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Reliability and Accuracy of Neural Networks for Exchange Rate

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ABSTRACT

Most exchange rates are volatile and mainly rely on the principle of supply and demand. Millions of people around the world are influenced, one way or another, by the variation in exchange rates. In this research we demonstrate that the Artificial Intelligence, specifically Artificial Neural Networks (ANN), can improve the accuracy of forecasting exchange rates compared to statistical techniques such as regression. When we compared the results from regression and artificial neural network, it was clear that the ANN outperformed regression in forecasting exchange rates. Moreover, it became clear that using ANNs instead of regression for forecasting exchange rates is rewarding and necessary because the average error given by an ANN is smaller than the average error given by regression. Accuracy in forecasting became a major issue and not a minor detail. It was the combination between Artificial Intelligence and Macro Economics that made these two models come into reality, making it possible to use computer sciences and engineering fields in the service of an economical problem.
The results of our research showed that using ANN with the right parameters and variables rather than using a regression model will yield a result with a lower error margin.

KEYWORDS

Artificial Neural Network, Regression, Exchange Rate, Forecasting, Inflation, Interest Rate, Multilayer Perceptron;

I. INTRODUCTION

Most exchange rates are volatile and mainly rely on the principle of supply and demand. Millions of people around the world are influenced, one way or another, by the variation in exchange rates. All international companies rely on exchange rates to make everyday business decisions such as buying goods, opening worldwide branches, investing in foreign countries, etc… Forecasting is an essential discipline in planning and running a business. Success hugely depends on getting those forecasts right. As we know, however, that the future is highly uncertain.

The purpose of this study is to demonstrate the power of Artificial Intelligence, specifically ANN, in forecasting exchange rates, and comparing the results to the statistical techniques' results.
For several decades, many techniques were used to forecast exchanges rates; some of them were proven to be better than others [1]. Specifically, regression was a very good technique to be considered [2]. But recently, artificial intelligence, and especially artificial neural networks, became a powerful tool for forecasting exchange rates [3]. At this stage, it is clear that the main research question about which technique is better in forecasting exchange rates.

Section II shows the importance of risk management for IT projects, where a good risk management plan can ensure the success of a project. In section III we can find an overview of ANNs and an overview about statistical techniques and regression. Section IV presents an overview of the state of knowledge concerning forecasting, ANNs, and regression. The procedures and the methodology of the system implementation are described in Section V. Section VI highlights the system specifications and presents preliminary results. Finally a conclusion is given in section VII.

II. IT PROJECTS RISK MANAGEMENT

Forecasting exchange rate can fail without good managing IT system, it may have some risks. IT can help to manage with a minimum risk and error for forecasting exchange rate. [4]
The Risk Management process is divided into six steps:

1) Goal Definition: review the stated goals for the project, refine them and define implicit goals and constraints explicitly.
2) Identification: identify potential threats to the project using multiple approaches.
3) Analysis: classify risks, complete risk scenarios, estimate risk effects and estimate probabilities and utility losses for risk scenarios.
4) Control and Planning: select the most important risks, propose controlling actions and the actions for implementation.
5) Control: implement the risk controlling actions.
6) Monitoring: monitor the risk situation.

Organizations need to keep IT projects on schedule and costs under control. However, organizations must also encourage managers to respond to changing business needs and exploit technological opportunities before their competitors do so.

III. OVERVIEW OF ARTIFICIAL NEURAL NETWORKS AND REGRESSION

A) Artificial Neural Networks (ANN)

An Artificial Neural Network's purpose is to recognize patterns in the available data by learning. After training the network with existing data samples, it becomes able to predict or forecast similar patterns or behavior in future data. In general, ANNs are more attractive and useful than traditional techniques because of their unique properties [5]. In many cases, ANNs offer a better alternative than algorithmic functions and expert systems [6]. In every situation where we cannot define the exact relation between inputs and outputs, or when the input-output relation is complex, ANNs can give an accurate approximation for this relation [7]. We can imagine an artificial neural network as a black box that can predict an output pattern when it recognizes a given input pattern. Inside ANNs, we can find a bunch of processing elements or PEs, connected between them with adjustable weights. Figure 1 shows an artificial neural networks structure.

The neural network must first be "trained" by having it process a large number of input patterns and showing it what output resulted from each input pattern. Once trained, the neural network is able to recognize similarities when presented with a new input pattern, resulting in a predicted output pattern [7].

