Notre Dame University-Louaize
Faculty of Business Administration & Economics
Graduate Division

&

Bordeaux Management School
Institute of International Business

Forecasting Exchange Rates Procedures: Artificial Intelligence or Statistical Techniques?

Submitted by: David Younan Semaan

Supervised by: Dr. Atef Harb

A Thesis Submitted in Partial Fulfillment of the Requirements for the Joint Degree of the Master of Business Administration (M.B.A.) and the Master of Science in International Business (M.I.B.)

NDU-Lebanon
2014

Approval Certificate

Forecasting Exchange Rates Procedures: Artificial Intelligence or Statistical Techniques?

BY

David Younan Semaan

GRADE: A-

Approved by

Supervisor's Name: Dr. Atef Harb

Reader's Name: Dr. Abdallah Kassem

Committee Chair Name and Signature: __________

GRADUATE DIVISION
FACULTY OF BUSINESS
ADMINISTRATION &
ECONOMICS

May 6, 2014

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Date

DECLARATION

I hereby declare that this Thesis is entirely my own work and that it has not been submitted as an exercise for a degree at any other University.

David Younan Semaan

Abstract

Purpose – 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.

Design/methodology/approach – The purpose of this research is to compare between these two techniques, thus to find out which one is more accurate. Considering the fact that a slight difference among exchange rates influences business and trading, it is crucial to accurately predict exchange rates. The research will take the Euro Dollar exchange rate as a working example, although the procedure can be applied on other rates.

Findings – 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.

Research limitations/implications – Some limitations are the scarcity of some information, the shortcomings of the ANN model, and the juvenility of the Euro Zone (Number of used data sets is 140). The result of this research has a great impact on many fields such as worldwide economies, decision makers, international companies, governments, etc…

Practical implications – This model can be practically used by decision makers and financial analysts who are interested in knowing the general trend of the exchange rate between any two currencies.

Originality/value – The originality of this research is the actual combination of a financial issue and 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, like the uniqueness of the comparison, the uniqueness of the model, the uniqueness of the parameters used in the models, etc…

Keywords – Artificial Intelligence, Artificial Neural Network, Balance of Payments, Exchange Rate, Financial Markets, Forecasting, Inflation, Interest Rate, Multilayer Perceptron, Regression

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Acknowledgments

Apart from my efforts, the success of any project depends largely on the encouragement and guidelines of many others. I take this opportunity to express my gratitude to the people who have been instrumental in the successful completion of this research.

I would like to acknowledge my endless appreciation to Dr. Atef Harb and Dr. Abdallah Kassem who were fully dedicated in assisting me thoroughly with all the necessary material required for my research completion.

I also thank Dr. Elie Menassa, Dr. Roy Khoueiry, and all NDU's faculty of business's professors and staff for giving me this once in a lifetime opportunity to prepare such an extensive study that taught me how to think outside the box.

I also thank BEM staff and professors who shared their knowledge and experience.

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Chapter 1 INTRODUCTION

1.1 General background about forecasting exchange rates

In general, commodity prices and exchange rates are determined by different factors such as the concept of supply and demand. In many countries, the most important factor in the country's economy is the exchange rate. This takes place when the exchange rate determines the balance of payments (BOP). So far, we cannot find a unified method for exchange rate determination. When it comes to practice, we can divide the determinants of exchange rates into the following categories:

- Speculation
- Foreign direct investment (FDI)
- Political situation
- Parity conditions
- The country's infrastructure

For short term exchange rate determination, to the best of our knowledge, there is no modal so far that can precisely determine it. Dealing with long term exchange rate determination, we can define many concepts that play a role in this rate: The current price of commodities reflects the available information about the commodity itself and the economy as a whole. That's why exchange rate fluctuations are only caused by unexpected incidents. The more important the incident is, the more the exchange rate fluctuates. Incidents can be seen as anticipated or unanticipated, real or nominal, economy wide or single industry, temporary or permanent, etc…

In his book entitled "*International Financial Markets: Prices and Policies*" published in 2001, Richard M. Levich mentioned that fundamental economic events play a major role in affecting the short term exchange rates, but at the same time economic models are not always reliable when it comes to short term forecasting. In order to explain and clarify exchange rate movements, economists have adopted the asset approach, where the role of expectations is stressed on. Furthermore, the author speaks about the monetary approach, which deals with establishing a relative price between two currencies through the exchange rate. Moreover, the relative risk and return of two currencies is reflected no doubt by exchange rates according to the portfolio-balance approach. Besides that, the author talks about many aspects of international finance which are affected by the exchange rate forecasting.

Forecasting exchange rates requires studying many areas and fields in a country, such as the social, political, and economic situations in that country.

In general, forecasting exchange rates is based on two approaches:

- Technical approach: Forecasting is based on using quantitative models and methods.
- Economic approach: Forecasting the future fair values of the currency's rate base on the basic of the country.

Forecasting exchange rates is considered as a major aspect for international finance, even though there are some debates around the accuracy and efficiency of forecasting exchange rates.

1.2 Purpose and need of the study

All international companies rely on exchange rates to make everyday business decisions such as buying goods, opening worldwide branches, investing in foreign countries, etc...
Every decision rests on a forecast – a view of the future. We know from everyday experience that many of the forecasts we have to undertake will prove mistaken. Yet this does not invalidate the case for basing decisions upon forecasts. Forecasts have to be formulated by a way or another in order to allow us to plan for a future course of action.
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. Thus, we are confronted with uncertainties throughout our life. There is, therefore, a fair chance of not making the right decisions all the time.
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. That is why this study is valuable, and we hope that a lot of people make the most out of the results of this study.

1.3 International perspective/application

In our days, big companies are going international, multinational, or transnational. In all cases, companies should deal with different currencies in different countries.
In 2011, the volume of trade between the U.S. and the European Union was $986 billion - $463 billion in exports and $523 billion in imports.
Moreover, according to the US-China Business Council (https://www.uschina.org/), in 2011, the volume of trade between the U.S. and China was $503.2 billion - $103.9 billion in exports and $399.3 billion in imports.
These huge numbers suggest a greater need for forecasting exchange rates, especially the Euro-US Dollar rate. It is clear that forecasting exchange rates has an obvious international perspective, or maybe we can say that the international perspective is the dominant and most important perspective.

1.4 Brief overview of next chapters

Chapter two is a literature review. It states theories related to the topic, including reviews and opinions from many references such as books and journals. It also includes an overview of the most common methods previously used to forecast exchange rates. Chapter two describes also some theories and previous researches about the topic, with a brief history about the evolution of forecasting exchange rates, with some techniques and methods used.

The chapter gives an overview about artificial intelligence (AI), artificial neural networks (ANN), statistical techniques, regression, and their use and relative performance in forecasting.

Chapter three explains the procedures and methodology used in the research. It explains the main hypothesis of our research, talking about the dependent and independent variables used, showing each one of them, along with the relationship between independent and dependent variables.

Chapter four explains the finding of this research by showing the features of both methods: Regression and ANN. A discussion of the findings is presented with the results of the empirical data.

Chapter five discusses the conclusions reached, along with the future recommendations.

Chapter 2 REVIEW OF LITERATURE

2.1 Introduction

In chapter one, we provided a general overview about forecasting exchange rates, and the importance of forecasting exchange rates, along with the international perspectives of this research area.

In this chapter, we talk about previous researches and studies about forecasting exchange rates, previous methods used in forecasting exchange rates; we will introduce Artificial Intelligence and Artificial Neural Networks along with regression and statistical techniques, and finally the performance of Artificial Neural Networks in forecasting will be explained.

2.2 State of knowledge

In a globalized world of business, exchange rates play an essential role in the volume of profit or loss for international companies. That's why it is very important for any business to know about the trend or the direction of exchange rates in the future.

Forecasting exchange rates is a scientific way to know at least the direction of these rates. The more this forecasting is accurate, the more companies and businesses are able to make right decisions.

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.

...

Many ways and techniques are available for the purpose of forecasting foreign exchange rates, but at the same time they contradict one the other. As a result, it is clear how difficult and critical it is for a company to get the right exchange rate in today's global economy.

...

Even though it is difficult to forecast the most suitable and accurate exchange rate, it does not mean it became less vital.

The best and overriding rules of forecasting exchange rates do not exist, yet one of the rules that is followed by fund managers and financial professional is based on making daily decisions on exchange-rate variables and variations.

Predictability issues with special reference to stock and foreign-exchange markets seem to attract increasing interest during the last few years. Concentration on forecasting developments related to exchange rates, in particular, is not only justified by the risk versus-return tradeoff, but as well by the fact that the exchange rate is often used as policy instrument for tackling macroeconomic targets; such as price stability or balance of payments equilibrium. But even in the cases in which the exchange-rate is allowed to fluctuate in the international markets within margins, which vary considerably depending on the case, the fact remains that the various central banks retain the power to intervene both in the domestic and international markets, manipulating the exchange-rate of their respective currencies whenever the need arises. Such interventions are usually of drastic nature, taking place either by foreign-exchange-reserves manipulation or by resorting to interest rate policy, thus increasing the noise level that characterizes the behavior of the time series involved. This issue introduces a considerable degree of difficulty when it comes to forecasting, although empirical evidence on the link between official intervention and exchange-rate expectations is rather unclear.

There have been many techniques used to forecast exchange rates. Statistical techniques (e.g. regression), are very used in this area. But recently, artificial intelligence, and especially artificial neural networks, became a powerful tool for forecasting exchange rates.

An Artificial Neural Network is a software that mimics the behavior of a human brain in making decisions. It is a computing system that can learn on its own.

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.

2.2.1 Purchasing Power Parity (PPP)

According to Alan M. Taylor and Mark P. Taylor, in order to preserve the value and the power of a unit of currency of one country when used in a foreign country, the theory of Purchasing Power parity (PPP) should be applied. This theory is about the nominal exchange rate between two currencies that should be equal to the ratio aggregate price levels between the two countries. The specific terminology of purchasing power parity was introduced in the years after the World War I during the international policy debate concerning the appropriate level for the nominal exchange rates among the major industrialized countries and after the large-scale inflations during and after the war. The PPP theory in general has left deep prints in the history of economics. The PPP influenced most of the international economists' way of thinking about the world. For instance, Dornbusch and Krugman (1976) mentioned that any international economist believes deeply in some variant of the PPP theory of the exchange rate. Rogoff (1996) expressed almost the same; PPP is taken by some literate economists as a short-term proposition, they do as well believe in purchasing power parity as a good start for long-run real exchange rates.

It is fundamental to know how exchange rates adjust to the exchange rate policy, seeing the fact that the countries with a fixed exchange rate should be informed of the equilibrium exchange rate, and those with variable exchange rates would like to have an idea about what to expect regarding the level and variation in real and nominal exchange rates.

To say it in a general and global way, it is a continuous question related to the extent the international macroeconomic system is self-equilibrating; is the exchange rate adjust toward a level established by PPP helpful in that case?

Due to its propaganda in all known economics books, the purchasing power parity is one of the most popular methods. Forecasting is based on the law of one price. This law states that identical goods should have the same price in different countries.

As an example, according to the purchasing power parity method, a chair (or any other good) should have the same price in both China and Canada, taking into account the exchange rates, and excluding shipping costs. Phrasing it differently, we would say; there should be no chance for a trader to buy a chair in one place and sell it in another place by making a profit.

According to the above principle, the purchasing power parity method states that the exchange rate will change to offset the price changes.

Let's say that the prices in China will increase by six percent in the next year, and let's assume that the prices in Canada will increase by one percent. The price change difference will be

6 - 1 = 5%

The purchasing power parity states that the exchange rate will change in a way to offset the change in prices.

Suppose that prices in China will increase by 8% for the next year, and prices in Canada will increase by 2%. The inflation differential between the two countries will be:

8% - 2% = 6%

This means that prices in the China are expected to rise faster relative to prices in Canada. Consequently, the purchasing power parity method expects that the Chinese currency would have to depreciate by approximately 6% to keep prices between both countries relatively equal. So, if the current exchange rate was70 cents of the Chinese currency for one Canadian dollar, then the purchasing power parity would forecast an exchange rate of:

(1 + 0.06) x (0.70 Chinese currency per Canadian Dollar) = 0.742 [Equation 2.1]

The Big Mac Index, published by the Economist journal, is a know application for the purchasing power parity method. This index measures whether a currency is under or over-valued, based on the price of Big Macs in different countries. Because Big Macs are universal and are found in all countries, a comparison of their prices can be taken as the basis for this index.

Elliott and Pesavento (2006) stress on the importance of PPP, especially in drawing a link among economic models of different countries. Economists, instead of abandoning this theory, they have tailored it accordingly since it is theoretically somehow a most in the world of economy. On the other hand, it is crucial to exclude the opinion about this theory and which says that it does not hold even in the very long run. To the service of this purpose, unit root tests have been proposed with the void and no mean reversion in the real exchange rate. This hypothesis wasn't successfully rejected by early univariate tests, which insisted researchers to find a higher power in testing. Gathering longer dataset and aiming for real exchange rates across many bilateral pairs and working on joint tests were the main points in the both approaches. Each approach has its own negative side; especially the long run tests which require including data from periods where the exchange rate arrangements were not similar to the current ones by any mean. Thus, the results and conclusions of the tests are irreversible even though the abundance of criticism saying that the earlier periods have mean reversion, while the later periods lack mean reversion. Talking about the pooling case, when there is a possibility of high power, one country's lack of mean of reversion causes the rejection of the pooled result for all the countries.

2.2.2 Relative Economic Strength Approach

This approach covers the strength of the economic growth in countries and its purpose is to forecast and predict the future direction of exchange rates. The logic of this method is based on the fact that strong economic entities and high growth will attract foreign investors. So, to purchase investments, an investor needs to purchase the country's currency, which increases the demand on the domestic currency, causing it to appreciate.

The Relative Economic Strength Approach takes a general view by looking to all the investments flows in the country. A major factor that attracts investors is interest rates: High interest rates appeal to investors looking for high yields. This causes the demand on the currency to increase, which leads exchange rates to appreciation. On the other hand; low interest rates cause investors to avoid investing in the country, which pushes the country's currency to depreciation.

This approach does not forecast the future of exchange rate as does the Purchasing Power Parity approach. It only gives a general view of whether the country's currency will depreciate or appreciate. In general, this approach is not used by itself. It is commonly used along with other known methods in order to have a better approach for forecasting exchange rates.

2.2.3 Econometric Models

The econometric models collect factors and parameters that affect the value of a currency and create a model that can correlate all these factors and variables with the actual exchange rate.

These factors are usually based on economic theories, but we can add other variables if we believe that these variables can affect exchange rates.

For example, if we want to forecast the Canadian Dollar/US Dollar exchange rate, we can suggest that the factors that affect this rate are:

- Interest Rate Differential between the two countries (IR)
- Inflation Differential between the two countries (IN)
- International Oil price (OP)

So we can build an econometric model as follows:

Canadian Dollar/US Dollar exchange rate = a*IR + b*IN + c*OP +d [Equation 2.2]

After building the model, we can use the variables to conclude the actual exchange rate. The coefficients a, b, c, and d will determine how much each factor can affect the exchange rate (positive or negative effect).

This approach is not only complex, but it is also time consuming because fine tuning the coefficients and finding the influential factors takes a lot of time and research. The advantage of this approach is that once it is built and the coefficients are set, it is easily used to determine the exchange rate.

