such as linear regression models, and the solutions provided by these models are characterized by high predictive strength (Michael 2016).

This explanatory and predictive ability for neural network models is derived from the principle of hebbian learning, which is the theoretical rationale for the process of repetitive activation of neurons, which increases the effectiveness of the engagement points between the inputs, and outputs layer, that improve the ability of artificial neural network models for adapting correlation relative weights to reach the optimal explanatory weights from train the network.

ANN Models for a New Loss Function

This previous discussion covered a comprehensive summary of the efficiency frontier method, how it is used to measure economic performance, and the effectiveness of macroeconomic policies. Below, this method will be used and attempted to develop it in line with the conditions of the Egyptian economy to measure the economic performance in Egypt, by building the optimal efficiency frontier, then comparing the actual performance of the Egyptian economy with that optimal performance, which includes the lowest possible variations for each inflation and output levels. It was mentioned that the coefficient of policymaker preferences λ, which depends on the policymaker's reaction to the fluctuations and purpose of confronting it within the economy, takes a value ranging from zero to one.

In view of these studies mentioned above, it is clear that they have been applied to a large number of developed countries, which have made great strides towards inflation targeting, the control of inflation rates in these countries has become the nominal anchor, and the ultimate goal that monetary policy seeks to achieve, from here, I can say that these countries can precisely use the mechanisms for predicting inflation rate in future periods; then the monetary policy maker can set the value of the preference factor of less than 0.2, in the periods in which the high inflation rate is expected.

But if the transition is made to the case of developing countries, including the Egyptian economy, which cannot shift towards an inflation targeting policy; we find that the response of the monetary authorities to changes in inflation rates comes somewhat slow; then it is difficult for the monetary policy makers in these countries to set the value of the policymaker preferences coefficient λ at a lower 0.2, in periods of high inflation, due to the lack of mechanisms for predicting inflation rates.

In an attempt by this study to overcome the controversy over the value of the policymaker preferences coefficient λ. And because this study seeks to use the efficiency frontier method to measure the Egyptian economic performance in line with the conditions of the Egyptian economy. And also because the change in the value of this parameter may lead to corresponding changes in the values of economic performance, and the effectiveness of macroeconomic policies. this study chose to place the value of the preferences coefficient at 0.3, in the periods when the inflation rates has increased and the economic authorities have tended to confront the rise of prices level at the expense of increasing the economic growth rate, that is, the periods when economic authorities actually tend to target the inflation rate of through a contractionary monetary policy, and the value of 0.8, in the periods when this rate fell, and the goal of the economic authorities was clear in controlling the rise in the general level of prices. These periods have been identified through the increase in the numbers of discount rates or overnight interbank rates, which is the operational objective of monetary policy in the Egyptian economy. As for other periods in which the contractionary pattern of monetary policy changes, the value of the preferences coefficient λ will be set to 0.8.

As for the transition to measuring the effectiveness of macroeconomic policies, we have previously mentioned the way in which the loss function is used to measure that, and given recent applied studies in this field, we find that it has settled on the fact that the optimal inflation rate variation is 2%, but—also—Since these studies have been applied to a large number of developed countries, which have made great strides towards inflation targeting, and controlling inflation rates in these countries has become the nominal anchor, and the ultimate goal that monetary policy seeks to achieve, then it can be said that the goal 2% is optimized, which can be achieved easily in developed countries. On the other hand, it is clear that this goal is difficult to achieve in many developing countries, including the state of the Egyptian economy, So that the developing countries studies seek to use a loss function to measure the economic performance in a manner appropriate to developing countries, so these studies computed the values of macroeconomic policies effectiveness are based on the fact that the inflation target rate is the average inflation rate prevailing during the study period.

Perhaps this average is realistic because the lowest inflation rate can be achieved under occasional or unforeseen economic conditions, and thus it is difficult to rely on, in addition to the above, any fluctuations above the average will be considered ineffective macroeconomic policies and bad economic performance. Any fluctuations below average will be considered effective macroeconomic policies and good economic performance.