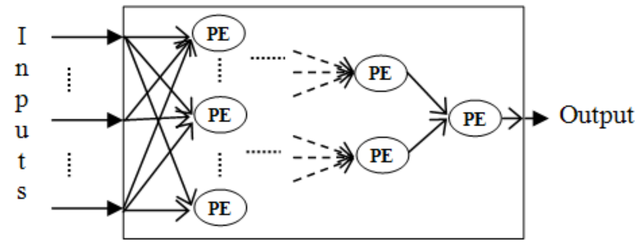

Fig. 1. Neural Network Structure

There are many types of artificial neural networks, and the most popular one is a Multilayer Perceptron or MLP. MLP always needs a target output in order to learn, that's why it is called a supervised network [7]. An MLP set a relation between inputs and the desired outputs, and it does so by using data that is previously stored. For an MLP to learn, it uses an algorithm called back propagation algorithm. By using this algorithm, the previously stored input data is fed into the neural network many times, and at each time the actual output is compared to the stored output, and an error is calculated based on the difference between these outputs. This error is then used to adjust the weights of the connections between neurons. After each iteration, the error magnitude should decrease (refer to figure 2) until it is less than a predefined number called error threshold. At the end, the calculated output is closer to the desired output.

The power of ANNs is shown in the fact that any complex pattern in a huge amount of data can be extracted by the Artificial Neural Network without the need to know the exact mathematical relationship between the dependent and independent variables [8][9]. This is exactly the case in forecasting exchange rates, where huge amounts of data are to be treated and analyzed in order to reach a final number that represents a forecasted exchange rate.

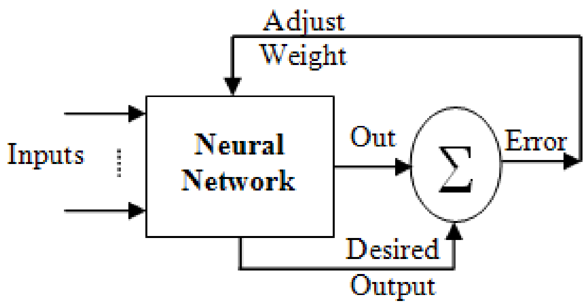

Fig. 2. Neural Network Learning Model

B) Useful Applications of ANNs

Besides being used as a forecasting method, ANN is widely used for many applications. One of these methods is Automatic Traffic Signs Recognition [10]. The steps of traffic signs recognition are:

1- Image processing: algorithms that are applied on the pixels values of the image to perform a specific process, such as enhancement and restoration.

2- Image features extraction: There are mainly two types of features; low level and high level features. Low level features can be extracted directly from the image, like edges, lines, textures, etc. A set of high level features can be extracted from low level features, which are useful in image understanding and content recognition.

3- Image Segmentation: Dividing the image into non-overlapping, homogenous, and connected regions.

4- Traffic Sign Image Recognition: The resultant image will pass through the recognition process, in which the image is entered into a trained neural network and the decision is made according to the result of the NN.

Another ANN application is a Controller for Robotic Manipulator [11], where ANN is used for inverse neural controller which is used to control the operation of six Degree Of Freedom (6DOF) robotic manipulator. A neural network is trained to identify (learn) the inverse of the plant dynamic with the aid of a set of training data then the trained neural network is used as a Fed Forward Controller.

C) Statistical Regression Models

Regression can be considered as a statistical tool that investigates the relation between one dependent variable and one or more independent variables. The relation, if it exists, proves the cause/effect relation between the variables. For example, the effect of interest rate on exchange rates, or the effect of fiscal policy on goods' prices [13]. The primary focus is on the analysis of the relation between one or more independent variables and one dependent variable. Regression tries to show how a dependent variable changes in response to the change of one independent variable, while keeping the other independent variables are kept unchanged. Regression analysis tries to set the relation between independent variables and the dependent variable through a function that we call the regression function. In practice, regression is used for forecasting and prediction. It can also be used to show which of the independent variables is greatly related to the dependent variable, and by which amount. In addition, the performance of regression depends on the method's form that generates data. In most of the cases, there are some assumptions that should be made to use regression (e.g. linearity of data, normal distribution, etc…). To obtain better results, these assumptions should be respected.

IV. State of Knowledge

Since the widespread introduction of floating exchange rate regimes amongst the major currencies in the early 1970s, the problem of correctly anticipating exchange rate fluctuations is one, and corporate treasurers of companies having any international dealings have had to face it in order to manage successfully the exchange risk inherent in international contracts.

A lot of entities are interested in forecasting at least the direction of some exchange rates. Using an exchange rate forecasting model that can guide businesses and traders in their decision making can be effective and essential in order to maximize profit and minimize the risk in any business.

Because all known forecasting exchange rate models have approximately the same efficiency, we can find a lot of them. This shows the amount of difficulty and complexity of generating an efficient and reliable exchange rate forecasting model.

In his book entitled "Exchange Rate Determination: Models and Strategies for Exchange Rate Forecasting", Michael Rosenberg explained that globalization and cross-border interaction contributed largely to redefining the worldwide business arena. He mentioned as well that success for the companies dealing with business in the arena is the result of forecasting and determining accurately and thoroughly the exchange rates.