2.2.4 Time Series Model

The time series model is a technical approach. It is not based on any economic theories. As an example of this model, we mention the ARMA method (ARMA stands for autoregressive moving average). This method states that past behavior and price patterns can be used to forecast the future price pattern. The data that can be used in the time series model is a time series of data that you can enter into a software program in order to forecast the coefficients.

The conclusion here is that forecasting exchange rates is a complex task. On the other hand; many investors see a big value in forecasting exchange rate that can bypass its complexity.

According to Rogoff (2009), to forecast nominal exchange rates is as usual a hard task to accomplish, even though there are many things that facilitate the path such as the proliferation of new floating currencies, the maturation of the floating rate period, the deepening of financial markets, and the development of more sophisticated econometric tests that benefit of the computing possibilities and opportunities we have nowadays. With all those facilities, it remains difficult to forecast exchange rates, but the models that are based on purchasing power parity or the current account are the most promising so far. But at the same time, it is good to note that these predict at a first place the real exchange real but not the nominal one. As a result, some of the adjustment is done when it comes to prices. At the end, it is good to know as well that panel methods could lend a hand in forecasting the exchange rate, mainly by allowing a better estimation of nonstructural factors such as shift parameter.

2.3 Previous researches

2.3.1 Theories and Previous Researches in Forecasting Exchange Rates

After the collapse of the Bretton Woods structure in 1973, a new challenge faced economists: Forecasting exchange rates. Quantitative methods became famous in the forecasting world. In general, macroeconomic collections like interest rates, price levels, balance of payments, and economic growth are needed for exchange rate prediction. Taking these collections as a basis, we can find many models for predicting exchange rates, like the Purchasing Power Parity and many other methods. These models necessitate that in any country, the price level is determined by the supply and demand of money.

Yongmiao Hong and Tae-Hwy Lee, in their research entitled "Inference on Predictability of Foreign Exchange Rates via Generalized Spectrum and Nonlinear Time Series Models", dealt in deep with the fact that a strong nonlinear serial dependence for exchange rate changes always exists, and it cannot be only attributed to the well-know volatility clustering. Besides that, useful tools that help learning about the nature of nonlinear dependence in the exchange rate changes are provided by the generalized spectrum. What is noticed in particular is that nonlinearity exists significantly in mean for exchange rate changes, but at the same time most exchange rates are serially unrelated. In order to forecast the neglected nonlinearity in mean, we take into consideration some nonlinear time series models and their combination as well. After using the white's (2000) test to filter out possible data-snooping, it is shown that some of them have a high predictive ability for JY and FF, and a lower one for CD, DM, and BP, to the martingale model, more specifically when it comes to trading returns and/or directional forecasts. Moreover, the forecast evaluation results are influenced in general by the choice of loss function. In most of the cases, it is found out that the combined forecast model is revealed to be the best.

Even though the in-sample inference and out-of-sample fore-casts have similar patterns in the degree of significance, the in-sample significant nonlinear serial dependence in mean does not carry over to significant out-of-sample forecasts in terms of some criteria, after allowing for data snooping. The nonlinear models might not be the most suitable ones. Alternatively, nonlinearity in mean, which may not be strong enough to be exploited for forecasting, may be dominated by parameter estimation uncertainty. Besides, nonlinearities may be exogenous, arising from outliers, structural shifts, and government intervention, which can cause various non-linearity tests to reject the null hypothesis of linearity while not being useful for out-of-sample forecasts. In this paper, the predictability of exchange rate changes in mean has been exploited without focusing on other sides. The generalized spectrum also reveals significant linear and nonlinear dependence in higher moments, where the predictability of higher-order moments and the entire density are clearly included and implied, which is important to assess accurately and correctly exchange rate risk. This is left for future work.

2.3.2 Fundamental Exchange Rate Forecasting

Chung-Ming Kuan and Tung Liu 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 (2001) 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 percent 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. In addition to higher-quality forecasts, the development cost and time are reduced when the training set sizes are minims.

2.3.3 History of Artificial Intelligence Use in Forecasting Exchange Rates

AI systems, such as expert systems, artificial neural networks, and genetic algorithms, have been used in many economic and financial areas. In particular, these AI fields were used for time series forecasting.

In this area, many studies showed the strengths and weaknesses of using AI for forecasting of financial issues.

A finite impulse response ANN model has been used by applying layer by layer optimization. ANNs have also been used for nonlinear time series forecasting. In this model, the following factors were tested by a computer experiment:

- Input nodes
- Sample size
- Hidden layers

The result of these experiments showed that ANNs are powerful tools for forecasting non-linear time series. In contrast, linear forecasting methods did not give the same good results.

Two factors were more important than other factors for nonlinear time-series forecasting:

- Input nodes
- Sample size

Khashei, Hejazi and Bijari 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.

Yu and Huarng applied neural networks by implementing fuzzy time series model. This method improved forecasting accuracy.

In their research entitled "Time Series Forecasting with Neural Network Ensembles: An Application for Exchange Rate Prediction", G. P. Zhang and V. L. Berardi, in order to improve time series forecasting performance of the traditional single keep-the-best (KTB) model, investigated the use of neural network combining methods. The ensemble methods are applied to the difficult problem of exchange rate forecasting. Two general approaches to combining neural networks are proposed and examined in predicting the exchange rate between the British pound and US dollar. Specifically, they propose to use systematic and serial partitioning methods to build neural network ensembles for time series forecasting. It is found that the basic ensemble approach created with non-varying network architectures trained using different initial random weights is not effective in improving the accuracy of prediction while ensemble models consisting of different neural network structures can consistently outperform predictions of the single 'best' network. Results also show that neural ensembles developed with the full training data in out-of-sample forecasting is not as effective as the neural ensembles based on different partitions of the data. Moreover, reducing correlation among forecasts made by the ensemble members by utilizing data partitioning techniques is the key to success for the neural ensemble models. Although our ensemble methods show remarkable advantages over the traditional KTB approach, they do not have significant improvement compared to the widely used random walk model in exchange rate forecasting.

2.4 Introduction to Artificial Intelligence

2.4.1 What is Artificial Intelligence?

Artificial Intelligence is defined as the study of intelligent systems. An intelligent system checks and defines its environment and has the ability to respond and take actions. It is the intelligence of machines, it is also the branch of software engineering that creates and programs intelligence for machines. According to John McCarthy, the first person who created this concept, AI is the science and engineering of making intelligent machines.

Artificial Intelligence can be divided into subfields; each subfield can be seen as independent and sometimes subfields find it hard to interact with each other.AI can also be divided based on technical matters and concerns. The aim of Artificial Intelligence is to approach problems by some qualities that include communication, knowledge, learning, and planning. AI has the ability to move and manipulate items in order to reach a specific goal.

Currently popular approaches include statistical methods, computational intelligence and traditional symbolic AI. There are an enormous number of tools used in AI, including versions of search and mathematical optimization, logic, methods based on probability and economics, and many others.

AI became today a part of the new technology in industry regarding the fact that it offers a solution for very difficult tasks in the computer science world.

The main idea behind Artificial Intelligence is that the human intelligence, along with other creatures' intelligence, can be described and simulated in a program. This idea raised an ethical question about the legitimacy of creating artificial entities that simulate and mimic natural intelligence.

When it comes to making complex judgment calls, computers can't replace people. But with artificial intelligence, computers could be trained to think like humans do. Artificial intelligence allows computers to learn from experience, recognize patterns in large amounts of complex data and make complex decisions based on human knowledge and reasoning skills. Artificial intelligence has become an important field of study with a wide spread of applications in fields starting with medicine until agriculture.

The domain of AI studies computational programs and devices that can act in an intelligent way. The history of AI goes back to the 50s of the previous century. The British scientist Alan Turing stated that, any machine that can pass a certain test (known as the Turing test), can be classified as intelligent.

2.4.2 History of AI

The history of Artificial Intelligence goes back to the era of Greek, with Greek Myths Crete and Talos, and the Bronze Robot of Hephaestus.

Alan Turing suggested a machine that can simulate any mathematical deduction by shuffling simple symbols such as 0 and 1. This led to the invention of programmable digital electronic computer.

In a conference at Dartmouth College in the year 1956, the field of AI research was officially created. Some of the participants in this conference, such as Marvin Minsky, John McCarthy, and Allen Newell, became leaders in the Artificial Intelligence field for many years, by writing computer programs that were amazing in their days: Solving algebra problems, speaking English.

In the 1980s, expert systems were introduced. An expert system is a form of intelligent program that can simulate the analytical skills of humans.

In the 1990s, Artificial Intelligence was used in medical diagnosis, data mining, as long with other fields.

In 1997, a computer named Deep Blue beat Garry Kasparov who was the world chess champion.

Artificial Intelligence is no longer exclusive to a certain country or certain field, but it is widely used all over the world and in almost all known industrial and non-industrial fields.

2.4.3 Artificial Neural Networks

Generally speaking, a neural network is a software that replicates the biological brain. A neural network has an intention of recognizing a pattern in the processed data. After training the network on predefined sets of samples from existing data, it can predict similar patterns in future data.

The branch of neural networks is part of a larger field called Artificial Intelligence. Under this larger field, we can also find other branches such as Genetic Algorithms and Fuzzy Logic.

A neural network is a programming environment that can represent and simulate complex relations between input variables and output variables, as shown in figure 2.1. A neural network was inspired from the mechanism of the human brain. A neural network and a human brain have many similarities. First, a neural network attains knowledge through learning. Second, a neural network's knowledge is stored within inter-neuron connection strengths known as synaptic weights.

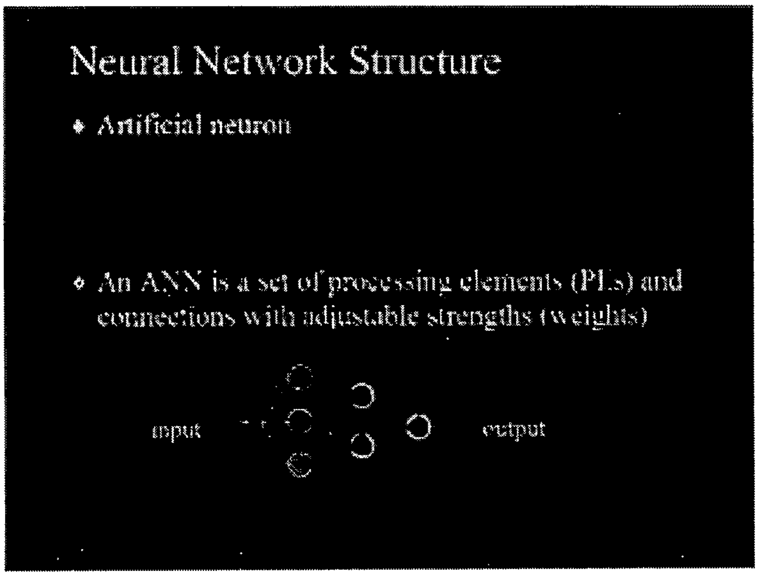

Figure 2.1 Neural Network Structure

(Source: www.neural-forecasting.com)

A neural network can refer to both artificial and biological option, but mostly refers to the artificial neural network.

From a mathematical point of view an artificial neural network is a non-linear function. Neurons are organized into layers, where the first layer connects to the input variables, and that's why it is called the input layer. The last layer interacts with the output variables, thus it is called the output layer. The rest of the layers are called hidden layers. Hidden layers have no interactions or connection with the input or output variables. More hidden layers generally mean a more complex neural network.

A biological neural network is very complex, consisting of billions of cells, while an artificial neural network is less complex, and that's why an artificial neural network is not able to accomplish the same tasks as its biological sister.

A neural network's great power is that it is able to represent complex non-linear relations. Such non-linear relations cannot be represents or modeled in a linear model.

Neural networks have many types, but the most common type is called a multilayer perceptron. It is a supervised network because it needs a target output in order for it to learn.

The MLP creates a model that can correctly correlate the inputs to the desired predefined outputs by using previously stored data. In this way the system can produce the right output even when the desired output is absent. Figure2.2 represents a block diagram for an MLP network.

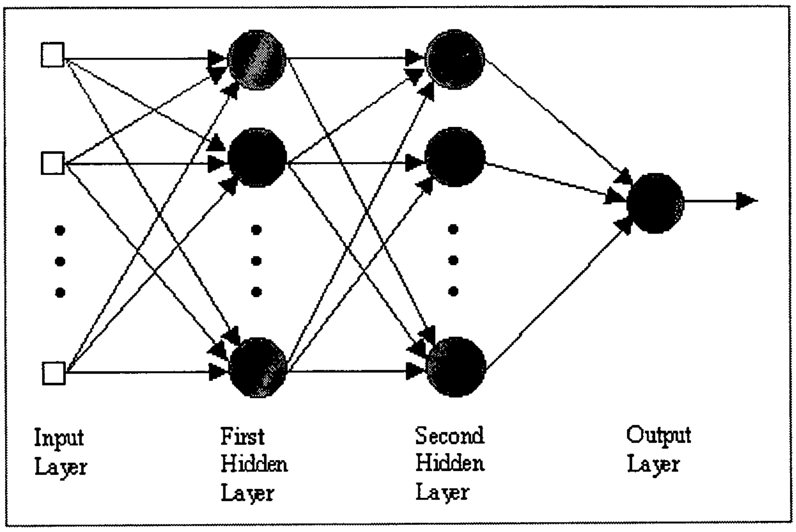

Figure 2.2 Block diagram of a two hidden layer multilayer perceptron (MLP)

(Source: www.osp.mans.edu.eg)

The learning procedure of an MLP network is done through the back propagation algorithm, where the input data is fed to the network many times, and the output is compared each time to the desired output, and an error is calculated. This error is used to adjust the weights of the connections between neurons. At each iteration, the error margin should decrease until it is less than a predefined error threshold. In this way the calculated output is closer to the desired output. This mechanism is called training. Figure 2.3 represents the training of ANN that represents the exclusive-or model.

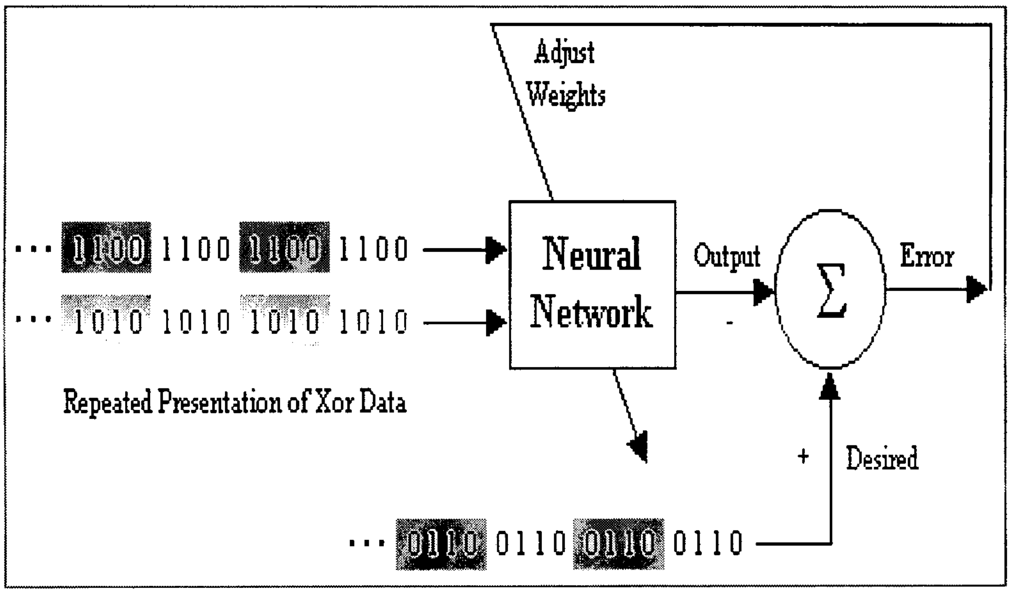

Figure 2.3 Demonstration of a neural network learning to model the exclusive-or (Xor) data

(Source: www.osp.mans.edu.eg)

A typical application of an artificial neural network is character recognition performed by scanners. A scanner scans a picture of a printed document, and the ANN performs the task of recognizing the images of each character and converting it into a word document. Figure 2.4 shows a neural network used for optical character recognition.