If the transition to the target or optimal output level is taken, then it is clear that the previously mentioned studies have calculated this level by the logarithmic trend values of output during the study period, as previously explained, given the logarithms of GDP as a function of time and taking the fitted values for it. This method of calculation is based on the consideration that the target level of output is that level that grows with time under the natural and expected conditions of the economy. As for the new contribution of this study, it is to calculate the optimal inflation rate and the optimal output level within the Egyptian economy through a model that combines the higher predictive power of feed forward neural network models, and the high explanatory power of auto regressive integrated moving average models—ARIMA—, in order to obtain the fitted values of the target level of output and the optimal inflation rate. This model assumes that the behavior of the output level, and inflation rate in the future is only a natural extension and a reflection of their behavior in the past, as well as a moving average of its behavior in the past, taking into account the abnormal circumstances and events that occur over time (Ayodele et al. 2014).

The study tends to use feed forward back propagation neural network models, where the method of back propagation is an organized method for training multilayer front networks, based on logical mathematical methods and chain rules for calculating derivatives in the error equation for the relative weights of the invisible, and output layer, in order to identify the differences between the expected results and the actual results of the network. This difference is used automatically by the network to adjust its internal weights until errors decrease. This process is repeated over and over, until the mean square errors reach the lowest possible degree, here, the network reaches the optimal solution. Determining the appropriate number of neurons in the hidden layer is one of the important decisions for the network to interact with the external environment and take into account the channels of transmission between the input, and output layers, and direct, indirect effects. Having fewer neurons than required may cause the network to fail to detect signals in complex data. On the other hand, using more neurons than necessary may increase the training time. This study uses a trial, and error method using anterior test as a clear method for determining the number of neurons in the hidden layer.

The study, at this stage, aims at estimating the proposed algorithm for augmented feed forward back propagation neural network, to reach the optimal output level GDP_t^* and the optimal inflation rate Inf_t^* in the Egyptian economy, as they are variables that follow the random walk and autoregressive models from order 1. In general, we write this as:

$$\begin{bmatrix} GDP_t^* \\ Inf_t^* \end{bmatrix} = \begin{bmatrix} \alpha_1 \\ \alpha_2 \end{bmatrix} + \begin{bmatrix} \beta_1 \\ \beta_2 \end{bmatrix} t + \begin{bmatrix} \phi_1 \\ \phi_2 \end{bmatrix} \begin{bmatrix} GDP_{t-1} \\ Inf_{t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{GDP_t} \\ \varepsilon_{Inf_t} \end{bmatrix}, \begin{matrix} \varepsilon_{GDP_t} \sim \mathcal{N}(0, \sigma^2_{GDP}) \\ \varepsilon_{Inf_t} \sim \mathcal{N}(0, \sigma^2_{Inf}) \end{matrix}, \tag{8}$$

where $\left[\varepsilon_{GDP_t}, \varepsilon_{Inf_t}\right]$ are pure random process for GDP_t, Inf_t autoregressive models, which are stationary $\left\{\varepsilon_t\right\}_{t=1}^{\infty}$, and all errors follow the normal distribution. From equations No.7, and 8, the first model of augmented feed forward back propagation neural network—which aims at estimating the optimal level of GDP in Egyptian economy that will be expressed and entered into the layers of ANN models as follows: The output layer, which is denoted by an abbreviation Output, and this layer contains inside it a quarter time series data from 1990Q1 to 2019Q2 forGDP_t, which is the endogenous variable that is interpreted from the model using the input layer, which is symbolized by Input, this layer contains the explanatory variables: GDP with lag period one, the time t, which express the natural extension and a reflection of their behavior in the past, as well as a moving average of its behavior in the past, taking into account the abnormal circumstances and events that occur over time.

The study starts by choosing a small number of neurons, and not just two cells in the hidden layer, then the neural network is trained and tested until the mean square errors reach 1%, which is the rate that the study chose to be the target rate to reach errors to the lowest possible degree.

After increasing the number of neurons in hidden layer, and repeating the training and selection process until the network reaches the optimal solution according to this target rate; it was concluded that two neurons in inputs layer, ten neurons in hidden layer and only one neuron in the output layer are constructing the optimal algorithm for estimating ANN models aimed at estimating the optimal level of output, and inflation in the Egyptian economy.