Authors in [14] worked on estimating and selecting feedforward and recurrent networks in a careful way, and they also wanted to evaluate the forecasting performance of selected networks in different periods, that's why they have proposed a two-step procedure. Different forecasting results were gathered, and they were not similar. Among five series which were evaluated, in only two out of them, networks with significant market timing ability (sign predictions) and/or significantly lower out-of-sample MSPE (relative to the random walk model) were found. The forecasting performance in the other remaining series is not as satisfying as in these two. According to their results, PSC is seen to be sensible in selecting networks and the two-step procedure that had been used could be as a standard network construction procedure in other applications. The results reveal that nonlinearity in exchange rates may be exploited in order to improve both point and sign forecasts. Although some of the results reported are quite motivating, they provide only limited evidence supporting the usefulness of neural network models.

Walczak [15] speaks about neural networks saying that they have been shown to be a promising tool for forecasting financial time series. Several design factors influenced significantly the accuracy of neural network forecasts. These factors include selection of input variables, architecture of the network, and quantity of training data. The issues about input variable selection and system architecture design have been widely researched, but regarding the information use in producing high-quality neural network models the issue remains unclear since it has not been adequately addressed. In this paper, the effects of different sizes of training sample sets on forecasting currency exchange rates are dealt with. Future currency exchange rates can be forecasted with 60% accuracy due to those neural networks which are given an appropriate amount of historical knowledge, while a worse forecasting performance is shown due to those neural networks trained on a larger training set.

Khashei and al. [16] proposed a hybrid model that gives better results when there are incomplete data sets. This hybrid model combines ANN with fuzzy regression. This model was empirically proven to give more accurate results in financial forecasting. More, Yu and Huarng [17] applied neural networks by implementing fuzzy time series model. This method improved forecasting accuracy.

Now that we had an overview about forecasting exchange rates, statistical techniques, regression, and ANNs, we are ready to investigate the efficiency and reliability of ANNs in forecasting exchange rates. This is accomplished by setting two models for forecasting, one is using regression, and the other is using an artificial neural network. After that we need to test the accuracy of each method by comparing error margins from each method.

V. PROCEDURES AND METHODOLOGY

Forecasting exchange rates is not anymore a theoretical field, but in fact it is based on empirical experiments and findings. Therefore; our empirical model that will be used needs a definition of the model and the parameters or factors of the model: Dependent Variable (model output) and independent variables (model inputs).

A. *Dependent Variables*

The only dependent variable that we have is the Euro/Dollar Exchange rate. When using Regression, the exchange rate is supposed to be the output of the equation generated by this technique. When using Artificial Neural Network, the exchange rate is the output of the MLP (Multilayer Perceptron) network. Theoretically, the exchange rate is the result of all the factors previously mentioned (e.g. interest rate, oil price, etc…).

B. *Independent Variables*

The first, and most important independent variable, is the interest rate. This variable is by far the most influential factor that affects the exchange rate. We are using to interest rates, representing two independent variables: One Year USD LIBOR, and One Year Euribor.

The second one is the inflation. It is well known that inflation rates affect a country's currency value. We are using to inflation rates, representing two independent variables: US Core Inflation Rate and Euro Area Core Inflation Rate. When a country's inflation rate rises relatively to that of another country, decreased exports and increased imports depress the high-inflation country's currency. High inflation rates increases the foreign exchange rates and hence weakens the local currency. Notice here that we used core inflation rates which excludes the prices of energy, to avoid double counting because oil price is counted is an independent variable.

Oil price is the third independent variable. In general, oil prices have noticeable influence on USD, and hence it has influence on the Euro/Dollar exchange rate. Figure 3 shows the main factors affecting the exchange rates used in this model.

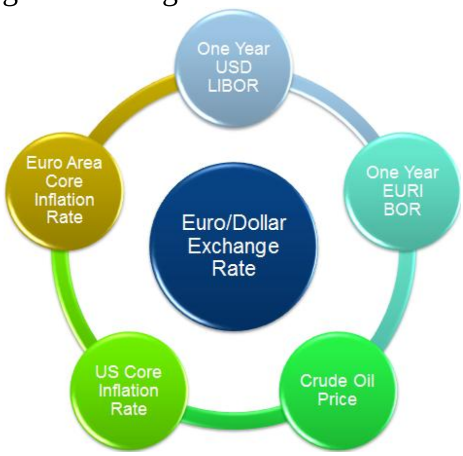

Fig. 3. Factors affecting the exchange rates.

VI. SPECIFICATIONS AND PRIMARY RESULTS

Two models are used: The first one uses regression techniques, and the second one uses an Artificial Neural Network. Both models are set using SPSS. The models will serve many purposes:

- To show the accuracy of each technique concerning forecasting exchange rates.
- To show the actual relationship between the independent and dependent variables used, and to show the influence of the independent variables on our dependent variable (Exchange rate).
- To be able to make a comparison between the two models concerning accuracy and fitness.
- To test the ability of an Artificial Neural Network to approximate the actual relationship between the dependent and independent variables. This relationship is in reality very complex and practically impossible to be represented in a clear mathematical equation.

A) *Model 1: Using Regression*

The first model that we are using is based on regression technique.