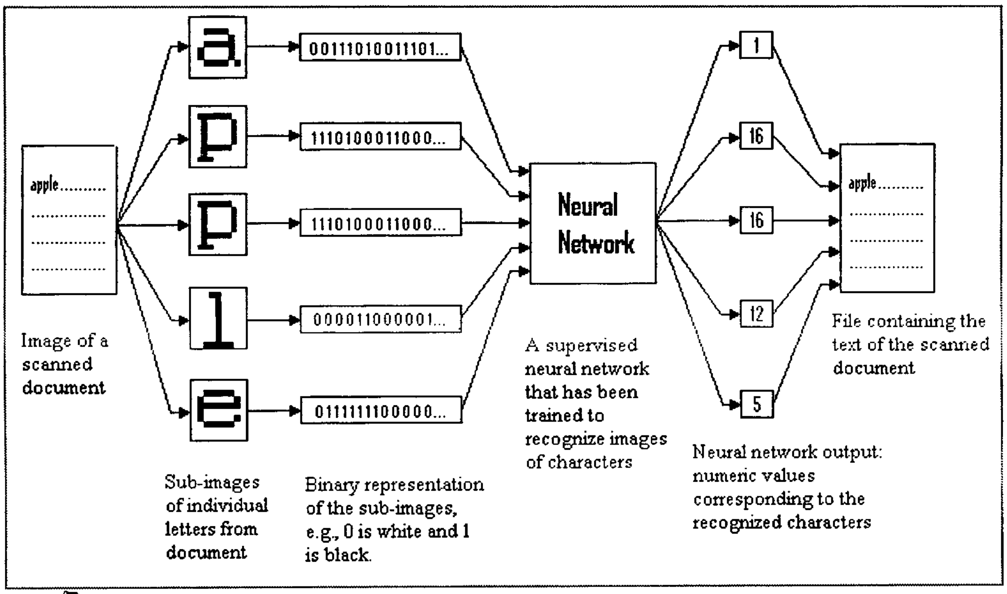

Figure 2.4 A neural network used within an optical character recognition (OCR) application

(Source: www.osp.mans.edu.eg)

Character recognition is not the only application for ANNs. In fact, Artificial Neural Networks have many applications in many fields, some of these applications are:

- Portfolio Management: ANNs can help in asset allocation in a portfolio in order to maximize the profit and minimize the risk
- Military Fields: Using videos and images to determine the presence or absence of a potential enemy.
- Machine Supervision: ANNs can supervise machine to detect a failure so that the machine can be automatically stopped.
- Plant Control: ANNs can be used for a plant to determine the best settings for controlling the plant.
- Medical Applications: An artificial neural network can help doctors in diagnosing some diseases by analyzing the patient's symptoms.

2.4.4 Why Neural Networks?

ANNs have many properties that make them attractive to be used instead of traditional techniques. Specifically, Artificial Neural Networks, in many situations, are better alternatives than expert systems and algorithmic solutions.

ANNs are perfect solutions for situations where there is a large quantity of data, but small information about the relation between data. Whenever the relation the input and output is very complex or hard to be defined, a neural network can work as an accurate approximation for this relationship.

2.4.5 The Learning Procedure

Learning is an essential part of any intelligent system. For a neural Network, learning occurs during a training phase. After training, the network is ready to be used by entering the production phase.

Figure 2.5 represents a flow chart of the training procedure for ANNs

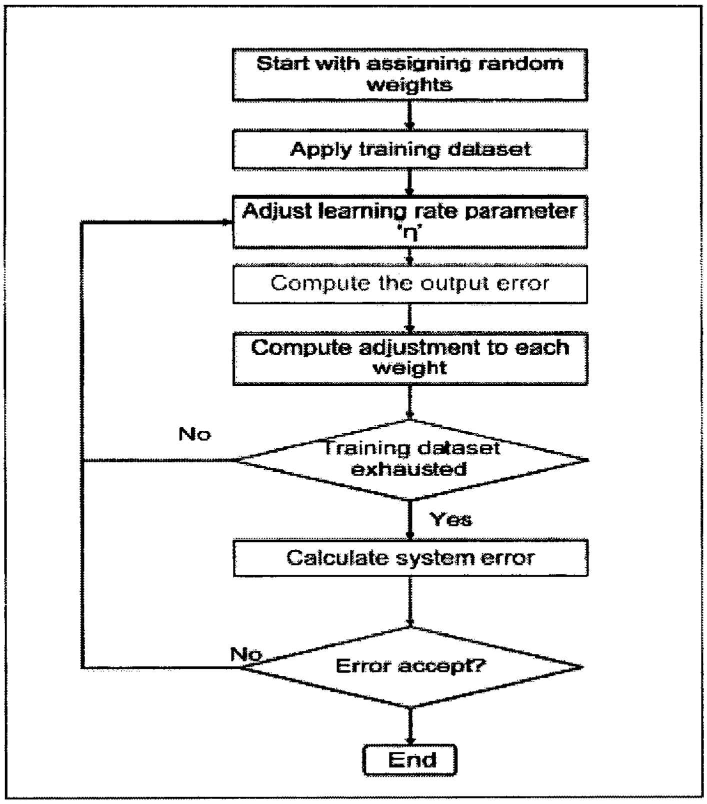

Figure 2.5 A flow chart that represents the training procedure for ANNs

(Source: http://iem.edu.in/)

Some systems are able to continue learning even during the production phase. These systems are called dynamical systems.

Learning can be unsupervised or supervised. It can also be both, in which case it is called a hybrid method.

There is one problem that can appear in training and during the learning phase is overtraining, which is the case when so many training examples are provided.

2.5 Statistical Techniques

2.5.1 Regression

Regression analysis is a statistical tool for the investigation of relationships between variables. The investigator usually seeks to ascertain the causal effect of one variable upon another—the effect of a price increase upon demand for example, or the effect of changes in the money supply upon the inflation rate. To explore such issues, the investigator assembles data on the underlying variables of interest and employs regression to estimate the quantitative effect of the causal variables upon the variable that they influence. The investigator also typically assesses the "statistical significance" of the estimated relationships, that is, the degree of confidence that the true relationship is close to the estimated relationship.

Regression techniques have long been central to the Weld of economic statistics ("econometrics"). Increasingly, they have become important to lawyers and legal policy makers as well. Regression has been offered as evidence of liability under Title VII of the Civil Rights Act of 1964, as evidence of racial bias in death penalty litigation, as evidence of damages in contract actions, as evidence of violations under the Voting Rights Act, and as evidence of damages in antitrust litigation, among other things.

Under the statistics domain, regression is a technique that estimates the relation between variables. 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.

Under the field of regression, least squares regression and linear regression are called parametric because the regression function is set in terms of a finite number of parameters.

We can also define non-parametric regression where the regression function lies in a predefined set of functions.

In practice, the performance of regression depends on the method's form that generates data. In many cases, the regression analysis includes making assumptions about the process. When using regression for forecasting, better results are taken if the assumptions are not violated often.

It is not uncommon that in some cases regression methods yield to misleading results, so care must be taken and empirical experiences must be done to test proof the results.

2.6 The relative performance of ANNs in forecasting

In their article entitled "Forecasting with artificial neural networks: The state of the art," published in the International Journal of Forecasting in 1998, Guoqiang Zhang, B. Eddy Patuwo, and Michael Y. Hu wrote that the performance of neural networks in forecasting should be taken into consideration especially when compared to the statistical methods that are widely used nowadays. Many contradicting reports were shown in the literature of the performance of ANNs. The main reasons affecting the forecasting ability of the networks are numerous such as the training method, the network structure, and the sample data. ANNs perform worse than linear statistical methods where the data is linear without much disturbance.

What they wrote is very true. In fact, we cannot expect an artificial neural network to perform better than a statistical linear model for a relationship that is purely a linear equation. On the other hand, artificial neural networks will perform much better for models that cannot be represented with a simple linear equation, and a good example of that would be forecasting exchange rates.

West and Brockett (1997) say that that when it comes to predicting the outcome of a known no compensatory choice rule, neural network models outperform statistical methods such as discriminant analysis and logistic regression. Even when the underlying choice rule is unknown, due to the flexible nature of the model the neural network shows a better out-of-sample predictive accuracy than traditional statistical methods. This better performance is because of the iterative process, whereby the model "learns" complex relationships between product attributes (image variables) and consumer choice (patronage frequency). Neural network models are not similar to other statistical procedures in that, the model does not suppose previously any linear or causal relationship (e.g., logistic regression, maximum likelihood factor analysis, discriminant analysis, etc.) between the input variables and the output ones. Combining the appropriate exponential terms and multiplicative interactions helped the statistic models to deal with nonlinear functional relationships. But the priority goes for the form of nonlinearity. Similarly, non-compensatory choice rules, such as satisfying and latitude of acceptance, can be modeled using traditional methods by estimating separate slopes for the regions above and below the attribute thresholds, but the exact form of the nonlinearity must be known precisely. The good thing about the neural network is its robustness to model misspecification.

2.7 Conclusion

In their paper entitled "Why is it so difficult to beat the random walk forecast of exchange rates?" Professor Lutz Kilian from University of Michigan and Professor Mark P. Taylor from University of Warwick wrote about the aim of exploiting economic models of exchange rate determination saying that it is until not vague and unclear, and that since Meese and Rogoff's extensive and leading work on exchange rate predictability. Many professional exchange rate forecasters as Cheung and Chinn (1999) see that standard economic models of exchange rate determination are inadequate, unlike a big number of economists who have other beliefs. The theory is seen to be deep and true, but its implementation as a linear statistical model is wrong and incomplete. That's why the economy tries to adjust in a nonlinear fashion.

There has been indeed some recent work documenting various nonlinearities in deviations of the spot exchange rate from economic fundamental (e.g. Balke and Fomby, 1997; Taylor and Peel, 2000; Taylor, Peel and Sarno, 2001). This literature, which is based on equilibrium conditions derived from economic theory, is not similar to the earlier literature on nonlinear exchange rate forecasting. Economic models of the exchange rate will be proven as useful in the forecasting domain if equipped with suitable nonlinear structure; this is what was expected by the evidence of nonlinear mean reversion in deviation from equilibrium.

The forecast performance of nonlinear models based on economic theory hasn't been explored at all, although the forecast accuracy has always been important to how credible an economic model of exchange rate determination is. This is due to many factors; such as technical difficulties in implementing forecast accuracy tests in nonlinear framework, and small samples of data available for empirical work.

A convincing economic explanation of the source of the nonlinearities found in empirical work has been lacking. The explanations available are about peso problems, fads, and transaction costs, but they all remain unsatisfactory. They do not explain the volatility in real and nominal exchange rates, as they do not deal with the long swings in nominal exchange rates such as the overvaluation off the dollar in the mid-1980's.

Professor Kilian and Professor Taylor are right because the representation of a forecasting model using traditional techniques will yield a quasi-chaotic result since such a complex behavior cannot be represented using those techniques. Moreover, exchange rate forecasting is by nature a nonlinear procedure, which proves that a linear statistical model cannot be a good approximation or representation for forecasting exchange rates. This leads us to think about a nonlinear model to approximate or represent exchange rate forecasting. A sophisticated application like Artificial Neural Network can, to a large extent, represent a good indicator for forecasting exchange rates; provided that good, reliable, and relevant data is to be used in the application (we are talking here about input parameters or data that will be used in a neural network to forecast exchange rates).

A fundamental question may be raised: Which forecasting technique is used and trusted by experts?

It is difficult to anticipate the likely winner among competing models, in light of the well-known difficulty of forecasting exchange rates. If there is anything that resembles a universal consensus in exchange rate economics, it is probably on the difficulty of forecasting exchange rates, especially for short horizons (one year or less). Fundamentals-based exchange rate models fail to outperform random-walk models, continue to hang over efforts in order to develop a forecasting model that applies to a wide set of currencies across a wide span of time and conditions.

In a working paper published by the International Monetary Fund (IMF), entitled "In Which Exchange Rate Models Do Forecasters Trust?", David Hauner, Jaewoo Lee, and Hajime Takizawa wrote the following:

The formation of exchange rate expectations by market forecasters is based on two strong factors; the inflation and the growth rate. When inflation is noted, a large subscription to a version of purchasing power parity is shown. When the growth rate is remarkable, the broad acceptance of the productivity-driven appreciation is noticed. Other factors such as including the current account balance do not have that much importance.

The two factors mentioned above are considered as fundamental determinants of exchange rates. Forecasters usually adhere to them since they are proven to be helpful, and they have a robust explanatory power.

(Source: http://www.imf.org/external/pubs/ft/wp/2011/wp11116.pdf)

In his article entitled "Forecasting Foreign Exchange Rates Using Recurrent Neural Network", PaoloTenti from Tenti Financial Management (Lugano, Switzerland) wrote that predicting exchange rates, which are characterized by nonlinearities and high noise, seems difficult, especially when using only high-frequency past prices. Moreover, the foreign exchange market which is not explained under the model of market efficiency suffers from a number of anomalies in the behavior.

In fact, it is nearly impossible to predict exchange rates on a short term basis (e.g. daily basis), because in this case, the factors that can effect exchange rates are myriad. It would be like forecasting the lottery numbers, which is practically impossible.

On the other hand, long term based prediction is more suitable and more logic, because the factors that affect the exchange rate in that case can be identified to a good extend. This is the reason why in our research we chose the year-to-year average exchange rate as our study target.

This research tries to prove that the determinants and factors that affect exchange rates are enormous and practically unlimited, but a good exchange rate forecasting model would be a model that takes the most influential factors into account in a preset proportion that takes into account the weight of each factor.

At this point, we need to mention what researchers Gill, A.K. and Goel, N., in the abstract of a working paper entitled "Indian currency exchange rate forecasting using neural networks" that was published in the Advanced Management Science (ICAMS), 2010 IEEE International Conference in Ludhiana, India, wrote that it is difficult to predict currency exchange rate and handle enormous data, so in that case, an artificial neural network may be suitable for the task. This artificial network can extract useful information from large sets of data, which could be helpful in describing a financial time series.

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 dependents and independent variables. 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.

A quick overview about forecasting exchange rates, statistical techniques already used in forecasting, and the advance of Artificial Intelligence, specifically Artificial Neural Networks, leads us to wonder about how efficient and useful would be to use AI techniques in forecasting exchange rates. In fact, this research is trying to prove that Artificial Neural Networks can be efficiently used to forecast exchange rates, and it can actually give more accurate and less mistaken results compared to statistical techniques. In this thesis, we will try to show which is more efficient in forecasting exchange rates: Artificial Neural Networks or statistical techniques?