ANN models takes the following functional form in what is known as augmented feed forward back propagation neural network, which allows direct effects from inputs layer to outputs layer $\left[\xi_1, \xi_2, \ldots, \xi_k\right]$ to be measured by estimating the relative short weights, and measuring the short term relative weights, also measuring the indirect effects from the inputs layer to hidden layer. Finally to the outputs layer, by estimating the long term relative weights $\left[\beta_{1N}, \beta_{2N}, \ldots, \beta_{kN}\right]$.

$$\begin{aligned} GDP_t^* = \gamma_0 &+ \frac{\omega_1}{1 + e^{-(\alpha_{01} + \beta_{11} GDP_{t-1} + \beta_{21} T)}} + \frac{\omega_2}{1 + e^{-(\alpha_{02} + \beta_{12} GDP_{t-1} + \beta_{22} T)}} + \cdots\cdots\cdots\cdots \\ &+ \frac{\omega_{10}}{1 + e^{-(\alpha_{10} + \beta_{110} GDP_{t-1} + \beta_{210} T)}} + \begin{bmatrix} \xi_1 \\ \xi_2 \end{bmatrix} \begin{bmatrix} GDP_{t-1} \\ T \end{bmatrix} \qquad ; \quad t = 1, 2, \ldots\ldots, T, \end{aligned} \tag{9}$$

Figure 4 shows the proposed algorithm for training and estimating augmented feed forward back propagation neural network, which illustrates how the direct effect transmits the inputs layer to the outputs layer, and the indirect effect from the inputs layer to the hidden layer, then to the outputs layer.

This network is trained using the *TRAINLM* function and the adaptation learning function known as *LEARNGD*. The purpose of these functions is to adjust the relative weights until the network reaches the desired outputs.

The previous training function chooses small initial proportional weights, then each pair of network outputs is compared with the targeted outputs and the error is calculated, through back propagation operations the proportional weights of the inputs are modified, then the learning function specializes in reducing errors between the network outputs and the actual output layer.

At each learning stage, the training patterns for the network progressively progress, and a layer passes through it, one layer after another until the outputs layer is obtained, the size of deviations between them, and the target output layer is obtained, then the values of these residues are used in the network feedback operations, and the relative weights in are adjusted in the direction reverse layer by layer until optimum weights, and target outputs are reached, as shown in Fig. 3.

After completing the first stage, which is the formulation of the proposed algorithm for training the augmented feed forward back propagation neural network model, the second step comes, which is training the neural network, in order to reach the optimal weights and the targeted outputs, based on the quarterly time series data for the layers that make up the augmented feed forward back propagation neural network model, as shown in the statistical appendix.

This data have been divided into the default ratios for neural networks modeling, which are 70% of the data for the training sample, 15% for the validation sample, and the other 15% as a test Sample. The study chose the Sigmoid function as an activation function, specializing exclusively with stimulating explanatory variables in the inputs layer, and the hidden layer to reach the best estimate of the neural network.

One of the most important types of nonlinear logistical activation functions and the one most used to activate explanatory variables within the input layer or hidden layer units within the network is the sigmoid function, denoted by an abbreviation *Logsig* within the proposed algorithm. With the training of neural network—as previously presented—, and from Fig. 5, it becomes clear that the results of the training and assessment came as follows:

$$\begin{aligned} GDP_t^* = {} & -1.3 + \frac{0.925}{1 + e^{-(-8.854+5.99\ GDP_{t-1}-6.51\ T)}} + \frac{0.397}{1 + e^{-(-8.053+4.60\ GDP_{t-1}+5.82\ T)}} + \cdots\cdots \\ & \cdots\cdots + \begin{bmatrix} 0.8625 \\ 2.1884 \end{bmatrix} \begin{bmatrix} GDP_{t-1} \\ T \end{bmatrix} \qquad ; \quad t = 1, 2, \ldots\ldots, 115, \end{aligned} \tag{10}$$

Given the results of training and assessment of the neural network presented in the functional form shown above, it is clear that: The existence of a direct positive relationship between the GDP_t^* as an endogenous variable, and GDP with lag period one, the time t, as an explanatory variables on the other hand, as the increase in the latter by 1% leads to an increase in GDP_t^* by 0.86, 2.18% respectively, as shown in panel (c) in Fig. 5.