To use regression, first we need to define our variables:

- One dependent variable: Exchange Rate
- Five independent variables: US Inflation, EU Inflation, Oil Price, One Year EURIBOR, and One Year USD LIBOR

After filling up all these variables, the result of using regression can be shown and analyzed.

Tables I till IV show the Coefficients, Frequencies, Model Summary and ANOVA tables, as taken from SPSS.

From the table III, we notice that Adjusted R Square=0.754, meaning that the independent variables used in our model explain 75.4% of the variability of the dependent variable (Exchange Rate). Moreover, we notice that R= 0.873 or 87.3%, which means that the independent variables correlate well with the dependent variable. In addition, from the ANOVA table IV, we notice that the Significance variable Sig. = 0, meaning that the probability that the results are by random chance is zero, so we can conclude that the model is significant. By looking at the bell shaped histogram in figure 4, we can conclude that the data is normally distributed.

Table I. Coefficients table.

Coefficients[a]							
Model		Unstandardized B	Unstandardized Std. Error	Standard. Beta	t	Sig.
1	(Constant)	1.111	.025		44.071	.000
	USInflation	.060	.010	.563	6.291	.000
	EUInfaltion	-.166	.017	-.890	-9.579	.000
	OilPrice	.004	.000	.882	18.227	.000
	Euribor1Year	.049	.009	.401	5.514	.000
	USDLibor1Year	-.020	.007	-.221	-3.047	.003

a. Dependent Variable: ExchangeRate

Table II. Frequencies table.

Statistics		USInflation	EUInflation	Oil Price	Euribor 1Year	USDLibor 1Year	Exchg. Rate
N	Valid	132	132	132	132	132	132
	Missing	0	0	0	0	0	0
Mean		2.4000	2.1265	66.11	2.65656	2.50564	1.28
Std. Dev.		1.3993	.80113	29.37	1.2194	1.618903	.1490
Skewness		-.677	-.892	.230	.553	.681	-.696
Std. Error of Skewness		.211	.211	.211	.211	.211	.211
Kurtosis		**1.101**	**2.297**	**-.992**	**-.617**	**-.987**	**.693**
Std. Error of Kurtosis		.419	.419	.419	.419	.419	.419

Table III. Model Summary table.

Model Summary[b]				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.873[a]	.763	.754	.073988

a. Predictors: (Constant), USDLibor1Year, OilPrice, EUInfaltion, Euribor1Year, USInflation

b. Dependent Variable: ExchangeRate

Now that we are sure that data are normally distributed, we can proceed by testing the model.

From table I, we can build the equation that relates the independent variables to the dependent variable, as follows:

$$ExchangeRate = 1.111 + 0.060 * USInflation - 0.166 * EUInfaltion + 0.004 * OilPrice + 0.049 * Euribor1Year - 0.020 * USDLibor1Year \quad (1)$$

Table IV. ANOVA table.

ANOVA[a]						
Model		Sum of Squares	Df	Mean Square	F	**Sig.**
1	Regression	2.220	5	.444	81.104	**.000[b]**
	Residual	.690	126	.005		
	Total	2.910	131			

a. Dependent Variable: ExchangeRate

b. Predictors: (Constant), USDLibor1Year, OilPrice, EUInfaltion, Euribor1Year, USInflation

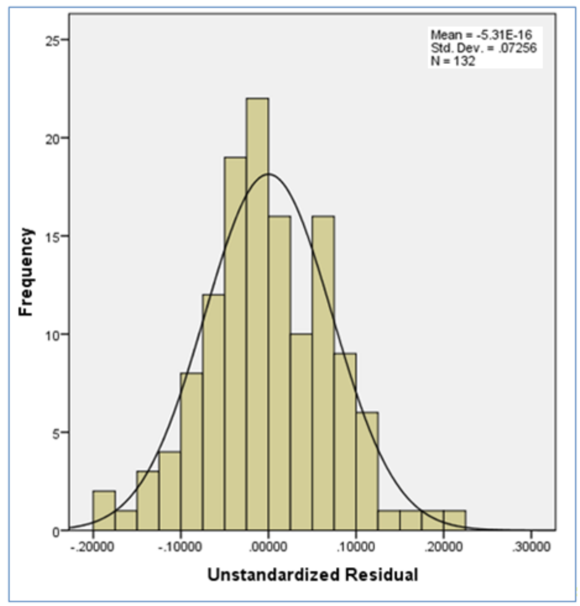

Fig. 4. Histogram of the unstandardized residual.

Note here that, in order to come up with this result, we used only 132 sets of data, between the years 2002 and 2012.

From Equation (1), we can notice the following:

- The parameter for USInflation is positive (+0.06), meaning that when the US core inflation increases, the US Dollar depreciates, and the Euro Dollar Exchange rate increases. This is a logical result.
- The parameter for EUInflation is negative (-0.166), meaning that when the EU core inflation increases, the Euro depreciates, and the Euro Dollar Exchange rate decreases. This is also a logical result.