What we learned from this chapter is that forecasting exchange rates suffers from the lack of accuracy in the results. The methods which are already used are not suitable for such a complicated procedure that is influenced by a myriad of factors and parameters. From here came the need for this research. Although exchange rate determination plays a very important role in macro and micro economics worldwide, it is still unclear how to forecast it in an efficient way. Introducing artificial intelligence adds a new dimension to forecasting exchange rates. The major problem that previous forecasting methods suffer from is the inability to approximate the relation between the various parameters that influence exchange rates and the exchange rate itself. An artificial Neural Network is supposed to accomplish this task, providing an efficient and reliable solution for exchange rate determination.

Chapter 3 PROCEDURES AND METHODOLOGY

3.1 Introduction

Forecasting exchange rates is becoming more and more vital, and the reasons were listed in the previous two chapters. For several decades, many techniques were used to forecast exchanges rates; some of them were proven to be better than others. Specifically, regression was a very good technique to be considered.

Artificial Intelligence is still considered a young and fresh field of study. Researchers are still exploring this new field. Many attempts were taken in using Artificial Intelligence, and especially Artificial Neural Networks (ANNs), in forecasting exchange rates; but the field is so wide and complex that enough time will be needed before reaching the perfect (or almost perfect) ANN that can forecast exchange rates with a minimum error margin.

In chapter two, we discussed various techniques previously used in forecasting exchange rates (e.g. Purchasing Power Parity and Time series model), with a brief history of forecasting exchange rates, then we discussed the main steps in the history of artificial intelligence in general and artificial neural networks in specific, with some explanation about the functionality and structure of an Artificial Neural Network. Later on we introduced regression with a brief explanation, and then we evaluated the relative performance of Artificial Neural Networks in forecasting, to conclude with the fact that ANNs are really powerful when it comes to forecasting.

This research is an attempt to show the power of ANNs in forecasting exchange rates, and to compare the result of forecasting between statistical techniques and Artificial Intelligence techniques.

For this reason, regression is used on behalf of statistical techniques, and artificial neural network is used on behalf of artificial intelligence.

From the above, we can deduce our research question:

Which is better in forecasting exchange rates: Artificial Intelligence or statistical techniques?

Note here that the answer to our research question is not finding the perfect application or procedure that would be able to forecast exchange rate with zero percent error, instead of that, we are trying to find a better procedure that can at least forecast exchange rates with a minimum error.

The problem here is that nobody can exactly forecast the future, due to the influence of different factors. But what we can do is at least forecast the trend of exchange rates, to check whether a certain currency will probably appreciate or depreciate in the near future according to a set of factors that directly or indirectly influence exchange rates.

As stated previously, the objectives of the research are to:

- Show the importance and need of forecasting exchange rates in international trading
- Explore the power and usefulness of Artificial Intelligence, mostly Artificial Neural Networks
- Explore statistical techniques (e.g. Regression), to forecast the Euro/Dollar exchange rate
- Build a useful Artificial Neural Network that can forecast exchange rates
- Compare the results of forecasting exchange rates given from both Regression and Artificial Neural Networks

3.2 Research questions

At this stage of our research, we are ready to draw our research questions that we will try to answer them. These questions are:

1. What is the importance of forecasting exchange rates? Why do we need to forecast exchange rates?
2. What techniques are used till today for forecasting exchange rates?
3. What is the international perspective in forecasting exchange rates?
4. Is it really rewarding to use Artificial Neural Networks in forecasting exchange rates?
5. What are the most influential factors in determining exchange rates? And in which order?
6. Is Artificial Intelligence a better way to forecast exchange rates than statistical techniques?

3.3 Hypotheses

After researching theories, articles, books, and reviews about exchange rates, we came up with seven main factors that can affect exchange rates. These factors do not have the same weights in their influence on exchange rates. Note here that the factors that affect the value of a currency are in hundreds. In this research, we will mention and use the most important and relevant factors.

Our hypotheses can be summarized as follows:

When used for forecasting exchange rates under specific conditions, ANNs will give better results than Regression Techniques because of the nature of the structure of ANNs as approximations for complex relations.

Below is a list of the most important factors affecting exchange rates, with a brief explanation of each factor, and the way each factor affects exchange rates:

Interest Rates

It is the amount charged, expressed as a percentage of principal, by a lender to a borrower for the use of assets. Interest rates are typically noted on an annual basis, known as the annual percentage rate (APR). The assets borrowed could include, cash, consumer goods, large assets, such as a vehicle or building. Interest is essentially a rental, or leasing charge to the borrower, for the asset's use. In the case of a large asset, like a vehicle or building, the interest rate is sometimes known as the "lease rate".

When the borrower is a low-risk party, they will usually be charged a low interest rate; if the borrower is considered high risk, the interest rate that they are charged will be higher.

It is a rate which is charged or paid for the use of money. An interest rate is often expressed as an annual percentage of the principal. It is calculated by dividing the amount of interest by the amount of principal. Interest rates often change as a result of inflation and Federal Reserve Board policies. For example, if a lender (such as a bank) charges a customer $80 in a year on a loan of $1000, then the interest rate would be 80/1000 *100% = 8%.

From a consumer's perspective, the interest rate is expressed as annual percentage yield (APY) when the interested is earned, for example, from a savings account or a certificate of deposit. When the interest is paid, for example, for a credit card, a mortgage, or a loan, the interest rate is expressed as annual percentage rate (APR).

Other things being equal, when interest rates in a certain country increase, foreign capital is attracted, and hence the demand of the country's currency increases, yielding to currency's appreciation.

Therefore; there is a proportional relation between interest rates and currency's value.

Note here that interest rate is the most influential factor on exchange rate and currency values.

Inflation

Inflation can be defined as the general rise in the prices' level of goods and services in a certain economy, over a certain time period. When prices rise, a currency unit can buy less goods or services. As a result, inflation implies a decline in the purchasing power of a currency. Inflation can be measured by the inflation rate, which is the annual percentage change in price index over time.

The effect of inflation on a certain economy can be positive and negative at the same time. Positive effects can include encouraging investments in non monetary ventures, while negative effects can include an increase in the opportunity cost of keeping money.

It is known that high inflation rates are caused by extreme growth of money supply, especially when money supply grows faster than economic growth.

In our present days, economic experts prefer a low and balanced inflation rate. The mission of keeping a low and steady inflation rate is granted to monetary authorities.

Economists believe that, particularly over longer periods of time, inflation and interest rates are correlated. This relationship especially holds when inflation and interest rates are higher. Since interest rates are the "fee" that lenders charge borrowers in order to forgo current consumption, lenders will charge higher "fees," or interest rates, when they expect inflation to increase the cost of future consumption. In this way, inflation leads to higher interest rates, which in turn may increase the value of a country's currency, changing exchange rates.

The relationships between inflation, interest rates and foreign currency exchange rates can be highly volatile. These relationships often only show a clear trend after a period of many years. In fact, many traders and arbitrage investors have made substantial money betting that the concept of interest rate parity will not hold over shorter periods of time.

In addition, governments and central banks often enact policy directly aimed at influencing exchange rates that can corrupt these relationships over shorter periods of time.

A general rule of thumb about inflation and its relationship to exchange rates is that lower inflation usually promotes higher currency exchange rates in that country. Conversely the opposite is also true. Countries experiencing high inflation rates typically experience a devaluation of their currency. For this reason, inflation is watched closely by economists charged with the responsibility of advising companies and governments about steps to take to offset or prevent possible negative repercussions of inflation.

As an example for the relation between inflation and exchange rate, in Bangladesh, the rate of inflation has increased steadily since July 2009, rising from an average of 2.3% during 2008-2009 to 12% in September 2011. The inflation rate declined to 10.1% in March 2012. The nominal exchange rate (defined as taka per one dollar) climbed from around Tk 70.2 in September 2010 to Tk 84.4 in January 2012.

Interest rates, currency exchange rates and inflation operate hand-in-hand, directly impacting each other. Central banks use interest rates to impact exchange rates and inflation. When currency exchange rates decline, a central bank can step in and raise interest rate, which in turn attracts foreign investment and boosts currency exchange rates. While this relationship sounds simple enough, high levels of inflation can lessen currency exchange rates if it is too high as compared with other country's rates. For that reason, there is often no quick fix to improving currency exchange rates until overall economic conditions improve for a specific country.

Monetary Policy

In general, monetary policy is the actions of a central bank, currency board or other regulatory committee that determine the size and rate of growth of the money supply. Monetary policy is maintained through actions such as increasing the interest rate, or changing the amount of money banks need to keep in the vault (bank reserves).

Monetary policy is what central banks use to manage the amount of liquidity in the economy. Liquidity is the total amount of money, including cash, credit and money market mutual funds. The important part of liquidity is credit, which includes loans, bonds, mortgages, and other agreements to repay.

In the United States, the Federal Reserve is in charge of monetary policy. Monetary policy is one of the ways that the U.S. government attempts to control the economy. If the money supply grows too fast, the rate of inflation will increase; if the growth of the money supply is slowed too much, then economic growth may also slow. In general, the U.S. sets inflation targets that are meant to maintain a steady inflation of 2% to 3%.

Other things being equal, it is known that when the central bank sets an expansionary monetary policy by increasing money supply, the currency depreciates. Hence, we can say that the relation between money supply and exchange rates is inversely proportional.

Political Situation

The political situation in a country is the overall political, economic, social, and military circumstances that a country has. In a globalized world where everything is connected to everything, the political situation has a great and direct influence on a country's economics. Any change in the political atmosphere will be reflected on the country's economy one way or the other, and the reverse is true. To understand the economy of a country and how it will progress, we definitely should take a look at the country's political situation.

The political situation can have either a positive or a negative influence on a country's business and economy, according to the country's situation.

In general, democracy has a positive influence on business.

Also, stability yields to a more suitable environment for investments.

Business and politics are correlated; politicians have great influence on business because they control the rules that regulate the manner trading is conducted.

Political situation in Europe

The European economy is still immersed in crisis. The International Monetary Fund (IMF) predicts that 2012 will end with growth of –0.4% and 2013 with 0.2%. The recession is particularly significant in the periphery, especially in Greece and the Spanish state (in the latter a fall of 1.5% and 1.3% in 2012 and 2013) and there is weak growth in the centre, with forecast of 0.9% growth for Germany. The general economic stagnation and austerity policies affect the latter in a negative way, as its exports to the rest of Europe tend to fall (down 11.4% as a whole, with falls of 15.8% to Portugal, 9% to Greece, and 8.6% to Italy) and are not offset by the increase in exports to the United States and China.

The crisis is generating tensions in the entire edifice of the EU and the Euro zone and accentuating the neo-colonial and centre-periphery internal dynamics. In this context, Mediterranean Europe has become the place where all the political and social tensions of the crisis are condensed. The future of the Euro remains uncertain, although the German policy for keeping the single currency, tightening the rope but without breaking it, is needed to promote their exports. Capital flight continues from the periphery to the centre (the Spanish state suffered outflows of capital from June 2011 to June 2012 of 296,000 million Euros, 27% of GDP in 2011, while Italy has registered outflows of 235 billion Euros, 15% of GDP in 2011), and the gap between the sovereign debt premiums for Germany and those of countries like Italy or the Spanish state show the situation of risk for the Euro.

In a nutshell, the political situation is Europe can is unstable, the Euro Zone is in danger of termination, and this situation affects the value of the Euro.

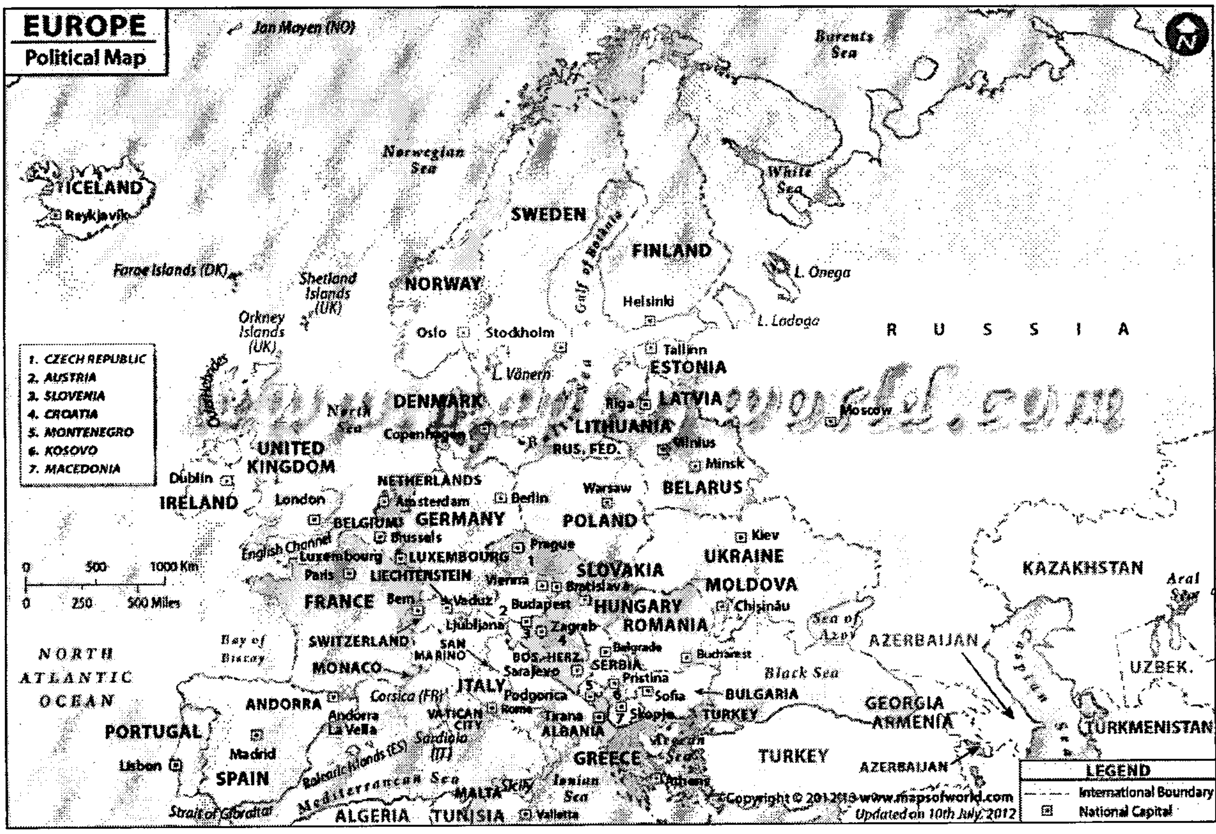

Figure 3.1 Political map of Europe

(Source: www.mapsofworld.com)

The process of integration in Europe has been evolving for many decades. All historical steps have been taken based on shared values like human rights, social justice, democracy, etc…

The goals of these steps were prosperity and economic growth. These steps and goals are now under serious test.

The Euro zone began to suffer from sovereign debt crisis in 2011, and this was the result of the global financial and economic crisis in 2008.

Today, the challenges that face the European Union are strategic. After the Lisbon treaty (2009), many enhancements and reforms were set, but the challenge is to continue with those reforms. Unfortunately, some of these decisions came late, but it is always better late than ever!

The sovereign debt crisis showed the importance of having a common treasury in the Euro Zone. Greater authority of the European Central Bank (ECB) and greater risk sharing are important steps in facing the economical problems of the Euro Zone.

There should be certain equilibrium between growth policies and austerity. Without growth, there would be no higher employment, and hence the EU could not become more strengthened.