The study resorted to estimating the long term elasticities mentioned in the estimation results presented in panel (A, B), in addition to those direct and short term previous effects. This proposed algorithm for training and estimating the augmented feed forward back propagation neural network model did not take long

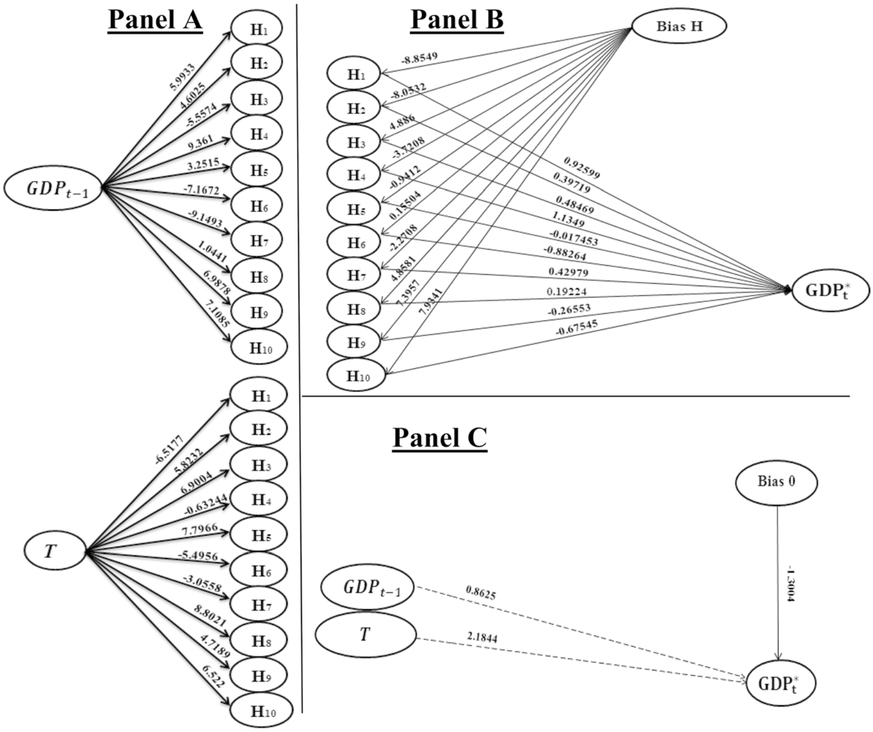


Fig. 5 Results of estimating neural network models; Source: This figure has been prepared by the researcher based on the results of estimating neural network models

time to reach its main goal, which is to reach mean square errors up to 1%, as shown in Fig. 6, the tendency of the gradient curve of residuals quickly towards this goal and less from that—also—until it scored a number that was not significantly different from zero in attempt No. 142, which indicates the goodness of fit for this model as a whole in the stages of testing, validation, and training respectively.

Looking at the following figure, it shows the strong correlation between the actual GDP_t^*, which represents the output layer within the neural network model, and the optimal fitted, by weighting long term elasticities with the possible values of the economic variables in inputs layer. Correlation coefficient between the actual GDP_t^*, and the optimal fitted is 0.997 in the training sample, which confirms that the residuals or deviations between the output layer and its target did not exceed 0.003, although the correlation coefficient between the actual GDP_t^*, and the fitted in the initial sample of the test, decreased, the *TRAINLM* training function, and *LEARNGD* learning function quickly enabled the neural network to explain the changes in the validation sample by 98.7%. This has contributed to the goodness of fit for this model as a whole, which shows that about 99.5% of the changes in the output layer are attributed to the two explanatory variables

