Applying Modified Genetic Radial Basis Function Neural Network (MGRBFNN) to Predicting exchange rate future movements
(An Empirical Study on a sample of currencies traded in Iraqi financial market)

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Abstract:

The research aims to take advantage of the distinctive capabilities of the neural networks in dealing with investment decisions in currencies, which depends on a large extent on the prediction of the nature of currency price movements. The technique (Modified Genetic Radial Basis Function Neural Network (MGRBFNN) was used to obtain the results compared with three techniques: genetic algorithm (GA), (Multilayer Perception) method, and (Hop Field NN) method. The research sample consists of four currencies traded in the Iraqi market for the period (2010-2018). The research found that using the MGRBFNN Technique gives a very high accuracy.

Key words: neural network, exchange rates, genetic algorithm, prediction, risk.

1- Introduction:

The currency mechanism is the core component of the global financial economy and the pole of contemporary economic thinking. Neural Network technology is characterized by its ability to process the inputs and facts of reality and bypassing the traditional techniques in
explaining the behavior of phenomena, which made it the focus of attention of many researchers in various fields, one of these phenomena is currency exchange rate movements.

Currency exchange rate movements gain the attention of companies and investors, especially after the adoption of float in determining the exchange values between currencies in most countries. This has led to a constant change in exchange rates, which is reflected in the value of assets, liabilities, expected profits and losses, as well as exposure to exchange rate risk, and this drives investors to search for appropriate means to increase their ability to anticipate exchange rate movements. Hence, the study problem is related to the question of the extent of the neural network's ability to provide a better understanding in anticipating exchange rate movements and improving the ability of investors to make the correct investment decision and provide a means for accurate inference and prediction of patterns of currency price movements. So, this study aimed to:

- To reach a new approach, in theory and methodology, in monitoring currency movements.
- Detecting the predictability of currency rates using an updated type of neural network.
- Building a model capable of describing those prices and specifying signals regarding the timing of buying or selling currencies.

In order to achieve the objectives of the study, four currencies were chosen as a field of study based on the closing price for the period (1/1/2015 to 12/29/2017) for the spot exchange rate. The following currency rates were chosen against the US dollar:
- Sterling pound.
- The Euro.
- Japanese Yen.
- The Russian Ruble.

2- Literature Review:

The exchange rate is defined as the number of units of a particular currency that can be exchanged for one unit of another currency (Solis 2012) or represents the currency of a particular country expressed in light of another currency (Jordan et al. 2011). It is also expressed as the rate at which a local currency is converted into a foreign currency (Bodie, Z.
Kane. Alex and Marcus. Alan (2011). It also indicates the price paid to convert one currency into another (Madhumathi and Ranganatham 2012).

Before 1973, the fixed exchange rate regime prevailed, based on the Bretton Woods agreement, after which it would shift towards floating exchange rates (Madura and Fox 2007; James 2012; Bodie et al. 2011).

The traditional framework for studying international currency markets is concentrated in the standard functions of the currency as a trading medium, unit of accounts and a store of value (Cohen 2009; Cechtti et al. 2011). The currency market is characterized by the diversity of its instruments and high competition, even if the dollar’s sovereignty appeared clear after it rose to the top of the reserves behind the pound sterling after it represented the highest percentage of reserves in 1945, then it decreased to 25% in 1965 (Cohen 2009; James 2012).

There are many factors that influence exchange rate fluctuations, such as inflation, interest rate, currency supply and demand, government control and expectations (Madura and Fox 2007).

The increase in risks associated with currency trading is pushing towards the search for the best way to predict its price movements, either to achieve profits or to implement specific policies, as well as attempts to find stable patterns of complex systems in many areas such as physics, chemistry and economics. Financial markets are complex systems involving millions of buyers, speculators, and many factors that are closely related, which requires determining whether patterns can follow a specific and predictable law (Mark 2008; James 2012).

Managers of companies and investors must understand forecasting techniques to assist in making hedging decisions from currency price movements or in making short and long-term financing decisions. There are many techniques used to predict currency exchange rate movements: Technical Analysis, Fundamental Analysis & Neural Networks.