India, as well as China will account for more than 20% of their spending on investment in R&D (Research and Development). In contrast Europe will suffer from a serious demographic problem because in 2025 it will represent less than 6.5% of the world's population, while Asia will represent around 61% and the US will represent around 38%. The bottom line is that the Euro Zone will suffer from a decline in competitiveness due to the absence of appropriate plans for health care, education, and immigration.

The Euro Zone must also make some reforms in the system of international relations. The world has changed, and it continues to change. The power today is no longer exclusive to the traditional western part of the world. New players have emerged and must be taken into consideration.

New strategic players are in action: China and Brazil can be viewed as new leaders, while Turkey and Russia can be seen as potential partners.

All these challenges are not simple or easy, but the Euro Zone should be put on the right track.

The political situation in the US

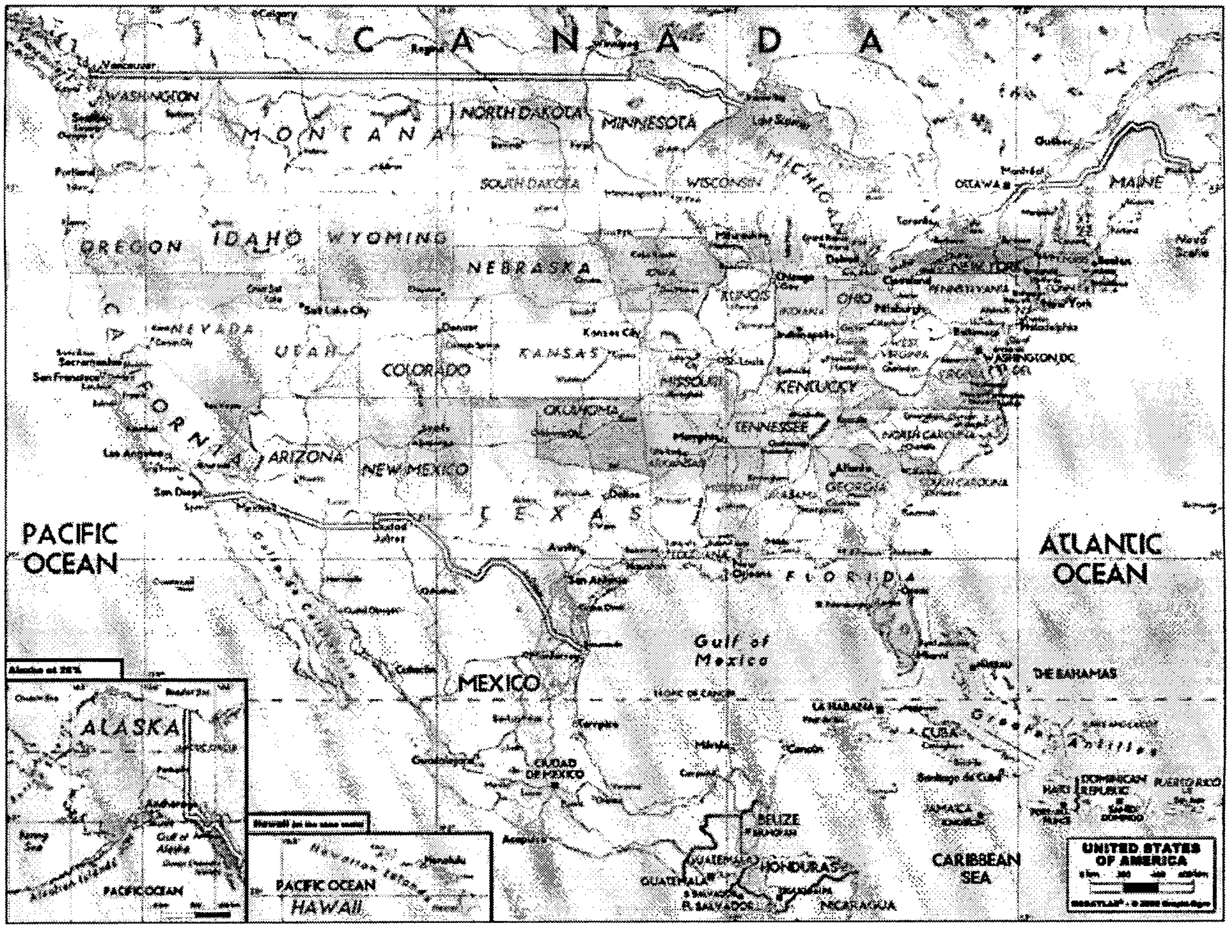

Figure 3.2 The US map

(Source: www.ezilon.com)

Today, the United States is facing many challenges, some of them are:

- The Unstable Economy: The economy of the United States is still under the influence of the 2008 economy crisis. Unemployment rates are still high (around 8%), and economic growth is still very low. The economy of the United States is considered vulnerable because the smallest shock can have drastic effects on the economy.
- The Iranian issue: Iran is gaining more and more interest from the American side for several reasons: It has influence on the Iraqi stability, it has power in the Afghanistan territories, it also has great influence in the Arab-Israel conflict. Moreover, the US and the international society refuse that Iran will gain a nuclear weapon in the near future.

The Obama administration is always concerned about a military Israeli attack on Iran, and from the fact that Iran will fight back with no limits to its reaction. The Iranian regime is considered a strategic enemy for the US. All these factors make the Iranian issue a delicate and complex matter that the US leaders should deal with.

- Internal Medical Issues: The government healthcare program known as Medicare is facing bankruptcy in the medium future (around the year 2024). This is due to two main issues: The growing cost of healthcare, and the early retirement of the generation. This delicate matter should be taken care of with great attention, because it is essential to the social security of the American society.
- The Relation between Obama and the Congress: Under president Obama's second presidential period, the Congress is still divided as follows: the Democrats have the majority in the senate, while the Republicans have control over the House of Representatives. This situation can block legislation, and can lead to inactivity and un-productivity in the political situation.
- The Budget Deficit: In 2011, president Obama and the Congress agreed on a plan to reduce the budget deficit over the long term, by preventing cuts to defense and social programs dear to both side, and the expiration of a temporary payroll tax cut and the low tax rates dating before Obama's presidency. This agreement is supposed to pull back the US from what is called a Fiscal Cliff, and it will mitigate the public deficit that reached 1.1 trillion dollars in the year 2012.

If a country faces political problems, confidence in its economy and currency decreases, and investors become unmotivated to invest in this country, and this yields to a downward pressure on the country's currency. So there is a proportional relationship between the political situation and the country's currency. The political situation plays an important role in determining the value of the currency, but it is extremely difficult to express the political situation as a discrete value. Therefore we will not use this factor in our research.

Balance of Payments

It is a set of accounts that record a country's international transactions, and which (because double entry bookkeeping is used) always balance out with no surplus or deficit shown on the overall basis. A surplus or deficit, however, can be shown in any of its three component accounts:

- Current account: covers export and import of goods and services
- Capital account: covers investment inflows and outflows
- Gold account: covers gold inflows and outflows

BOP accounting serves to highlight a country's competitive strengths and weaknesses, and helps in achieving balanced economic-growth.

According to Kindle Berger, "The balance of payments of a country is a systematic record of all economic transactions between the residents of the reporting country and residents of foreign countries during a given period of time".

The balance of payment record is maintained in a standard double-entry book-keeping method. International transactions enter in to the record as credit or debit. The payments received from foreign countries enter as credit and payments made to other countries as debit.

Speculation

Speculation is the buying, holding, and selling of stocks, commodities, currencies, collectibles, real estate, or any valuable thing to profit from fluctuations in its price as opposed to buying it for use or for income - dividends, rent etc...

It is the act of knowingly investing funds in a venture carrying higher-than-average risks in the hope of making above-average profits. Speculators expect to make a profit because of price changes.

When talking about exchange rate fluctuations, speculation plays a role in defining the exchange rates. For example, if speculators expect that the Euro will appreciate against the Dollar, investors will be encouraged to buy Euro to benefit from a future Euro appreciation; therefore pushing the Euro to appreciate in response to a growing demand.

Investing is buying and holding an asset for the long haul with the expectation that it will appreciate in value. Speculation is seeking immediate profits by frequently buying and selling.

Speculators play one of four primary roles in financial markets, along with hedgers who engage in transactions to offset some other pre-existing risk, arbitrageurs who seek to profit from situations where fungible instruments trade at different prices in different market segments, and investors who seek profit through long-term ownership of an instrument's underlying attributes. The role of speculators is to absorb excess risk that other participants do not want, and to provide liquidity in the marketplace by buying or selling when no participants from the other categories are available. Successful speculation entails collecting an adequate level of monetary compensation in return for providing immediate liquidity and assuming additional risk so that, over time, the inevitable losses are offset by larger profits.

From the above, we can notice that speculation plays an important role in determining exchange rates, since it directly affects the supply and demand of a certain currency. The problem is that speculation itself cannot be speculated! Therefore, there is no general rule or law that can guess or quantify speculation. For this reason, speculation will not be included as an independent variable in our model.

The problem with speculation is that it cannot be translated into a discrete value or a real number, or if it can be, it needs an extremely complex procedure to do it. Therefore; for the sake of this research, speculation will **not** be used as an independent variable, knowing that it plays a role in determining exchange rates.

Oil Price

OPEC

OPEC (Organization of Petroleum Exporting Countries) is an international organization established in Iraq-Baghdad in the year 1960. It first held five countries: Iraq, Iran, Venezuela and Kuwait. These countries agreed to coordinate their efforts to gain more control over the oil market. This was done through two ways:

- Export policy coordination
- Production level control

In 1973, seven new countries joined the organization, making it control over 67% of the world oil production.

In that year also, Arab OPEC members placed a block on the United States and the Netherlands because these two countries supported Israel in its war against Arab countries. This led to oil shortage in the US and in Europe.

In 1980, Iran and Iraq, two main OPEC members engaged into war, resulting in oil price to fall in 1982 because of this war and because many countries exporting oil started looking for alternative energy resources.

Each OPEC member was assigned a production quota, but members usually broke their quotas.

In the year 1986, the revenues for oil producers decreased by two third.

In the 1990s of the previous decade, oil prices remained low. Only in the year 1990 there was a small peak in oil prices because of the Iraqi Kuwaiti war. That war drove oil prices very high because of the international fear from oil shortages. That peak lived for a short time, and soon after that oil prices became normal.

In the beginning of the twenty first century, demand for oil increased and prices were booming, until the year 2008, when the world financial crisis caused oil prices to fall by 80 percent. OPEC members agreed then to cut production to help price recovery.

Later in 2009, oil prices recovered. Presently, there are twelve countries who are OPEC members:

- Algeria
- Angola
- Ecuador

- Iran
- Iraq
- Kuwait
- Libya
- Nigeria
- Qatar
- Saudi Arabia
- United Arab Emirates
- Venezuela

These countries have more than 80% of the world's proven oil reserves. The organization keeps working to insure the interests of its members. Figure 3.11 shows the historical oil prices until 2011.

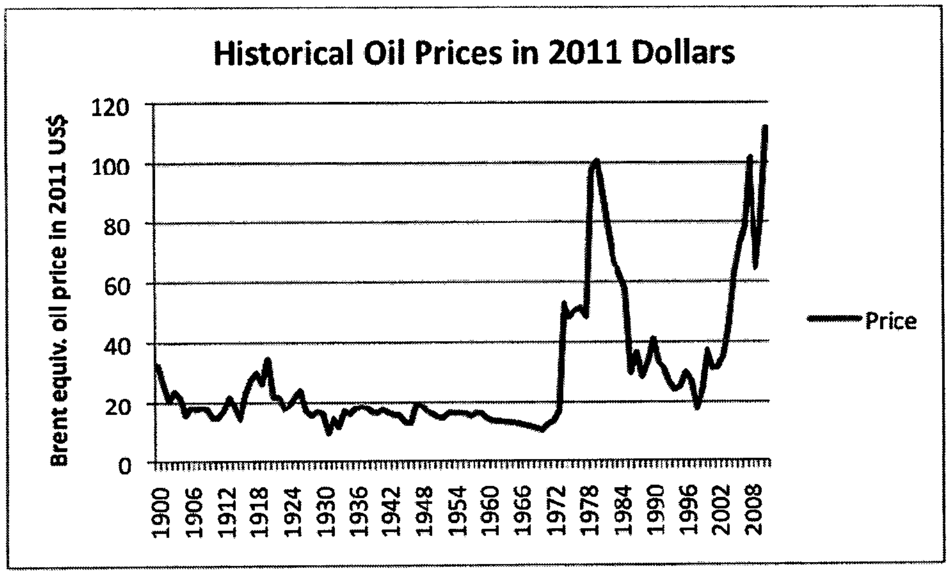

Figure 3.3 Historical oil prices

(Source: www.time.com)

Other Factors

In addition to the most important factors, previously listed, that affect exchange rates, there are also other factors that affect exchange rates. Although these factors have less influence on exchange rates, they should be briefly mentioned here. Note here that no one can actually cover or list all the factors that really affect interest rates, they are infinite, but we are trying to create a fundamental image about the factors that can affect exchange rates.

Following is a list of factors that can somehow affect exchange rates with a brief description of each one:

Relative Growth of an Economy

Economic growth is the increase in the amount of the goods and services produced by an economy over time. It is conventionally measured as the percent rate of increase in real gross domestic product, or real GDP. Growth is usually calculated in real terms, i.e. inflation-adjusted terms, in order to obviate the distorting effect of inflation on the price of the goods produced.

Since economic growth is measured as the annual percent change of gross domestic product (GDP), it has all the advantages and drawbacks of that measure.

Economic growth has traditionally been attributed to the accumulation of human and physical capital, and increased productivity arising from technological innovation. Economic growth was also the result of developing new products and services, which have been described as "demand creating".

The economic growth rate provides insight into the general direction and magnitude of growth for the overall economy. In the United States, for example, the long-term economic growth rate is around 2-5%, this lower rate is seen in most highly industrialized countries. Fast-growing economies, on the other hand, see rates as high as 10% although this rate of growth is not likely to be sustainable over the long term.

Public Debt

Public debt is at an important position when it comes to exchange rate determination. In general, many countries will finance its public sector projects and governmental funding through lending. Such projects stimulate the economy by providing new employment opportunities, but large public deficits yield to inflation, and high inflation leads to currency devaluation.

Governments can print money to pay its debt, but this scenario leads to inflation. A country's debt rating provided by financial rating authorities such as Standard & Poor's and Moody's plays a crucial role for the country's exchange rate. A negative rating puts pressure on the country currency, while a positive rating leads to currency's appreciation.

Reasons for not selecting the other factors

As mentioned earlier, not all the factors that affect the exchange rate will be selected and used in this study. There are many reasons for this, as follows:

- Availability of data: Some factors might look important or relevant in exchange rate determination, but data relative to those factors are unavailable or unreachable. For example, the balance of payments for the Euro Zone is unavailable as a historical data.
- Difficulty of transforming the factors into usable data: Some factors are important and relevant, and they actually have a weighted influence in exchange rate determination, but these factors are not easily transformed into discrete values that can be used in our model. For example, speculation is an essential factor in exchange rate determination, but the problem is that it is extremely difficult to transform speculation in discrete data or meaningful numbers that can be used in our model.
- Relevance of a factor: Factor importance and relevance differ from one factor to another. Some factors are available and can be represented as discrete numbers, but they are not essential in exchange rate determination; in reality, they have minor effect on exchange rates. As an example, a country's unemployment rate has an available data and can be presented in discrete numbers, but its influence and exchange rate are parts of the side effect; therefore it will not be included as a factor in our model.