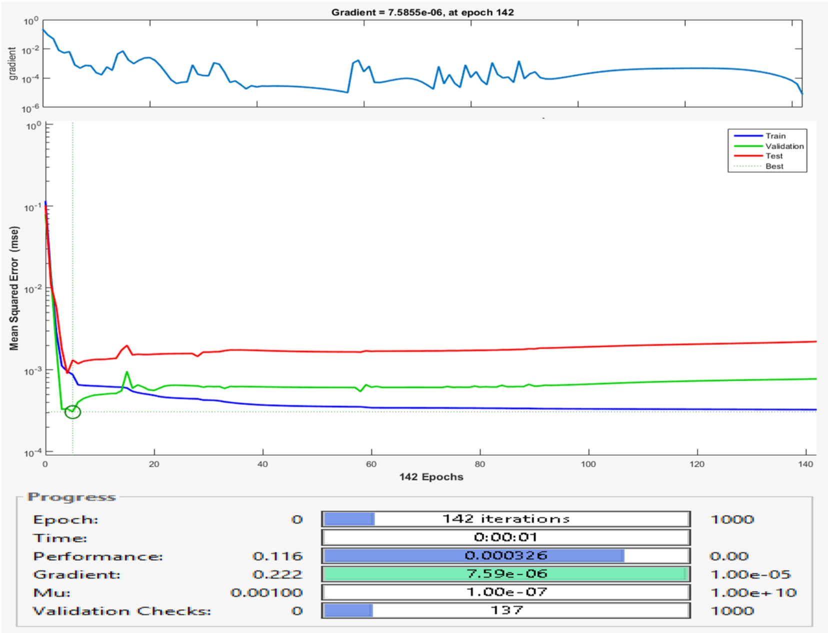


Fig. 6 Attempts of neural network models to reach target errors; Source: This figure has been prepared by the researcher based on the data provided in the statistical appendix, and on the basis of the MATLAB 2018 software package

in the inputs layer and the ten transmission channels of their effects in the hidden layer.

The study aims at this stage to explain the new methodology for modeling the economic performance in Egypt, after augmented feed forward back propagation neural network model has ended the first stage, which is the stage of recognition with the determinants of GDP_t^*, Short term parameters, and estimation of long term parameters that this approach considers important and normative values for estimating the optimal output level GDP_t^*, Which was obtained by the fitted values of GDP_t^* through the results of neural network models. By following the simulation effect of this previous model in order to estimate the optimal inflation rate Inf_t^*, this model was formulated and its results obtained as below:

$$Inf_t^* = 3.51 + \frac{-2.04}{1 + e^{-(-2.90 - 0.78\,Inf_{t-1} + 0.12\,T)}} + \frac{1.43}{1 + e^{-(0.124 + 4.60\,Inf_{t-1} + 2.36\,T)}} + \cdots\cdots$$
$$\cdots\cdots + \begin{bmatrix} 0.50 \\ 0.19 \end{bmatrix} \begin{bmatrix} Inf_{t-1} \\ T \end{bmatrix} \quad ; \quad t = 1, 2, \ldots\ldots, 115, \tag{11}$$

After estimating the optimal output level GDP_t^*, and the optimal inflation rate Inf_t^* in the Egyptian economy through the fitted value of them from the proposed algorithm for augmented feed forward back propagation neural network model, it is possible to derive the following new loss function to measure the Egyptian economic performance, which can be derived by replacing GDP_t^*, Inf_t^* from Eqs. 10, 11, respectively in Eq. 2.

$$MP_i = \lambda\left[var(\pi_i) - var\left[\begin{matrix} 3.51 + \dfrac{-2.04}{1+e^{-(-2.90-0.78\,Inf_{t-1}+0.12\,T)}} + \dfrac{1.43}{1+e^{-(0.124+4.60\,Inf_{t-1}+2.36\,T)}} + \cdots\cdots \\ \cdots\cdots + \begin{bmatrix} 0.50 \\ 0.19 \end{bmatrix}\begin{bmatrix} Inf_{t-1} \\ T \end{bmatrix} \end{matrix}\right]\right] + (1-\lambda)\left[var(y_i) - var\left[\begin{matrix} -1.3 + \dfrac{0.925}{1+e^{-(-8.854+5.99\,GDP_{t-1}-6.51\,T)}} + \dfrac{0.397}{1+e^{-(-8.053+4.60\,GDP_{t-1}+5.82\,T)}} + \cdots\cdots \\ \cdots\cdots + \begin{bmatrix} 0.8625 \\ 2.1884 \end{bmatrix}\begin{bmatrix} GDP_{t-1} \\ T \end{bmatrix} \end{matrix}\right]\right], \tag{12}$$