- The parameter for OilPrice is positive (+0.004), meaning that when the oil price increases, the Euro Dollar Exchange rate increases. This is a bit confusing but it can be explained as follows: Since the United States is the most important oil importer around the world, and since its economy is highly related to energy; it could be clearly said that any rising in oil prices, would first affect or even damage the U.S. economy.
- The parameter for Euribor1Year is positive (+0.049), meaning that when the Euro Zone's interest rates increase, the Euro appreciates, and the Euro Dollar Exchange rate increases. This is also a logical result.
- The parameter for USDLibor1Year is negative (-0.020), meaning that when the US Dollar's interest rates increase, the US Dollar appreciates, and the Euro Dollar Exchange rate decreases. This is also a logical result.

Table V shows the results of plugging the data of 2013 (first eight months) into our regression equation.

Table V. Eight Months Regression results

Date	USInf.	EUInf.	Oil Price	Eur ibor 1Y	USD Libor 1Y	Exch. Rate	Reg. Rate	Regr. % Err.
Jan-13	1.6	1.97	105.04	0.5753	0.814	1.33	1.31	1.38
Feb-13	2	1.84	107.66	0.5942	0.762	1.34	1.37	2.57
Mar-13	1.5	1.73	102.61	0.545	0.735	1.30	1.34	3.09
Apr-13	1.1	1.18	98.85	0.5284	0.717	1.30	1.39	6.57
May-13	1.4	1.42	99.35	0.4838	0.694	1.30	1.37	5.30
Jun-13	1.8	1.6	99.74	0.5071	0.684	1.32	1.36	3.49
Jul-13	2	1.61	105.21	0.5254	0.684	1.31	1.40	6.80
Aug-13	1.5	1.34	108.06	0.5423	0.668	1.33	1.42	6.95
Av.% Error								4.52
	Para meter	Para meter	Para meter	Para meter	Para meter	Cons tant		
	0.06	-0.17	0.004	0.049	-0.02	1.11		

B) *Model 2: Using Artificial Neural Network*

The second model uses one famous type of Artificial Neural Networks, known as a Multilayer Perceptron (MLP-ANN). It has a five neurons input layer, a three neurons hidden layer, and a one neuron output layer as shown in figure 5. Under the input layer, each input variable is assigned a neuron. As well, under the input layer, each input variable is fed to a neuron after a standardization procedure that transforms the input values to the [-1,1] interval. In addition to the input values, we can find a constant input with a value of 1, this input is called the bias. Under the hidden layer, the value from the input neurons are multiplied by a weight and added to yield to a combined value this value is fed to a transfer function that outputs another value which in turn is fed to the output layer. Under the output layer, each value arriving from the hidden layer is multiplied by a different weight, and the resulting values are added to produce a new value. This value is fed to a transfer function that outputs a new value transferred to the output of the network. In the MLP model, the same set of data as in the first model, i.e. Oil price, US core inflation, Euro Zone core inflation, One Year EURIBOR, and One Year USDLIBOR as independent variables, and the Euro/Dollar Exchange Rate as the dependent variable are used.

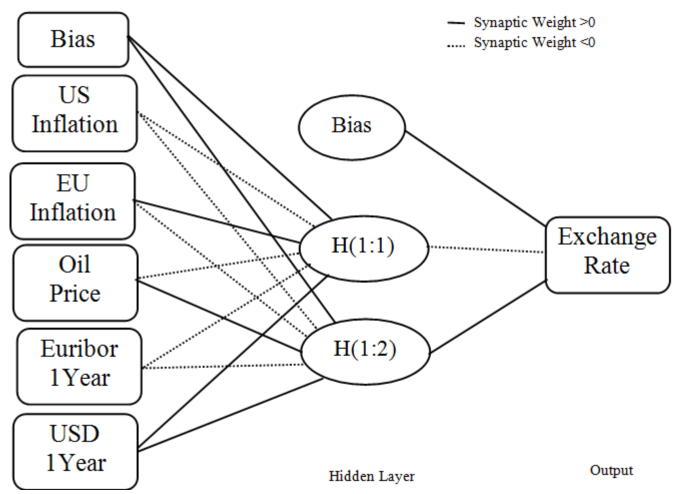

Fig. 5. MLP-ANN Architecture.

After filling up the Dependent variable (ExchangeRate), the Covariates or independent variables, and all the other required parameters; we choose the partitions tab to add the following parameters:

Training: 100; Test: 32; Holdout: 8

The holdout option is very important. It means that one or more set of data will not be included in the training of the network. Instead, it will be used after training to test the efficiency of the network [18].