3.4 Selected Variables

According to Paul De Grauwe, a Professor of Economics at the Catholic University of Leuven, some important and functional insights in the foreign exchange market are the fruit of the recent theoretical developments in exchange rate economics. The 1970's simple models, which could not resist the empirical evaluation, were followed by more complex models that were remarkable in many areas such as microstructure of financial markets and open economy macroeconomics. Besides that, some powerful and up-to-date techniques allow researchers to use exchange rates in strong empirical analysis.

It is now clear that 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. Our following step will be about defining the parameters of the model: Dependent Variables (model output) and independent variables (model inputs).

3.4.1 Dependent Variables

Exchange Rate

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...). In reality, the factors that affect the exchange rate are countless. In this research, we try to focus on the most important and most influential factors that affect exchange rates. We also try to focus on factors that have availability of data, and factors that can be expressed in discrete values.

3.4.2 Independent Variables

Interest Rates

The first, and most important independent variable, is the interest. 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: It is the one year LIBOR in the US currency. So what is LIBOR? It stands for London Interbank Offered Rate, and it is the average interest rate that London banks would be charged with in case of borrowing from other banks.It is officially abbreviated to BBA Libor (for British Bankers' Association Libor) or the trademark BBA Libor. BBA Libor is the essential benchmark for short term interest rates. Besides it is the Euribor. At least $350 trillion in derivatives and other financial products are tied to the Libor. Most of the financial institutions rely on the BBA Libor, and mortgage lenders as well. They define their own rates by referring to it. Libor rates are published every day at 11:30 am (London time), it has been calculated for ten currencies and fifteen borrowing periods starting from overnight going to one year length.

One Year Euribor: It is the one year Euribor in the euro currency. It is the rate within the EU zone, and it is about how the deposits are offered among banks in this zone. These banks are of first class market standing. It is published at 11:00 a.m. (CET) for spot value (T+2). The selection of banks quoting for Euribor® is based on market criteria, they have been selected to ensure that the diversity of the euro money market is adequately reflected, and in order to make Euribor an efficient and representative benchmark.

Relationship between interest rates and the exchange rate

There has been a special interest in the link between exchange rates and interest rates recently, and that in both advanced and developing countries. This is understandable, since these variables play an important role in determining developments in the nominal and real sides of the economy, including the behavior of domestic inflation, real output, exports and imports.

There is a strong, two-way relation between exchange rates and interest rates. Central banks usually manipulate interest rates to influence exchange rate levels. If interest rates increase, lenders will be offered higher returns relative to foreign countries, yielding to exchange rate rise.

If interest rates decrease, lenders will be offered lower returns relative to foreign countries, yielding to exchange rate fall.

Ceteris Paribus, higher interest rate yields currency appreciation.

<u>Inflation Rates</u>

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: It is the monthly core inflation rate in the US. It is a measure of inflation; it excludes some items that face volatile price movements. Products that can have temporary price shocks are eliminated by core inflation because these shocks may track out from the overall trend of inflation and consequently give a false measure of inflation. Core inflation is most often calculated by taking the Consumer Price Index (CPI) and excluding certain items such as energy and food from the index. Underlying long-term inflation is normally indicated the best by core inflation.
- Euro Area Core Inflation Rate: It is the monthly core inflation rate in the Euro Zone. Note here that we are using core inflation because it excludes oil price, which is used as an independent variable, in this way we avoid double counting of oil price.

Relationship between inflation rate and the exchange 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.

The theory of Purchasing Power Parity (PPP) focuses on that "under free international trade, perfect information and free floating exchange rate the prices of traded goods, when expressed in a common currency, are equalized across two countries".

High inflation rates increases the foreign exchange rates and hence weakens the local currency. This, in turn reduces the purchasing power of a country whose ripple effect can only worsen the situation.

Oil Price

Another independent variable used in our model is oil price. It is not an essential factor influencing exchange rates, but it certainly has influence on exchange rate.

Relationship between oil price and the exchange rate

Because the world oil markets are dollarized, there is a strong relation between the US Dollar value and oil prices. Needless to say that oil is an essential commodity that is used in the production of all goods. Therefore; all industrial countries are affected with even moderate changes in oil supply.

Oil trading is accomplished in US Dollars, even when the United States is not a direct contributor or trade partner.

Also, Oil exporting countries (e.g. Gulf countries) use the US Dollar in their trading.

Oil price affects exchange rates, and the dollar in particular.

We can here conclude that there is a negative relation between oil price and the US Dollar exchange rate. When oil prices increase, the US terms of trade will depreciate, leading to currency depreciation. But the picture is not complete this way. Another reasoning states that other counties like China and Europe will suffer more from an increase in oil prices and thus the US Dollar will appreciate in result of oil price increase. This reasoning is backed up with the fact that oil prices are in dollar, and so an increase in oil price will yield in more demand for US Dollar, and the US Dollar will appreciate accordingly.

In their paper entitled "Oil Price and the Dollar", which was posted in the "Forthcoming in Energy Studies Review" in February 2008, Virginie Coudert, Valerie Mignon and Alexis Penot wrote the following:

Overall, our study has given some clarification about the quite complex interactions between the two variables, especially at a theoretical level. Our empirical results highlight the existence of a long-term relation (i.e. a co integration relation) between the two series over the period 1974-2004. According to some previous studies, an increase in oil price is linked to a dollar appreciation in the long run. The result of the causality tests shows that the direction of the causality is from oil prices to the dollar exchange rate. To explain more, one could say that an increase in oil price is likely to improve the U.S. net foreign asset position compared to the rest *of the world, thus the dollar is affected positively and has a high appreciation among other currencies. On the other hand, the adjustment speed of the dollar real effective exchange rate to the long-term target is very slow: the estimation of a vector error correction model has reported half life of deviations to be about six years and a half. We then interpret our results through an exhaustive set of alternative theoretical explanations. Among all proposed explanations, only one is able to match the found sign and direction of the relation.*

3.5 Data Used

Euro/Dollar Exchange Rates

The main target of our research is to forecast exchange rates. For that reason, we used the historical data of the Euro/Dollar exchange rate between January 2002 and August 2013. The rate used was the monthly average rate. It makes a sum of 140 rates taken over 12 years.

To view the monthly the Euro/Dollar exchange rates please refer to Appendix B.

Interest Rates

The first and most important factor that influences exchange rates is the interest rate.

Two Independent variables were used:

1. The One Year USD LIBOR
2. The One Year EURI BOR

We used the historical data between January 2002 and August 2012. The rate used was the monthly average rate. It makes a sum of 132 rates taken over 12 years.

To view the monthly rates please refer to Appendix B.

Inflation Rates

Two Independent variables were used:

1. The US Core Inflation Rate
2. The Euro Area Core Inflation Rate

We used the historical data between January 2002 and August 2012. The rate used was the monthly average rate. It makes a sum of 132 rates taken over 11 years.

To view the monthly inflation rates please refer to Appendix B.

Oil Prices

Oil prices are highly affected by the supply and demand, and thus by the conditions of the international economies. Specifically, oil prices and the US Dollar are interrelated. We used the historical data between January 2002 and August 2013. The prices used were the monthly average oil prices. It makes a sum of 140 average prices taken over 12 years.

To view the monthly oil prices please refer to Appendix B.

3.6 International Perspective

It is commonly argued that there is a real element in the exchange rate. Thus, changes in the real exchange rate can cause reallocation of resources across industries. The real element in the exchange rate can affect the domestic economy and hence domestic stock returns, because stock market prices provide a signal of real activity.

The impact that the real exchange rate has on the stock market depends upon trade-flow elasticities. Both the demand-side and supply-side interpretation can be invoked to illustrate the role of the real exchange rate as a valid economic force.

On the demand side, the immediate impact of domestic currency depreciation relative to the currencies of a country's major trading partners causes an upward pressure on the inflation due to increased costs of imports. This, in turn, leads to a reduction in real income and domestic demand. The adverse impact on the real sector will adversely impact the stock market. Nonetheless, the demand-side story of currency depreciation is forceful enough to employ the real exchange rate as the relevant economic determinant of stock returns.

Currency depreciation could improve the position of a typical domestic producer by encouraging exports or through the expansion of import substitution. This change has a potentially positive impact on stock prices. That is why the real exchange rate's impact depends on the relative magnitude of trade elasticities in the import and export sectors of the domestic economy. By the same token, multinational firms whose operations are diversified across currency regions may be partially hedged against real exchange rate fluctuations. Thus, while there is an economic linkage between real exchange rate and stock returns, determination of the sign of the relationship remains an empirical issue.

Rapid technological innovation and the proliferation of transnational organizations are driving the formation of a global economy that sometimes conflicts with nationalistic concerns about maintaining comparative advantage and competitiveness. It is indeed a time of transition for firms and governments alike.

Any minor change in exchange rates will have direct impact on the country's economy as a whole. In addition to that, exchange rate determination and anticipation are becoming an integral part of any health business that goes internationally.

As a result, we can say that people around the world are more and more concerned about exchange rate fluctuations, since it directly affects their businesses and profit-loss balance. Nobody toady is isolated from the rest of the world. In fact, any event that takes place anywhere in the world will have a certain impact on everybody. Prices are globally inter-dependent, and worldwide businesses are deeply affected by exchange rate fluctuations.

3.7 The Models

Now that we have defined our data, dependent and independent variables, and the relationship between them, it is time to set the model that will be used in our research.

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.

Model 1: Using Regression

In our first model, we use a statistical technique, regression. Generally speaking, regression is a statistical approach to forecasting change in a dependent variable on the basis of change in one or more independent variables. Regression is known also as curve fitting or line fitting because a regression analysis equation can be used in fitting a curve or line to data points, in a manner such that the differences in the distances of data points from the curve or line are minimized.

With five independent variables and one dependent variable, the regression model sets a relationship between dependent and independent variables.

Model 2: Using Artificial Neural Network

Our second model uses one famous type of Artificial Neural Networks, known as a Multilayer Perceptron (MLP). The diagram shown in figure 3.13 illustrates a perceptron network with three layers.

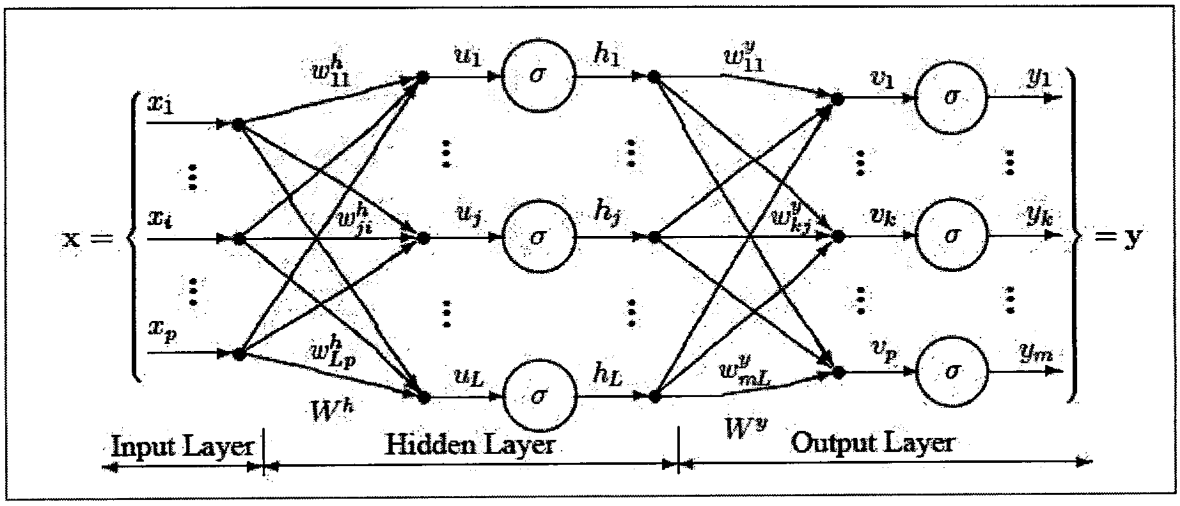

Figure 3.4 A diagram of a Multilayer Perceptron

(Source: www.dtreg.com)

The MLP ANN shown has a three neurons input layer, a three neurons hidden layer, and a three neurons output layer.

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.

There could be a single neuron in the output layer, or we can have N neurons corresponding to N output values.

In the MLP model, we use 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.

Our MLP model consists of one input layer with five neurons (representing the five independent variables), one hidden layer, and one output layer with one neuron (representing the dependent variable).Analysis and interpretation of the data follows in the next chapter.

3.8 Conclusion

The determination of an exchange rate is governed by so many factors. These factors do not have the same weight. For instance, the interest rate is a major component in the determination of the value of a currency. But the interest rate by itself cannot determine the trend of exchange rates. In reality, the aggregation of all factors that play a major role in exchange rate determination will yield to the final value of a currency.

At this point of our research, we tried to focus on the major components that influence the exchange rate, and we tried to show the importance of each factor and the relationship between these factors and the Euro/Dollar exchange rate.

Seven major factors were selected to be the most influential on exchange rates. These factors are:

1. Interest Rate
2. Inflation
3. Balance of Payments

4. Speculation
5. Oil Price
6. Political Situation
7. Monetary Policy

Out of these factors, five were selected as independent variables in our model. These factors are:

1. One Year USDLIBOR
2. One Year EURIBOR
3. US Core Inflation
4. Euro Area Core Inflation
5. Oil Price

Many reasons were behind our selection of these five variables. First, these factors are known to be the most influential factors in determining exchange rates. Second, these factors can be represented as discrete numbers, unlike the remaining factors (e.g. speculation, political situation, and the monetary policy) which are very hard to be represented as discrete numbers. Third, the selected factors' data are available and can be used.

Chapter 4 Findings

4.1 Introduction

In chapter two, we looked over the theories and practices related to forecasting exchange rates, we described some known procedures used in forecasting, and we introduced artificial intelligence and artificial neural networks. In chapter three, we defined the problem in hand, we listed and described the factors that affect exchange rates; we listed the factors that should be used in our models. Afterwards, we set our two models: Using regression and using artificial neural network.

After defining the problem, setting the models and listing the inputs and outputs, it is time to test the models to get the results that should lead us to answering the hypothesis questions.

Our basic hypothesis question was as follows: Under our predefined conditions, which technique among statistical techniques and artificial intelligence is more suitable for forecasting exchange rates? The answer to this question will be clarified throughout this chapter after having checked the results of our models.

4.2 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. Thousand 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.

4.3 Features of the regression model

The first model that we are using is based on regression. Recalling that regression is a statistical approach to forecasting change in a dependent variable (exchange rate, for example) on the basis of change in one or more independent variables (interest rate and inflation, for example). Known also as curve fitting or line fitting because a regression analysis equation can be used in fitting a curve or line to data points, in a manner such that the differences in the distances of data points from the curve or line are minimized. Relationships depicted in a regression analysis are, however, associative only, and any cause-effect (causal) inference is purely subjective.

After filling up the Dependent variable (ExchangeRate), the independent variables (USInfaltion, EUInflation, OilPrice, EURIBOR1Year, and USDLibor1Year), and all the other required parameters, the results of the analysis can be observed from the output window, under the Coefficients table, as shown in table 4.1.