The technique (Modified Genetic Radial Basis Function Neural Network (MGRBFNN)) is one of the artificial intelligence fields, which is one of new branches of knowledge and a scientific field that seeks to understand what is human intelligence and find ways to accomplish smart tasks and reach a high level of performance to solve various problems and issues (Tan 2014).
MGRBFNN is a paradigm of biological and neurological sciences that is interested in studying how organisms can develop solutions for survival (Tan 2014; Kumar and Walia 2006) simulate the human neural network model. (Thawornwong and Enke 2004).

The network’s work based on a mathematical architecture based on an adaptive response to inputs. Using learning rules, it carries out an ongoing series of training to achieve the required tasks. It is characterized by the performance of non-linear modeling and is classified as one of the data-oriented methods which, unlike the methods directed by models, does not require estimation of features that are used for prediction or pre-employment during the modeling process (Thawornwong and Enke 2004).

(MGRBFNN) is characterized by the ease of building and dealing with a large volume of data and solving a variety of problems in different ways as well as solving problems that are difficult for experts to solve (Tan 2014). The use of the network requires an appropriate volume of data and contain information through which to describe the problem and understand network tools. (Kumar and Walia 2006). The researchers identify the most important applications of the neural network in the following: (Kumar and Walia 2006; Widrow et al. 1994)

- Classification of patterns
- Predicting time series
- Optimization

It provides a tool that statistical and economic models cannot quantify due to its complexity and the inability to find its own functions. The use of the neural network in the financial field has increased, especially in light of the development of information and communication technology technologies, which provided a wide range of investment options to investors. (Maditinos and chatzoglou 2002) Which requires the use of tools capable of assisting investors in predicting the movements of investment tools and making the appropriate decision in buying or selling these tools. According to many studies, the neural network is more accurate in predicting the movements of the S&P index (Kutsurelis 1998) or to the cash flow of banks (Kumar and Walia 2006). Stock indices, currencies, short-term interest rates (Vieira 2013), stock market movements in Taiwan (Chen, Leung and Daouk 2003), and daily stock exchange forecasting for the NASDAQ (Moghaddam et al. 2016).

An RBFN is a neural network that operates as activation functions using a radial base. It is a linear combination of the features of the radial base. RBF is based upon a network with three layers, the input layer is simply fan-out layer and does not process. A non-linear mapping of
the input space into the high dimensional area, where the patterns can become linearly separated, is carried out in the second or hidden layer. A weighted sum with a linear yield is carried out in the end layer. RBFs are networks that use the distance between the input vector and the vector prototype for activating concealed units. Because of its velocity, this network is can be used in multiple domains becoming popular where it can be considered the main competitor of a multi-layered teacher. Much of RBF's inspiration came from traditional statistical pattern classification techniques. (Seenivasagam & Arumugadevi 2012)

The Second Technique was used in this study. The Moore–Penrose pseudo inverse: It is a matrix used in linear systems to calculate the least square error in linear systems solutions (best solution). It was also used in data analysis and digital image processing. (Barata & Hussein 2012)

The Third Technique is Genetic algorithm (GA) is a heuristic simultaneous research that is inspired by the method of natural choice and basic components of genetic engineering. The genetic algorithm involves two activities, namely crossover and mutations, which correspond to two probabilities: the likelihood of crossover P_c and the likelihood of mutation P_m. Inadequate configurations of P_c and P_m may lead to different search issues like not converging or premature converting gene. (Lu et al. 2017).

3- Materials and Methods:

In this paper, we used modified Genetic Radial Basis Function Neural Network with 14 input nodes, 12 hidden nodes, and 2 output. Using the data table as input to give the final result. The process of selecting the ideal number of nodes for the hidden layer gives the best results for the network and the fastest in the training process, to identify the best data given the first step is the process of generating a new generation (weights) of the neural network by using Moore-Penrose pseudo-inverse to update the Weights, then weights are passed to genetic algorithms where weights are trained and choose the best weights that bear the least cost be the best fitness where training is done modified RBFNN and arranged results as a new generation and conduct the mating process with the provision of some characteristics in the data entered, and then conduct an operation and mutation to produce the ideal generation is stored results and then enter new data and So for a number of iteration. The biggest number of iteration to train set value 200. The process of learning and training the network stops if there is an error in the weights where the weights are adjusted to be close to the desired ideal value and the expected output from the output of this algorithm from the generation process to the
production of a new generation will give the expected process of selection and rise of the
currency and predict what kind of currency (data) The input will increase during the specified
period, Fig. 1. Describes the Flow Chart of the (MGRBFNN) mechanism.