There are many different activation functions, some of the most commonly used are:
Threshold:

$$g(x) = \begin{Bmatrix} 1 & \text{if } x+t>0 \\ 0 & \text{if } x+t\le 0 \end{Bmatrix} \tag{2}$$

Sigmoid:

$$g(x) = \frac{1}{1+e^{-2s(x+t)}} \tag{3}$$

Hyperbolic tangent:

$$g(x) = \tanh(s(x+t)) = \frac{\sinh(s(x+t))}{\cosh(s(x+t))}$$
$$= \frac{e^{s(x+t)} - e^{-s(x+t)}}{e^{s(x+t)} + e^{-s(x+t)}} = \frac{e^{2(s(x+t))}-1}{e^{2(s(x+t))}+1} \tag{4}$$

Where ***t*** is the value that pushes the center of the activation function away from zero and ***s*** is a steepness parameter. Sigmoid and hyperbolic tangent are both smooth differentiable functions, with very similar graphs, the only major difference is that hyperbolic tangent has output that ranges from -1 to 1 and sigmoid has output that ranges from 0 to 1. A graph of a sigmoid function is given in figure 6, to illustrate how the activation function looks like.

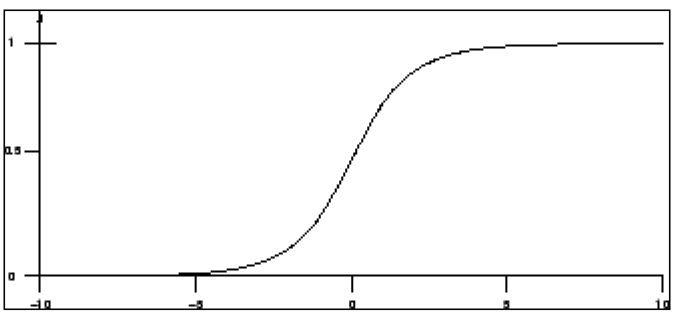

Fig. 6. A graph of a sigmoid function with ***s***= 0.5 and ***t***=0

The ***t*** parameter in an artificial neuron can be seen as the amount of incoming pulses needed to activate a real neuron. This parameter, together with the weights, is the parameter adjusted when the neuron learns.

In addition to the activation function, there are many parameters that should be defined for ANNs, some of them are:

- Dependent variables
  - Nominal
  - Ordinal
  - Scale
- The method for rescaling covariates
  - Standardized
  - Normalized
  - Adjusted Normalized
  - None
- Partition
  - Training
  - Test
  - Holdout
- Architecture
  - Number of Hidden Layers
- *Output layer a*ctivation function
  - Identity
  - Softmax
  - Hyperbolic tangent
  - Sigmoid
- Activation Function: The activation function "links" the weighted sums of units in a layer to the values of units in the succeeding layer
  - Hyperbolic tangent
  - Sigmoid
- Type of Training: The training type determines how the network processes the records
  - Batch
  - Online
  - Mini-batch
- Optimization Algorithm: This is the method used to estimate the synaptic weights
  - Scaled conjugate gradient
  - Gradient descent
- Training options for the scaled conjugate gradient algorithm
  - Initial Lambda
  - Initial Sigma
  - Interval Center and Interval Offset
- Training options for the gradient descent algorithm
  - Initial Learning Rate
  - Lower Boundary of Learning Rate
  - Momentum
  - Learning rate reduction, in Epochs
- Stopping Rules: These are the rules that determine when to stop training the neural network
  - Maximum steps without a decrease in error
  - Maximum training time

- Maximum Training Epochs
- Minimum relative change in training error
- Minimum relative change in training error ratio

When using an MLP Neural Network, there is an important option called "Independent variable importance analysis". This option allows us to evaluate each independent variable according to its importance and influence on the dependent variable. It performs a sensitivity analysis, which computes the importance of each predictor in determining the neural network. The analysis is based on the combined training and testing samples or only on the training sample if there is no testing sample. This creates a table and a chart displaying the importance and normalized importance for each predictor. Note that sensitivity analysis is computationally expensive and time-consuming if there are large numbers of predictors or cases.

Figure 7 represents the normalized importance of the independent variables.

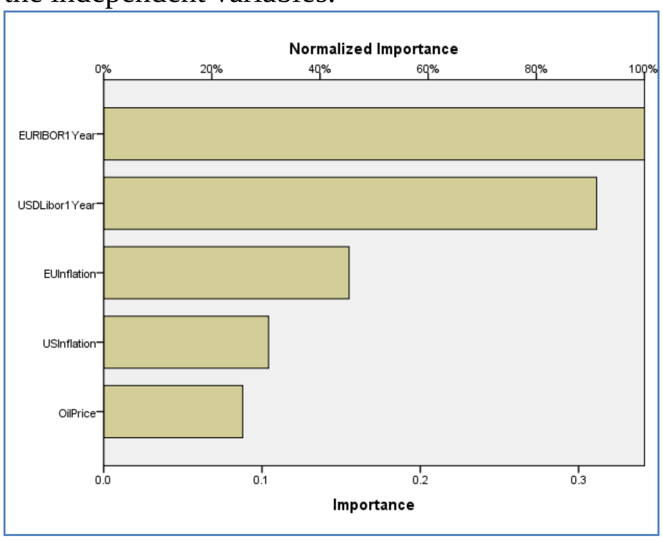

Fig. 7. Normalized importance of the independent variables

From this table and chart, we can notice the following:

- It is clear that the interest rates are the most important factors in determining the exchange rate. This conclusion is conformant with our previous assumptions, and also with the economic theories.
- Inflation rate comes second in importance after the interest rate, but with less importance and influence.
- The oil price has the least importance, its influence on exchange rate is not that important, although it still has some influence.