where the optimal output level $GDP_t^* = (y_i)^*$, and the optimal inflation rate $Inf_t^* = (\pi_i)^*$ in the Egyptian economy, and by applying this model to the quarterly data of the Egyptian economy to estimate the path of the Egyptian economic performance during the study period, it is clear that the results of the study have been largely identical to the actual performance of the Egyptian economy as presented below in the conclusion. From these values, it is evident that the Egyptian economic performance decreased by 0.783 point for the fiscal year 1990/1991 compared to the previous years. This, if anything, indicates the supremacy of a macroeconomic instability state, and the failure of the economic policies followed in general, and monetary policy in particular for targeting the economic growth rate required achieving, which was reflected in the high volatility of domestic price levels, and the exchange rate. With the adoption of the economic reform program by the Egyptian economic authorities, we note that at the beginning years of the reformation, the real GDP growth rate witnessed a sharp decline, especially in the first two years. This rate reached about 1.1% in 1991, and then increased slightly to reach about 2.5% in 1993, and the reason for that may be due to the restrictive monetary and financial policies that were adopted in order to reduce inflationary pressures, and to maintain the stability of the Egyptian pound exchange rate against the dollar at a fixed level, which is in line with the results of the proposed indicator to measure the Egyptian economic performance. The green color indicator indicates the improvement of the Egyptian economic performance that rose from 0.04 to 0.079 points during the same period (Subramanian 1997).

However, the monetary authorities soon reduced the discount rate from 17% in 1993 to 12.25% in 1997, which contributed to a decrease in interest rates and the encouragement of investment expenditure, and then the real GDP growth rate increased to 5.7% in 1997, hence, it was not strange that the government opened the door to open market operations, which came in line with the step of liberalizing the interest rates referred to above, through the issuance of short term treasury bills for periods of 91, 182 and 365 days, provided that these issues are offered for subscription either by banks, bodies, companies, or individuals. The Central Bank has acted as the regulator of the issuance market, as a representative of the Ministry of Finance, in weekly auctions at competitive prices. In addition, the important role that treasury bills played in increasing the supply of foreign exchange, attracting

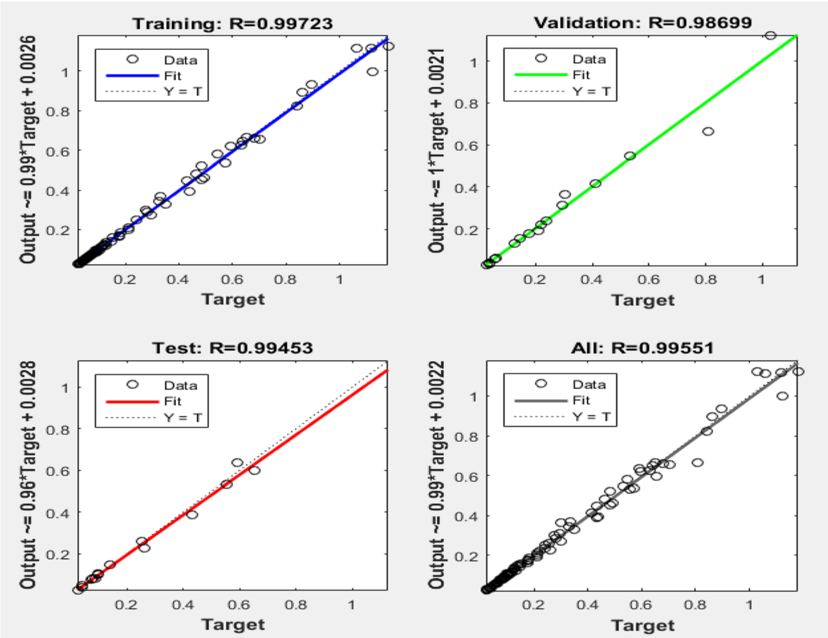


Fig. 7 Correlation and regression coefficients between actual and fitted outputs layer for neural network models; Source: This figure has been prepared by the researcher based on the data provided in the statistical appendix, and on the basis of the MATLAB 2018 software package

foreign capital, increasing savings in the local currency, and reducing the demand for savings in foreign currencies and real estate markets, which reduced the trade deficit, increasing the net foreign assets balances with banks, and the use of with real savings, allowed the central bank to reduce monetary expansion further and remove one of the main sources of inflationary pressures in the Egyptian economy (Fig. 7).