Figure 1. Flow Chart of the (MGRBFNN) mechanism
4- Results:

Descriptive Analysis:

Table (1) shows a summary of the study data by specifying the highest and lowest exchange rates for the currency and the average price achieved. It is noted that the highest standard deviation was for the Japanese yen against the dollar, which reflects the high volatility of this currency, followed by the Russian ruble, while the exchange rate of the euro and the pound sterling was more stable, especially for the euro, as the standard deviation did not exceed (0.03). This clearly appears in the margin difference between the lowest price and the highest price, as the margin was high for the yen and ruble currencies and the lowest for the pound relative to the euro.

<table>
<thead>
<tr>
<th>Currency</th>
<th>Stand. Dev.</th>
<th>Mean</th>
<th>Min.</th>
<th>Max.</th>
</tr>
</thead>
<tbody>
<tr>
<td>EUR</td>
<td>0.038277</td>
<td>1.1155</td>
<td>1.0387</td>
<td>1.2104</td>
</tr>
<tr>
<td>GBP</td>
<td>0.117495</td>
<td>1.4078</td>
<td>1.2048</td>
<td>1.5884</td>
</tr>
<tr>
<td>JPY</td>
<td>6.344488</td>
<td>113.335</td>
<td>99.89</td>
<td>125.62</td>
</tr>
<tr>
<td>RUB</td>
<td>5.865057</td>
<td>61.95235</td>
<td>49.0687</td>
<td>82.6813</td>
</tr>
</tbody>
</table>

Table 1. Highest and lowest value for currencies, average and standard deviation

Figures 2, 3, 4, and 5 shows the direction of the (EUR, GBP, JPY, RUB) exchange rates movements against the dollar respectively. Although there was no high margin for the difference between the highest and lowest price, the period witnessed a clear fluctuation between ups and downs, even if it was not within high limits.

Figure 2. Closing price of the EUR / USD exchange rate

Figure 3. Closing price of the GBP/USD exchange rate
Prediction of exchange rates:

In this study, MGRBFNN technique will be used to predict exchange rates for the study sample currencies. Currency rates and trading days are inputs. All procedures can be summarized in the following steps:
Algorithm 1: MGRBFNN

**Input:** input number of data \( H \) (currency

**Output:** optimal number of production currency.

**Start**

**Step 1.** Encoding the Chromosome: Initialize RBFN network (initialization the number of variable to the Layer: - center \( c \), width, weights, spread and the tolerance \( \text{tol} \) value. A tolerance \( \text{tol} \) must be greater than 0, the radial basis function for a neuron has a center and a radius (also called a spread)

**Step 2:** Initialize Input layer with total number of \( H \).

**Step 3:** Execute the following for some number of iterations : (Evaluation Function)

1. Initialize the weight vector \( \text{Wight} \) kept as fixed while the hidden To output weights are learned with minimum distance .

2. Update the value of weight vector using Moore-Penrose pseudo-inverse as follows:

\[
(W)kj = wkj, (\Phi)pj = \Phi (xp), \text{and } (T)pk = \{tkp\}.
\]

- \( D \) dimensional input vector \( xp = \{x_p : i = 1,..., D\} \)
- \( K \) dimensional target output \( tp = \{t_p : k = 1,..., K\} \).

- Widths \( \{\sigma_j\} \) Wight \( wkj \)

**Step 5:** Choose a winner \( Q \) from all the short distance whose is minimum \( E_{ij} \) as follows: \( Q = \min E_{ij} \)

// in Hidden layer

The outputs of the training it will be calculate their training cost then Calculate the “fitness , the lowest cost will have the highest fitness , the maximum fitness will choose to population

**Step 6:** Take the smallest Euclidean distance of \( B_{ij} \) for each \( H \).

**Step 7:** Initialization Procedure :

1- opt NNs depending on a probability system according to their fitness
2- Crossover the genes (data) of the NN. This will create a “child” NN.
3- Mutate the genes (data) of the child

**Step 8:** Operators Implement steps (3 — 7 iteratively) for the number of NNs in the population. Then store the “children” created, in a new population and deployment the new population to the variable containing the old population

**Step 9:** Opt a good set(solution) of operators for the final algorithm

**End**
5- Discussion:

The performance of the MGRBFNN that used to evaluated on historical data sets of (2015-2018) starting from the 1st of January to December. by used four currencies include (JPY,RUB,GBP,EUR). The propose system give the optimal result that shoed in table. Tables 2,3,4 and 5 give the accuracy. The final results have been obtained after averaging the 4 individual results, each from an independent evolutionary run carried out for proposed method and then compare with other method to evaluate our system accuracy the proposed system having 98.791% accuracy on average, The results validate the efficiency of the networks generated for currency production in Iraqi banc center.