What is the significance of the importance analysis of the independent variables?

The importance analysis shows the importance and the influence of each independent variable on the dependent variable. As mentioned in chapters two and three the most important and influential factor on exchange rate is the interest rate. The result from the importance analysis confirmed that fact and it became clear that the leader variable in determining exchange rate is the interest rate.

Moreover, inflation came second in the importance analysis, which also confirms the theories of macro-economic that clearly state that inflation plays a major role in the exchange rate determination.

Above all this, the importance analysis showed that our Artificial Neural Network model was actually able to approximate the real complex relationship between the independent and dependent variables.

So comparing the results of the regression model and the ANN model, we can notice that the ANN model was able to give a better approximation model than the regression model according to the importance analysis of the independent variables for both models.

Table VI shows the average error resulting from using the two models, using data sets for eight months (January 2013 to August 2013).

Table VI. Resulting average error

Date	Reg. Rate	Regr. % Err.	ANN Rate	ANN % Err.
Jan-13	1.31	1.38	1.29	3.30
Feb-13	1.37	2.57	1.31	2.21
Mar-13	1.34	3.09	1.30	0.04
Apr-13	1.39	6.57	1.32	1.57
May-13	1.37	5.30	1.31	0.76
Jun-13	1.36	3.49	1.31	0.94
Jul-13	1.40	6.80	1.32	0.85
Aug-13	1.42	6.95	1.34	0.69
Aver% Error		**4.52**		**1.29**

Note that the same parameters and constant from table V are used in table VI. From this table, we can notice the following:

- Concerning the Regression Model, the average percentage error over the 8 sets of data is 4.52%.
- Concerning the ANN Model, the average percentage error over the 8 sets of data is 1.29%. The ANN model is very accurate, and it was able to approximate the relation between the dependent and independent variable within a 1.29% average error margin. This error margin is considered very low and the system is hence reliable for forecasting.

Now let's calculate the average error for both methods. Referring to the tables, we can calculate the error as follows:

- For the regression model, we can calculate the percent error for each month between January 2002 and December 2012 using the following formula:

$$\text{Regression Monthly Error} = \frac{\text{ABS(ExchangeRate - Regression)}}{\text{ExchangeRate}} \qquad (5)$$

The average error of all 132 data sets between January 2002 and December 2012, is:

$$\text{Average Regression Error} = 4.69\%$$

- For the ANN model, we can calculate the percent error for each month between January 2002 and December 2012 using the following formula:

$$\text{ANN Monthy Error} = \frac{\text{ABS(ExchangeRate - ANN)}}{\text{ExchangeRate}} \qquad (6)$$

And the average error for the same data set is:

$$\text{Average ANN Error} = 2.17\%$$

In addition, according to the eight data sets used for testing both shown in table VI:

$$\text{Average Regression Error from testing samples} = 4.52\%$$

$$\text{Average ANN Error from testing samples} = 1.29\%$$

So the ANN model gave lower error margin, and hence more accurate results!

C) *What's new in this research*

Forecasting exchange rates has been the target of many researches and financial analysts since the 70s of the last century. Thousands of papers and researches were written, and researches were more and more advanced. On the other hand, Artificial Intelligence is still considered a fresh field, with promising results in many areas. Forecasting exchange rates is still considered a challenge nowadays. Combining artificial intelligence with financial issues such as forecasting exchange rates requires enough knowledge in both fields.

The originality of this research is the actual combination of a financial issue (i.e. forecasting exchange rates) with a methodology that can be considered as a software mimic of the human brain. Many points can be considered as new or original in this research, as follows:

- The uniqueness of the comparison: To the best of our knowledge, it is the first time that an actual comparison is made between the two techniques (regression versus artificial neural network). Many researches were done before; discussing one of these two techniques, but it is the first time that an actual, empirical, and realistic comparison was made based on a discrete model for both techniques.
- The uniqueness of the model: To the best of our knowledge, the two models set in this research are the result of our own work and research; the two models were not partly or entirely used before.
- The uniqueness of the parameters used in the models: Using an artificial neural network in an effective way requires an exhaustive fine tuning that should be done by a professional who knows what to change and how to change. The parameters used in an artificial neural network include, but are not limited to, the following:
  - The type of the neural network that best fits the problem at hand (e.g. Multi Layer Perceptron versus Radial Basis Function).
  - The number and type of the input layers.
  - The number of the hidden layers.
  - The number of neuron in each hidden layer.
  - The type of training.
  - The initial values of the inner parameters.
  - The activation function.
  - The optimization algorithm.
  - The network structure.

- The network performance.

All these parameters, in addition to many others, have to be carefully selected and fine-tuned in order to get an optimized result. The fine tuning effectively consumes a lot of time, using trial and error, and experimenting many combinations.