Hence, it can be said that the adopted monetary policy and economic reform procedures have contributed to absorb liquidity and low growth rates from 27.49% in 1991 to 10.46% in 1997, which has resulted in a decrease in the inflation rate from 19.7% in 1991 to 7.2% in 1997, and of course the result was that real interest rates jumped from pent paced levels before reform to achieve a positive real rate of 2.58% in 1997.

This pervious scenario contributed to the improvement of the Egyptian economic performance by 0.243 point in 1997, according to the results of the proposed index to measure the Egyptian economic performance.

However, due to the exposure of the Egyptian economy to internal crises, such as: the recession and liquidity crisis, speculation on the exchange rate and its decline against the dollar, in addition to the economy being affected by external crises, such as the Asian financial crisis, the events of 11th September and Iraq, and the impact of those crises on foreign exchange resources through lack of revenue from the Suez Canal, tourism, unilateral transfers from abroad, low oil prices, and the depletion of international reserves, all of which led to a decrease in the real GDP growth rate to reach 3.1% in 2003. The decision to liberalize the exchange rate in late January 2003 was followed by high inflation rates throughout the year 2003, and continued to rise during the first and second quarters of the fiscal year 2004, to record at the end of the year 16.5%, as the deterioration of the Egyptian pound's value against the US dollar contributed to much higher prices of imported goods from abroad, in addition to the high prices of many raw materials and intermediate goods included in the production of domestic final goods. This has led to an increase in the general level of prices in the Egyptian economy in general, whether as a result of the actual rise in the cost of goods and services or the reason for producers and manufacturers to increase the price and exaggerate the price increase, which explains the matching of the actual performance of the Egyptian economy during this period with the results of the proposed index to measure Egyptian economic performance (Hans 2009).

As long as this period in which the Egyptian economy lived under the umbrella of the managed floating regime did not last long, until the Egyptian economic performance refuses to be on the right path of sustainability. As soon as the global economic crisis erupted by the second half of 2007, when the crisis of high risk mortgages worsened in USA, and caused panic in the global financial and credit markets, and the repercussions of the crisis spread to all economic activities, unless the crisis overshadowed the sky of the Egyptian economy, which contributed to the decline in the Egyptian economic performance by 0.094 point in 2009. As soon as the Egyptian economy started implementing the first stages of plans for developing the banking sector and improving economic performance, the results of the Egyptian economic performance index improved by 0.21 point in 2010, but the winds come in what the ships do not want, and tensions, security, political, economic, and social crises escalate from 25 January 2011 to 30 June, and beyond. The political events witnessed by the Egyptian economy since 25 January 2011 have caused more negative repercussions on the Egyptian economy, foremost among which is the state of security instability, and its negative impact on the movement of tourism, trade, transport, investment, and the decrease in employment, production rates, which contributed to a decrease in the economic growth rate, it recorded 1.9% by the end of 2011, which contributed to the arrival of the proposed indicator to measure the Egyptian economic performance, as the red color indicator to deterioration point by 0.164 point in 2011.

The Egyptian economic performance index has started to oscillate sometimes between ups and downs until it became clear by 2016 the inconsistency between the way in which macroeconomic policies applied within the Egyptian economy are set with the method of managing the exchange rate, which resulted in an unstable economic environment, within which the fluctuations in the real exchange rate increased in light of the different exchange rate regimes applied in the Egyptian economy. The effectiveness of monetary policy decreased and levels of financial deficit increased, which led to an increase in transaction costs, and weak competitiveness of national industries, which was reflected in the form of a depletion of the level of net international reserves held by monetary authorities, and decreased economic growth rates, investment, employment, and output. This has led to high inflation rates and the accumulation of gross domestic debt levels to rates that are difficult for the Egyptian economy to continue to bear, and it was logical for the proposed indicator of the