Coefficients[a]						
		Unstandardized Coefficients		Standardized Coefficients		
Model		B	Std. Error	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 4.1 Coefficients table taken from SPSS

Before testing the regression's results, let's have a look over the parameters of the regression model.

Frequencies Table

Table 4.2 shows the frequencies table.

Statistics							
		USInflation	EUInfaltion	OilPrice	Euribor1Year	USDLibor1Year	ExchangeRate
N	Valid	132	132	132	132	132	132
	Missing	0	0	0	0	0	0
Mean		2.4000	2.1265	66.1104	2.656557	2.50564	1.27805
Std. Deviation		1.39929	.80113	29.37387	1.2193672	1.618903	.149034
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 4.2 Frequencies table

Kurtosis: It is a measure of the extent to which observations cluster around a central point. Since all kurtosis values are between -3 and 3, we can conclude that all items are normally distributed.

Model Summary

Table 4.3 shows the model summary.

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				

Table 4.3 Model Summary

From the table 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.

ANOVA (ANalysis Of VAriance)

Table 4.4 is the 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						

Table 4.4 ANOVA

From the ANOVA table 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.

Histogram

Figure 4.1 shows the histogram of the unstandardized residual.

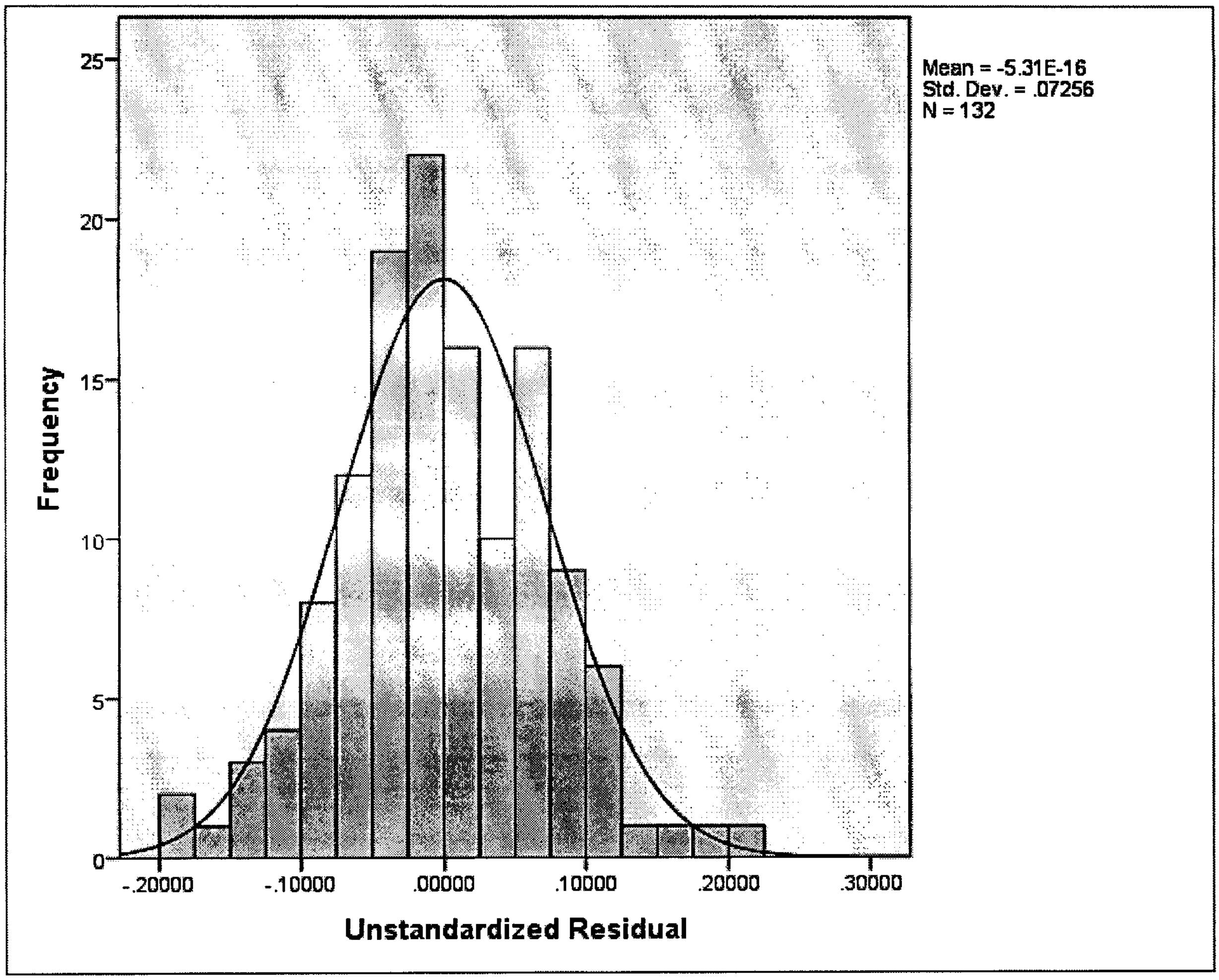

Figure 4.1 Histogram of the unstandardized residual

By looking at the bell shaped histogram, we can conclude that the data is normally distributed.

Now that we are sure that data are normally distributed, we can proceed by testing the model. From table 4.1, 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
[Equation 4.1]

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 4.1, 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.

Now we need to test the data from the year 2013 (first eight months) to know how effective this method is.

Table 4.5 shows the results of plugging the data of 2013 (first eight months) into our regression equation.

Date	USInf.	EUInf.	OilPrice	Euribor1Y	USDLibor1Y	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
Average % Error								**4.52**
	Parameter	**Parameter**	**Parameter**	**Parameter**	**Parameter**	**Constant**		
	0.06	-0.166	0.004	0.049	-0.02	1.11		

Table 4.5 Eight Months Regression results

Interpretation of these results comes later on in this chapter.

4.4 Features of the ANN model

Despite the fact that the model used in this research is original and new, it has also some interesting features, some of them are:

- Flexibility regarding the number of variables: The MLP used can be easily adjusted to accept new parameters as independent variables, or even as dependent variables, if we wanted to forecast a new variable in addition to the exchange rate.
- Flexibility regarding the number of input/output pairs: In our present model, we have eleven pairs or sets of input/output variables, taken between the years 2002 and 2012. As time progresses, we can add new sets for the upcoming years 2013, 2014, etc... This can be easily done by simply adding the new sets to the present one, and retraining the MLP network to get better results.

The process of forecasting exchange rates is an evolving process that will continue to progress with time and further researches. It is true that the future is unpredictable, but it is also true that the same conditions will yield the same outcomes. The difference between one forecasting model and another is how the cause is connected to the effect, i.e. the settings and parameters of the model that connects the causes to the effects.

After setting and defining our two models, and after testing these models it is time to show the results.

The settings of our models are as follows:

- Each model has five acting inputs and one output.
- The inputs are:
  a. One Year USDLIBOR
  b. One Year EURIBOR
  c. US Core Inflation
  d. Euro Area Core Inflation
  e. Oil Price
- The output is the monthly Euro/Dollar exchange rate.
- As we mentioned before, there are many other parameters that affect exchange rates, but it is now clear why we only chose four inputs.

After filling up the Dependent variable (ExchangeRate), the Covariates or independent variables (One Year USD LIBOR, One Year EURI BOR, US Core Inflation, Euro Area Core Inflation, and Oil Price), 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.

Please refer to appendix B to check the full results of the two models

Table 4.6 shows the average error resulting from using the two models, using data sets for eight months (January 2013 to August 2013):

Date	USInf.	EUInf.	OilPrice	Euribor1Y	USDLibor1Y	Exch.Rate	Reg. Rate	Regr. % Err.	ANN Rate	ANN % Err.
Jan-13	1.6	1.97	105.04	0.5753	0.814	1.33	1.31	1.38	1.29	3.30
Feb-13	2	1.84	107.66	0.5942	0.762	1.34	1.37	2.57	1.31	2.21
Mar-13	1.5	1.73	102.61	0.545	0.735	1.30	1.34	3.09	1.30	0.04
Apr-13	1.1	1.18	98.85	0.5284	0.717	1.30	1.39	6.57	1.32	1.57
May-13	1.4	1.42	99.35	0.4838	0.694	1.30	1.37	5.30	1.31	0.76
Jun-13	1.8	1.6	99.74	0.5071	0.684	1.32	1.36	3.49	1.31	0.94
Jul-13	2	1.61	105.21	0.5254	0.684	1.31	1.40	6.80	1.32	0.85
Aug-13	1.5	1.34	108.06	0.5423	0.668	1.33	1.42	6.95	1.34	0.69
Average % Error								**4.52**		**1.29**
	Parameter	**Parameter**	**Parameter**	**Parameter**	**Parameter**	**Constant**				
	0.06	-0.166	0.004	0.049	-0.02	1.11				

Table 4.6 The average errors of the two used models

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 table in Appendix B, 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:

  Regression Monthly Error = ABS(ExchangeRate – Regression)/ExchangeRate
  [Equation 4.2]
  If we take the average error of all 132 data sets between January 2002 and December 2012, we get:
  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:

  ANN Monthly Error = ABS(ExchangeRate – ANN)/ExchangeRate
  [Equation 4.3]
  If we take the average error of all 132 data sets between January 2002 and December 2012, we get:
  Average ANN Error = 2.17%

In addition, according to the eight data sets used for testing both models (refer to table 4.3):

Average Regression Error from testing samples = 4.52%

Average ANN Error from testing samples = 1.29%

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

4.5 Discussion of the findings

4.5.1 Regression Standardized Coefficients

Previously we showed the coefficients table (Table 4.1). Under this table, we showed the standardized coefficients for the independent variables. The absolute value of these coefficients can show the importance and significance of each independent variable. So from table 4.1, we can notice the following:

- In absolute value, the beta value of the standardized coefficient for the "EUInflation" independent variable is the highest (0.890), meaning that this variable has the highest influence on the interest rate according to our regression model.
- In absolute value, the beta value of the standardized coefficient for the "OilPrice" independent variable comes second (0.882), meaning that this variable comes second in influence on the interest rate according to our regression model.
- The independent variable "USInflation" is less important (third rank) in influencing the interest rate values (0.563).
- The independent variable "Euribor1Year" is less important (before last) in influencing the interest rate values (0.401).
- The independent variable "USDLibor1Year" is the least important in influencing the interest rate values (0.221).

These results do not fit with the macro economics theories which state that in general, interest rates are the most important factors for exchange rate determination.

4.5.2 MLP Importance Analysis

Under SPSS, 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 4.2 represents the normalized importance of the independent variables.

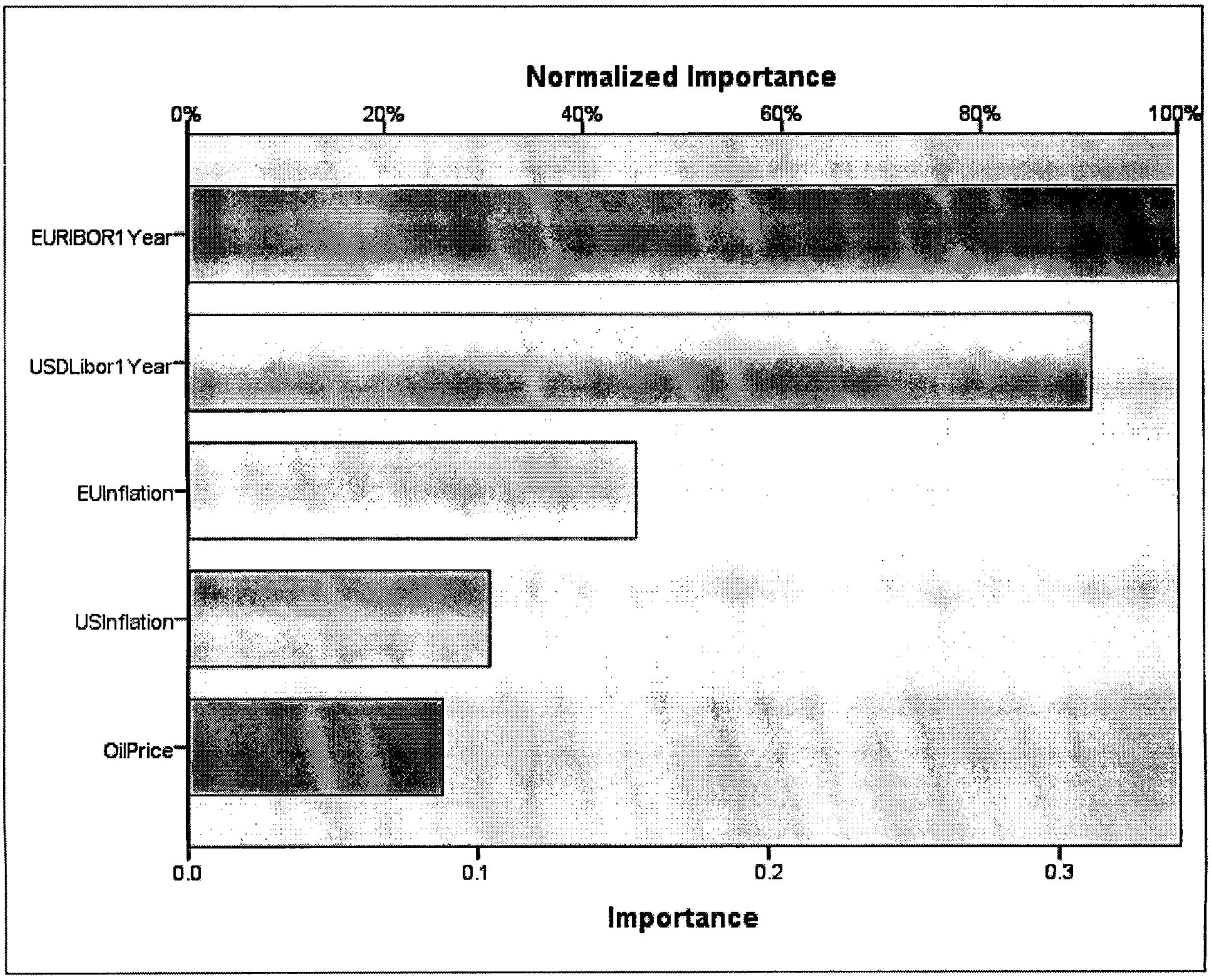

Figure 4.2 The normalized importance of the independent variables

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 economics 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.

4.5.3 Other Findings

From the average error table shown in table 4.3, it is clear that, on average, an MLP Neural Network gives a more precise, and hence a less error prone, result regarding exchange rate prediction. Remember that the objective here is not precisely to predict or estimate the exchange rate (it is practically impossible), but at least to come up with a model that can give some reliable information with minimized error.

4.6 Discussion of the hypotheses

The fourth research question was: Is it really rewarding to use Artificial Neural Networks in forecasting exchange rates?

To answer this question, first we need to look at the table that shows the average percentage error using the two methods. From the table, we notice the following:

- Using the first method (Regression), the average error between the calculated values of the exchange rate and the real values was 4.52%
- Using the second method (Artificial Neural Network), the average error between the calculated values of the exchange rate and the real values was 1.29%

The improvement between regression and ANN is around 3.2%. If we want to really know whether it is a rewarding improvement or a negligible improvement, we need to remember that we are talking about forecasting exchange rate, an operation that includes hundreds of millions dollars on a daily basis, in both directions (from Euro to US Dollar and vice versa).