VII. CONCLUSION

A comparison between two methods the artificial neural network and the regression method in forecasting exchange rates is detailed in this paper. It was a serious effort toward finding an “adequate” system that can forecast the Euro/Dollar exchange rate with an acceptable error margin. Both methods were set according to our thorough research in the fields of forecasting, macro-economics, statistical techniques, and artificial intelligence.

The obtained result shows that exchange rates can be forecasted with a minimum margin of error, and therefore our ANN model can be used in forecasting. It can have an impact on many economical aspects. International companies can no longer pretend that they have no idea about the future rate of currencies.

This implementation also has many advantages. First, future international transactions will become safer and less prone to exchange rate fluctuations since it is now feasible to know the trend of currencies. Second, international companies will suffer from fewer losses when doing international transactions or when signing future contracts in different international currencies. This all leads to more profit for these companies.

On the other hand, this method has a slight disadvantage because companies and individuals might completely rely on such methods in order to forecast exchange rates, disregarding other external factors that may affect currency rates. To prevent such inconvenience, fine tuning and enhancements to this method are essential to minimize the error margin and maximize accuracy.

REFERENCES

1. Pacelli, V., "Forecasting Exchange Rates: a Comparative Analysis", International Journal of Business and Social Science, vol. 3, no. 10, 2012.
2. Sandler, Ralph, “Forecasting Exchange Rates Within the Context of an International Financial Management Course”, Advances in Financial Education. Vol. 6, pp. 119-135, 2008.
3. Pacelli V., Bevilacqua V. and Azzollini M., “An Artificial Neural Network Model to Forecast Exchange Rates", in Journal of Intelligent Learning Systems and Applications, Vol. 3, n. 2/2011, pp. 57-69, 2011.
4. Amine NEHARI TALET, Razali MAT-ZIN and Maaradj HOUARI, "Risk Management and Information Technology Projects", International Journal of Digital Information and Wireless Communications (IJDIWC), Vol. 4, No. 1, pp. 1-9, 2014.
5. Andreou, A.S., Georgopoulos, E.F., and Likothanassis, S.D., "Exchange rate forecasting: A hybrid algorithm based on genetically optimized adaptive neural network", Computational Economics, vol. 20, no. 3, pp. 191-210, 2002.
6. Mohamad Hassoun, "Fundamentals of Artificial Neural Networks”, Massachusetts Institute of Technology, MIT Press, 1995.
7. Delashmit W.H. and Manry M.T., “Recent developments in multilayer perceptron neural networks”, Proceedings of the 7th Annual Memphis Area Engineering and Science Conference (MAESC 2005), 2005.
8. BingXiang Liu; Hua Wang; Xiang Cheng, "Exchange Rate Forecasting Method Based on Particle Swarm Optimization and Probabilistic Neural Network Model," *International Conference on Network Computing and Information Security (NCIS)*, , vol.1, pp.288-292, 2011.
9. Gill, S.S., Gill, A.K. and Goel, N., “Indian currency exchange rate forecasting using neural networks”, IEEE, International Conference on Advanced Management Science, pp. 196-199, 2010.
10. Mohammad A. N. Al-Azawi, "Neural Network Based Automatic Traffic Signs Recognition", International Journal of Digital Information and Wireless Communications (IJDIWC), Vol. 1, No. 4, pp. 753-766, 2011.
11. Baker Al-Bahri and Zainab Al-Qurashi, "Practical Neural Controller for Robotic Manipulator", International Journal of Digital Information and Wireless Communications (IJDIWC), Vol. 2, No. 1, pp. 33-39, 2012.
12. Levich, R.M. “International Financial Markets: Prices and Policies”, second edition. McGraw-Hill/Irwin, 2001.
13. Chung-Ming, K., & Liu, T., “Forecasting Exchange Rates Using Feedforward and recurrent Networks”, The Journal of Applied Econometrics, Vol. 10, pp. 347-364, 1995.
14. Walczak, S., “An Empirical Analysis of Data Requirements for Financial Forecasting with Neural Networks”, Journal of Management Information Systems, Vol. 17, No. 4, pp. 203-222, 2001.
15. Khashei, M., Hejazi S.R., Bijari, M."A new hybrid artificial neural networks and fuzzy regression model for time series forecasting", Journal of Fuzzy Sets and Systems, Vol. 159, Iss.7, pp. 769-786, 2008.
16. Yu T.H. and Huarng K., "A neural network-based fuzzy time series model to improve forecasting", An International Journal of Expert Systems with Applications, Vol. 37, Iss.4, pp. 3366-3372, 2010.
17. De Grauwe, P., “Exchange Rate Economics, Where Do We Stand?” CESifo seminar series. MIT Press, Massachusetts, USA., 2005.
18. David Semaan, Atef Harb and Abdallah Kassem, “Forecasting Exchange Rates: Artificial Neural Networks Vs Regression”, will appear in the Third International Conference on e-Technologies and Networks for Development (**ICeND2014**), 2014.