Egyptian economic performance measurement to record a period of its worst results when its rate of decline reached 0.127 point by the end of 2016. Once the Executive Board of the International Monetary Fund agreed in November 2016 to provide financial assistance to Egypt through an agreement to benefit from “Extended Fund Facility”—EFF—with a value of 8.59 billion SDR, about 12 billion USD, the program achieved its key objective of macroeconomic stability, which is a precondition to attract investment, raise growth, and create jobs. Current account deficits have fallen and foreign exchange reserves are at all–time high levels. Growth has recovered from around 4 to 5.5% now, and is expected to reach 6% by next year, while unemployment has fallen below 9% to its lowest level in over a decade. Public debt has begun to decline and inflation has fallen steadily on track to reach single digits by next year. This sets the stage for broader reforms, such as improving the business climate, which can lead to higher private sector–led investment and job creation. This previous scenario contributed to the improvement in the Egyptian economic performance to witness one of the periods that the Egyptian economy did not live in for long periods, when the proposed economic performance index recorded two consecutive increases of 0.14 and 0.04 points, respectively, in the years 2017, 2018. A follower of this previous scenario and the statistical appendix concluded the extent of the essential congruence between the actual Egyptian economic performance during the study period and the economic performance index that was built through the new contribution of this study.

Conclusion

In this study I develop a new representation for efficiency frontier method through a proposed algorithm for artificial neural network models—ANN—in line with the conditions of the Egyptian economy to measure the economic performance and the effectiveness of macroeconomic policies in Egypt, via building an optimal efficiency frontier and then comparing the actual performance of the Egyptian economy with that limit, that includes the lowest possible fluctuations for both inflation and output. In an attempt by this study to overcome the controversy over value of the policymaker preferences coefficient λ, and because this study seeks to use the efficiency frontier method to measure the Egyptian economic performance in line with the conditions of the Egyptian economy. As the change in the value of this parameter may lead to corresponding changes in the values of economic performance, and the effectiveness of macroeconomic policies, this study chose to place the value of the preferences coefficient at 0.3, in the periods when the inflation rates have increased and the economic authorities have tended to confront the rise of prices level at the expense of increasing the economic growth rate, i.e., the periods when economic authorities actually tend to target the inflation rate through a contractionary monetary policy, and the value of 0.8, in the periods when this rate fell, and the goal of the economic authorities was clear in controlling the rise in the general level of prices. These periods have been identified through the increase in the numbers of discount rates or overnight interbank rates, which is the operational objective of monetary policy in the Egyptian economy. As for other periods in which the contractionary pattern of monetary policy changes, the value of the preferences coefficient λ will be set to 0.8.

As for the new contribution to this study, it calculates the optimal inflation rate and the optimal output level in the Egyptian economy through a model that combines the higher predictive power of feed forward neural network models, and the high explanatory power of auto regressive integrated moving average models—ARIMA—, in order to obtain the fitted values of the optimal output level GDP_t^*, and the optimal inflation rate Inf_t^*, from the proposed algorithm for augmented feed forward back propagation neural network. The study then concluded those two neurons in inputs layer, ten neurons in hidden layer, only one neuron in the outputs layer, training function known as the TRAINLM, the adaptation learning function known as the LEARNGD, and the sigmoid function as an activation function, denoted by an abbreviation Logsig; is the optimal algorithm for augmented feed forward back propagation neural network model aimed at estimation the optimal level of output, inflation in the Egyptian economy. The quarter time series data from 1990Q1 to 2019Q2 have been divided into the default ratios for neural networks modeling, which are 70% of the data for the training sample, 15% for the validation sample, and the other 15% as a test sample. After estimating the optimal output level GDP_t^*, and the optimal inflation rate Inf_t^* in the Egyptian economy, through the fitted value of them from the proposed algorithm for augmented feed forward back propagation neural network model, it was possible to derive the new loss function as shown in Eq. 12 to measure the Egyptian economic performance. It is clear from the results of the study, the extent of the essential congruence between the actual Egyptian economic performance during the study period and the economic performance index that was built through the new contribution of this study, and that this indicator is suitable to be the true mirror of the Egyptian economy to judge the path of the economic reform program, the economic performance, and the effectiveness of macroeconomic policies in Egypt.

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