The assessment of network performance will depend on the deviation of the forecast value from the actual price of the currency. The prediction was first made for four sub-periods of the study period. As shown in the table (2), the highest forecast accuracy for the year 2015 was for the British pound and reached (98.55%), followed by the euro that recorded (98.53%), while the value of the prediction for the yen and ruble (98.27%) and (98.26%) respectively.

Table 2. The test findings on the precision of modified genetic-RBFN for different currencies predict on started day information history, from (January _ Dec) year 2015.

<table>
<thead>
<tr>
<th>Currency type</th>
<th>100</th>
<th>150</th>
<th>200</th>
<th>250</th>
<th>300</th>
<th>400</th>
<th>500</th>
<th>600</th>
<th>700</th>
</tr>
</thead>
<tbody>
<tr>
<td>USD</td>
<td>98.538</td>
<td>98.698</td>
<td>98.677</td>
<td>98.566</td>
<td>98.791</td>
<td>98.743</td>
<td>98.686</td>
<td>98.614</td>
<td>98.791</td>
</tr>
<tr>
<td>JPY</td>
<td>98.248</td>
<td>98.166</td>
<td>98.188</td>
<td>98.276</td>
<td>98.281</td>
<td>98.112</td>
<td>98.257</td>
<td>98.233</td>
<td>98.277</td>
</tr>
<tr>
<td>RUB</td>
<td>98.2701</td>
<td>98.134</td>
<td>98.099</td>
<td>98.296</td>
<td>98.171</td>
<td>98.281</td>
<td>98.228</td>
<td>98.252</td>
<td>98.264</td>
</tr>
<tr>
<td>GBP</td>
<td>98.3808</td>
<td>98.302</td>
<td>98.31</td>
<td>98.498</td>
<td>98.461</td>
<td>98.45</td>
<td>98.399</td>
<td>98.321</td>
<td>98.554</td>
</tr>
<tr>
<td>EUR</td>
<td>98.463</td>
<td>98.403</td>
<td>98.521</td>
<td>98.6</td>
<td>98.422</td>
<td>98.441</td>
<td>98.433</td>
<td>98.457</td>
<td>98.536</td>
</tr>
</tbody>
</table>

As for the year 2016 as indicated in the table (3), the lowest prediction error was for the euro currency, whose accuracy of prediction reached (98.5%) and the pound currency (98.4%), while the accuracy of the prediction for the ruble (98.3%) and the yen (98.2%).
Table 3: The test findings on the precision of modified genetic-RBFN for different currencies predict on started day information history, from (January _ Dec) year 2016.

<table>
<thead>
<tr>
<th>Currency type</th>
<th>100</th>
<th>150</th>
<th>200</th>
<th>250</th>
<th>300</th>
<th>400</th>
<th>500</th>
<th>600</th>
<th>700</th>
</tr>
</thead>
<tbody>
<tr>
<td>USD</td>
<td>98.791</td>
<td>98.77</td>
<td>98.621</td>
<td>98.75</td>
<td>98.651</td>
<td>98.619</td>
<td>98.67</td>
<td>98.791</td>
<td>98.791</td>
</tr>
<tr>
<td>JPY</td>
<td>98.201</td>
<td>98.208</td>
<td>98.132</td>
<td>98.202</td>
<td>98.241</td>
<td>98.288</td>
<td>98.341</td>
<td>98.209</td>
<td>98.203</td>
</tr>
<tr>
<td>RUB</td>
<td>98.3129</td>
<td>98.306</td>
<td>98.343</td>
<td>98.304</td>
<td>98.331</td>
<td>98.357</td>
<td>98.312</td>
<td>98.328</td>
<td>98.3129</td>
</tr>
<tr>
<td>GBP</td>
<td>98.491</td>
<td>98.471</td>
<td>98.421</td>
<td>98.441</td>
<td>98.451</td>
<td>98.419</td>
<td>98.427</td>
<td>98.494</td>
<td>98.4915</td>
</tr>
<tr>
<td>EUR</td>
<td>98.565</td>
<td>98.511</td>
<td>98.453</td>
<td>98.453</td>
<td>98.458</td>
<td>98.47</td>
<td>98.523</td>
<td>98.55</td>
<td>98.552</td>
</tr>
</tbody>
</table>

In line with the foregoing, the accuracy of the prediction of currency prices for the year 2017 was also high, as the error rate did not exceed (2%) and was the highest accuracy for the euro, which reached (98.5%) and the lowest for the pound (98.11%) and as shown in this table (4).

Table 4. The test findings on the precision of MGRBFN for different currencies predict on started day information history, from (January _ Dec) year 2017.

<table>
<thead>
<tr>
<th>Currency type</th>
<th>100</th>
<th>150</th>
<th>200</th>
<th>250</th>
<th>300</th>
<th>400</th>
<th>500</th>
<th>600</th>
<th>700</th>
</tr>
</thead>
<tbody>
<tr>
<td>USD</td>
<td>98.791</td>
<td>98.771</td>
<td>98.755</td>
<td>98.745</td>
<td>98.755</td>
<td>98.707</td>
<td>98.746</td>
<td>98.757</td>
<td>98.791</td>
</tr>
<tr>
<td>JPY</td>
<td>98.144</td>
<td>98.156</td>
<td>98.122</td>
<td>98.132</td>
<td>98.161</td>
<td>98.173</td>
<td>98.152</td>
<td>98.118</td>
<td>98.115</td>
</tr>
<tr>
<td>RUB</td>
<td>98.324</td>
<td>98.3</td>
<td>98.352</td>
<td>98.332</td>
<td>98.342</td>
<td>98.365</td>
<td>98.31</td>
<td>98.327</td>
<td>98.3136</td>
</tr>
<tr>
<td>GBP</td>
<td>98.383</td>
<td>98.346</td>
<td>98.332</td>
<td>98.343</td>
<td>98.485</td>
<td>98.32</td>
<td>98.312</td>
<td>98.454</td>
<td>98.436</td>
</tr>
<tr>
<td>EUR</td>
<td>98.56</td>
<td>98.533</td>
<td>98.533</td>
<td>98.562</td>
<td>98.562</td>
<td>97.558</td>
<td>98.561</td>
<td>98.532</td>
<td>98.516</td>
</tr>
</tbody>
</table>

While the accuracy of the prediction was very high for the year 2018 and was not less than (98%) and for the four currencies as shown in the table (5).

Table 5. The test findings on the precision of MGRBFN for different currencies predict on started day information history, from (January _ Dec) year 2018.

<table>
<thead>
<tr>
<th>Currency type</th>
<th>100</th>
<th>150</th>
<th>200</th>
<th>250</th>
<th>300</th>
<th>400</th>
<th>500</th>
<th>600</th>
<th>700</th>
</tr>
</thead>
<tbody>
<tr>
<td>USD</td>
<td>98.744</td>
<td>98.746</td>
<td>98.7236</td>
<td>98.723</td>
<td>98.746</td>
<td>98.745</td>
<td>98.756</td>
<td>98.756</td>
<td>98.791</td>
</tr>
<tr>
<td>JPY</td>
<td>98.132</td>
<td>98.122</td>
<td>98.11</td>
<td>98.11</td>
<td>98.13</td>
<td>98.132</td>
<td>98.133</td>
<td>98.101</td>
<td>98.102</td>
</tr>
<tr>
<td>GBP</td>
<td>98.424</td>
<td>98.43</td>
<td>98.392</td>
<td>98.372</td>
<td>98.382</td>
<td>98.365</td>
<td>98.391</td>
<td>98.327</td>
<td>98.415</td>
</tr>
<tr>
<td>RUB</td>
<td>98.383</td>
<td>98.336</td>
<td>98.332</td>
<td>98.234</td>
<td>98.385</td>
<td>98.32</td>
<td>98.312</td>
<td>98.354</td>
<td>98.336</td>
</tr>
<tr>
<td>EUR</td>
<td>98.56</td>
<td>98.533</td>
<td>98.533</td>
<td>98.562</td>
<td>98.562</td>
<td>97.558</td>
<td>98.561</td>
<td>98.532</td>
<td>98.56</td>
</tr>
</tbody>
</table>
The previous results reflect a very low deviation in forecasting exchange rates from actual movements. For the purpose of determining the accuracy of the technique (MGRBFNN) versus other methods of forecasting to determine the extent to which it can be relied upon by investors to follow and predict exchange rate movements, the table (6) shows a comparison with three methods of forecasting, as it appears that the technology (MGRBFNN) is superior to other methods and a difference significant accuracy in prediction as the accuracy of prediction reached (98.79%), while the genetic algorithm recorded GA (70.1%), while (Multilayer Perception) method achieved (69.7%), and (Hop Field NN) method scored (60.8%).

Table 6. Comparative between different methods to give optimal production

<table>
<thead>
<tr>
<th>Methods</th>
<th>Accuracy %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Multilayer Perception</td>
<td>69.7</td>
</tr>
<tr>
<td>GA</td>
<td>70.1</td>
</tr>
<tr>
<td>Hopfield neural network</td>
<td>60.8</td>
</tr>
<tr>
<td>MGRBFNN</td>
<td>98.791</td>
</tr>
</tbody>
</table>

Table 7 shows The main currency rates in the Central Bank of Iraq for the years (2015-2018)

While Figure 6. shows a graphical illustration of the possibility of methods in accurate prediction of currency prices, as it reflects the possibility and ability of the method used in this study to generate better results in monitoring and discovering patterns of exchange rate movements.

Table 7. The main currency rates in the Central Bank of Iraq for the years (2015-2018)

<table>
<thead>
<tr>
<th>Years</th>
<th>USD</th>
<th>RUB</th>
<th>JPY</th>
<th>GBP</th>
<th>EUR</th>
</tr>
</thead>
<tbody>
<tr>
<td>2015 (Jan.-Dec)</td>
<td>1164.000-</td>
<td>58.048-</td>
<td>9.688-</td>
<td>1777.727-</td>
<td>1338.594-</td>
</tr>
<tr>
<td></td>
<td>1180.000</td>
<td>72.999</td>
<td>9.804</td>
<td>1749.667</td>
<td>1290.807</td>
</tr>
<tr>
<td>2016 (Jan.-Dec)</td>
<td>1180.000</td>
<td>73.165</td>
<td>9.885</td>
<td>1744.941</td>
<td>1287.500</td>
</tr>
<tr>
<td></td>
<td>1180.000</td>
<td>61.272</td>
<td>10.119</td>
<td>1447.817</td>
<td>1234.927</td>
</tr>
<tr>
<td>2017 (Jan.-Dec)</td>
<td>1182.000</td>
<td>60.913</td>
<td>-----/10.452</td>
<td>1454.290</td>
<td>1228.969</td>
</tr>
<tr>
<td></td>
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<td>57.611</td>
<td>10.452</td>
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<td>1412.279</td>
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<tr>
<td>2018 (Jan.-Dec)</td>
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<td>57.515</td>
<td>10.540</td>
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<td>59.08</td>
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</table>
6- Conclusion:

In this paper, an integrated technique of genetic algorithm and one of the types of anterior feeding neural networks were used for the purpose of giving the best predictions of the circulating currency in the CBI for the years 2015_2018. The results showed the best performance, indicating that the proposed method had the ability to choose the best possible advantage of the network structure and how to communicate in order to predict the prices of the currency in circulation in the bank. The results also show that the accuracy of the network increases with an increasing number of observations pathways, thereby improving the capabilities of the network integrated with the genetic algorithm to predict future data.

Acknowledgments:

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References:


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*Business and Science Journal 35*(2).

Appendix:

Figure 7: year 2015 (June-DES)

![Predication currency sale](image)

Figure 8: year 2016 (June-DES)

![Predication currency sale](image)

Figure 9: year 2017 (June-DES)

![Predication currency sale](image)
Figure 10: year 2018 (June-DES)

Figure 11: Currency Issued & Outside Banks

Figure 12: predication with true data (four type currency)
Figure 13: Annual Inflation Rate & Core Inflation for 2015-2018

![Bar chart showing Annual Inflation Rate & Core Inflation for 2015-2018]

Figure 14: Money Supply & Contributing Factors

![Bar chart showing Money Supply & Contributing Factors for 2015, 2016, 2017, and 2018]