According to the Bank for International Settlements, as of April 2010, the average daily turnover in global foreign exchange markets is estimated at $3.98 trillion, a growth of approximately 20% over the $3.21 trillion daily volume as of April 2007. Some firms specializing on foreign exchange market had put the average daily turnover in excess of US$4 trillion.

The $3.98 trillion break-down is as follows:

- $1.490 trillion in spot transactions
- $475 billion in outright forwards
- $1.765 trillion in foreign exchange swaps
- $43 billion currency swaps
- $207 billion in options and other products

Therefore; an improvement in forecasting error by 3.2% can save huge amounts of money on transactions between the two currencies. The conclusion here is that it is indeed rewarding to use ANNs instead of regression for exchange rate prediction.

Question five: What are the most influential factors in determining exchange rates? And in which order?

First, the most influential factors on exchange rates were previously discussed, with details about each factor. Some of these factors were excluded from our model because it was very difficult to quantify these factors in discrete numbers.

Now to answer this question, we need to refer to the importance analysis previously conducted for the MLP network; this analysis 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.

The importance analysis by itself was enough to answer this question, by ordering the variables or parameters that affect exchange rates according to their importance, as follows:

- The interest rate EURIBOR1Year is the most important factor in determining the exchange rate. This conclusion is conformant with our previous assumptions, and also with the economical theories. Its importance is estimated to be 0.342 on a scale of one.
- The interest rate USDLIBOR1Year is the second most important factor in determining the exchange rate. This conclusion is conformant with our previous assumptions, and also with the economical theories. Its importance is estimated to be 0.311 on a scale of one.
- EUInflation comes third in importance; its importance is estimated to be 0.155 on a scale of one.

- USInflation comes fourth in importance; its importance is estimated to be 0.104 on a scale of one.
- Oil price comes last in importance. Its importance is estimated to be 0.088 on a scale of one.

Question six: Is artificial intelligence a better way to forecast exchange rates than statistical techniques?

This question is rather a generic question. Let's first note down the following observations:

- The model that we used to forecast exchange rate is a simple one used for illustration purposes. This model can be a starting point for a more complex and sophisticated one.
- With this simple model, it was obvious that the average error has improved by approximately 3.2%.
- Further enhancements on this model will yield better results.
- When talking about exchange rate prediction, keep in mind that a minor improvement in the forecasting procedure means a saving of huge amounts of money that could have been otherwise lost because of faulty prediction.

From the above, we can draw the following conclusion: On average, and with the right parameters, artificial intelligence using artificial neural networks is for sure a better way to forecast exchange rates!

4.7 Conclusion

In this chapter, we examined the main findings or our research. First we showed an overview of the new features in this research, then the main features of the Artificial Neural Network model were described, and after that we examined the main results that the research reached, including a comparison between our basic models: Regression and Multi Layer Perceptron Neural Network.

A thorough discussion of the findings was presented, with details of the research questions and answers to each question.

At this stage, it is clear that the main research question about which technique is better in forecasting exchange rates, and the main hypothesis that we started from, was fulfilled. This research confirms our main hypothesis that forecasting exchange rates can be better estimated with Artificial Intelligence (Specifically Artificial Neural Network) than with statistical techniques (Regression).

The settings of the two models used in this research were thoroughly fine tuned to give the best outcomes. We should mention here that the technical issues of both models, along with all the technical and purely scientific details were not mentioned here, because it is not the scope or the target if this research to go into such details.

The main contribution in this research so far is that we were able to set a working model that can approximate a complex relation between our independent and dependent variables. This method is simple and complex at the same time. It is simple because all we need to do is to set the previous data of the independent and dependent variables to get the prediction results of the dependent variables. On the other hand; it is a complex method because of the nature of the relation between the independent and dependent variables. The complexity is enclosed in the ANN itself, and the user of this method needs not to know about the real connections inside the network.

Going back to our hypotheses, we conclude the following:

- Setting the right model with the right variables can actually lead to forecasting exchange rates with an acceptable error margin
- An artificial Neural Network is indeed an efficient method that can be used to forecast exchange rate
- An Artificial Neural Network was able to give better results than regression techniques because of the nature of the structure of ANNs as approximations for complex relations
- Even though the parameters and variables that affect exchange rates are countless, the most important and influential variables can be used to determine or forecast future exchange rates, and that was evident because our model used few, but very influential, variables and was able to approximate the real relation between the independent and dependent variables.

Here we can say that the hypotheses were accepted and empirically proven in this research.

Now that we reached this result we should look into its implications and effects.

This result means that exchange rates can be forecasted with a minimum margin of error, and therefore our ANN model can be used in forecasting. This result has an impact on many economical aspects. International companies can no longer pretend that they have no idea about the future rate of currencies. In contrary, these companies should enhance such models and make it a standard for forecasting exchange rates. Governments also should use an enhanced version of this model to forecast exchange rates that have a big impact on its economies.

It is not an exaggeration to say that every individual can be affected by the use of this method or an enhanced version of this method. This is because our globalized world is more interconnected, even a small shop in a tiny village is affected by exchange rates.

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.

Chapter 5 Conclusions and Recommendations

5.1 Introduction

This research was a serious effort toward finding an "adequate" system that can forecast the Euro/Dollar exchange rate with an acceptable error margin. There was a comparison between the old school of forecasting, using regression, and the new trend, using an artificial neural network. Both methods were set according to our thorough research in the fields of forecasting, macro economics, statistical techniques, and artificial intelligence.

The results that came up from this research matched our initial hypothesis, conforming that artificial intelligence is a better forecasting tool than statistical techniques.

5.2 Main findings

The world of forecasting exchange rates is very wide and ever expanding. Each day brings new studies and new ideas to this field. What we did in this research is a new perspective to look at how forecasting exchange rates can be enhanced.

After the world's financial crisis in 2008, central banks and even private banks urged the need to have efficient methods for estimating marked risks. One of these risks would be the volatility of exchange rates. To deal with this risk, a need for effective forecasting methods has immerged.

Our objective was to build a model able to forecast exchange rates using artificial neural networks with a minimum error margin, and to compare this model to a regression model. After building the two models and putting them into action, the results came up to be conformant with our initial hypotheses:

1. The first and most interesting result is that an artificial neural network can actually be set to forecast exchange rates with an acceptable error margin. The nature of artificial neural networks, being perfect estimators for non linear relations, makes it an excellent tool for forecasting exchange rates. The secret is to find the right inputs and the right parameters, and the rest is up to the network itself. We do not need to worry about the exact relation between inputs and outputs. Instead, we can consider the network as a black box that we feed it with the right inputs to give the right outputs without concerning about what happens to the data inside the neural network.
2. When we compared the results from regression and artificial neural network, it was clear that the ANN outperformed some regression in forecasting exchange rates. This

conclusion was reached after calculating the mean square error coming from both models and comparing them.

3. All previous researches and theories were focusing on the fact the artificial intelligence is actually an excellent tool for forecasting in general. This research, with its empirical tests and results, confirmed what has been written in theory.
4. 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 much smaller than the average error given by regression. Baring in mind that the daily currency transactions are in trillions of dollars. Accuracy in forecasting becomes a major issue and not a minor detail.
5. It was the combination between Artificial Intelligence and Macro Economics that made these two models come into reality, making it possible to use a computer sciences field in the service of an economical problem.

5.3 Limitations of the research

Scarcity of some information

While carrying out our research, some information was missing, or was unreachable. For example, there was not enough and clear information about the Euro Zone's balance of payments for the last 10 years. This information, in case it was found would have been an added value to our models, as it can be added as another independent variable to the models.

Shortcomings of ANN model

An important drawback is represented by the fact that there is no rule for designing ANNs. This is an empirical process of trial and error, through which, one adds and removes hidden layers and/or neural units from the structure of the network until a minimum value for the loss function is reached. This process is time consuming and requires considerable computing resources. Another limitation is the small number of benchmark models necessary to assess the predictive power of the network. For further research, one can consider more than one econometric model and a larger battery of tests and indicators in order to achieve a better comparison between the models.

Juvenility of the Euro Zone

It is well know that the euro zone is not an old concept. In fact, it is not until the beginning of this century that the euro zone was officially born (the years 2001-2002). Before that date, there was no existence for the Euro as a currency; each European country had its own currency and economic metrics. This was an important drawback to our models, especially to the artificial neural network model, because an ANN models relies greatly on previous data and information to accurately predict future data. The more the previous data is available, the more accurate the ANN model becomes. This drawback will be solved with time, because as time passes, more data will be available and it can be added to the model.

Time Limitation

As is the case with all researches, time is always short, time "flies", and it is always a race against time to give the best results in the available time. This research took around ten months, which is basically a short time for such a research. Maybe giving it more time would have yielded enhanced results.

5.4 Managerial implications

In general, top level management is concerned with optimizing the benefits and gain of companies. This is done through enhancing all sorts of the company's actions in a way that saves money and brings welfare. International companies, who have branches all over the world, are always concerned with exchange rate fluctuations, because it directly affects their profit margin. That's why forecasting exchange rates is becoming an important and essential tool for those companies and businesses that have to deal with different currencies on a daily basis. It all leads to the fact that a better method for forecasting exchange rates will for sure lead to a more profitable business. This is the main concern of multinational companies because they all suffer from the lack of information about the future trend or tendency in different exchange rate for different currencies. It is therefore important to have a reliable and efficient method to forecast exchange rates, with a minimum possible error margin. Therefore; this research can offer all those companies and businesses a starting point toward finding an optimized method for forecasting exchange rate, after doing the necessary additions and customization that best fits each business. Examples of these additions can be:

- Adding more independent variables to enhance the forecasting procedure
- Adding more data from past time to enhance the results of forecasting
- Changing the currencies and countries who's currency rates need to be forecasted (e.g. forecasting the Japanese Yen versus the Euro)

5.5 Recommendations

5.5.1 Recommendations for decisions makers, top level management, and governments

Any research that doesn't have a practical application is useless. Our main idea in this research was to introduce an efficient and reliable method for forecasting exchange rates. This method can, and has to be used by many entities.

Decisions makers and top level management are directly concerned with the results of this research. Every day decisions and deals made by multinational companies involve transactions between different currencies. Therefore it is recommended for decision makers to, at least, have an idea about the trend of all currencies that they deal with. This can save huge amounts of money in companies by hedging themselves from unexpected currency fluctuations.

As for governments, it is also vital for different politicians and official decision makers to use and ameliorate such a model, because we live in an interconnected world and every single event all over the globe can have influence anywhere and everywhere. Some economical decisions taken by governments and officials are directly related to exchange rate, and therefore it is much better to know how some currencies are moving and in which direction. A small investment in such methods can save huge amounts of money for the future.

At the end of this research, it is necessary to review what we have done so far, where we stand from this research subject, and what can be done as future research guidelines.

Two conclusions can be observed:

1. Using an artificial neural network will give better result than using regression for forecasting exchange rates.
2. There is no ultimate solution for forecasting exchange rates, because it is a complex procedure that is influenced by hundreds of nested factors, and mostly because forecasting the future is, by itself, a complex and nearly impossible procedure.

From these conclusions, we can restart to enhance the results that we have reached so far, by going through two ways: Introducing new variables, introducing a hybrid artificial intelligence system.

5.5.2 Introducing new variables

The first enhancement that can be done is by introducing new independent variables to our existing models: We have already mentioned that some independent were suppressed from our model, for three main reasons:

1. Lack of information: Some information about specific variables that influence exchange rates were, partly or totally, unavailable. This problem can be surpassed by carrying some more research and finding those missing data.
2. Ability to quantify variables: If we take speculation as an example of an independent variable that influences exchange rates, we can observe that this variable is difficult to be quantified into discrete data that can be used into our model. On the other hand, a thorough and extensive research can yield to acceptable results, to quantify such kinds of variables, and hence to be able to use it in some enhanced and more sophisticated model.
3. Introducing new variables: So far, hundreds of variables were proven to influence exchange rates, with variable level of importance. Another way to enhance our model would be by introducing new variables, and proving that these variables actually affect exchange rates.

5.5.3 Introducing a hybrid artificial intelligence system

We have used an Artificial Intelligence model using a pure Artificial Neural Network so far. This worked fine for now, but it is not the perfect solution for forecasting exchange rates. Introducing a hybrid artificial intelligence system will definitely improve the forecasting result.

The world of Artificial Intelligence is still a new born, but it is also wide and diverse. Two main sub-branches of AI are interesting and can offer great improvements to our model: Genetic Algorithms and Fuzzy Logic.

Genetic Algorithms

Genetic Algorithms (GA) are models that optimize rules by mimicking the Darwinian Law of survival of the fittest. A set of rules are chosen by those that work the best. The weakest are discarded. In addition, two successful rules can be combined (the equivalent to genetic cross-overs) to produce offspring rules. The offspring can replace the parents, or they will be discarded if less successful than the parents. Mutation is also accomplished by randomly changing elements. Mutation and cross-over occur with low probability, as in nature.

GA is an evolutionary algorithm which generates each individual from some encoded form known as a "chromosome" or "genome". Chromosomes are combined or mutated to breed new individuals. "Crossover", the kind of recombination of chromosomes found in sexual reproduction in nature, is often also used in GAs. Here, an offspring's chromosome is created by joining segments chosen alternately from each of two parents' chromosomes which are of fixed length.

GAs are useful for multidimensional optimization problems in which the chromosome can encode the values for the different variables being optimized.

One way of using Genetic Algorithms with ANNs for forecasting exchange rates is by introducing a genetic algorithm that can choose the best combination from a set of hundreds of independent variables that influence exchange rates. A perfect combination that excludes the less important factors and include the most important factors or variables that influence exchange rates can lead to an optimized hybrid system that can give better results in forecasting exchange rates.

Fuzzy Logic

Fuzzy logic is an approach to computing based on "degrees of truth" rather than the usual "true or false" (1 or 0) Boolean logic on which the modern computer is based. The idea of fuzzy logic was first advanced by Dr. Lotfi Zadeh of the University of California at Berkeley in the 1960s. Dr. Zadeh was working on the problem of computer understanding of natural language. Natural language (like most other activities in life and indeed the universe) is not easily translated into the absolute terms of 0 and 1. (Whether everything is ultimately describable in binary terms is a philosophical question worth pursuing, but in practice much data we might want to feed a computer is in some state in between and so, frequently, are the results of computing.)

Fuzzy logic includes 0 and 1 as extreme cases of truth (or "the state of matters" or "fact") but also includes the various states of truth in between so that, for example, the result of a comparison between two things could be not "thin" or "thick" but "44% of thickness."

Fuzzy logic seems closer to the way our brains work. We aggregate data and form a number of partial truths, which we aggregate further into higher truths, which in turn, when certain thresholds are exceeded, cause certain further results such as motor reaction. A similar kind of process is used in artificial computer neural network and expert systems.

It may help to see fuzzy logic as the way reasoning really works and binary or Boolean logic is simply a special case of it.

So, instead of using a pure ANN for forecasting exchange rates, a fuzzy logic procedure may help by showing the degree of influence that each variable has on exchange rates, because a variable might influence exchange rate in a 40% degree, while other variables influence exchange rates in a 70% degree. These degrees and their influence can be anticipated by a fuzzy logic system, which in return, can feed its results to an Artificial Neural Network.

A combination of the three algorithms (Artificial Neural Networks, Genetic Algorithm, and Fuzzy Logic) can be extremely helpful in the domain of forecasting in general, and especially in forecasting exchange rates. Who knows, such a system may be the future of forecasting some day!

At this point, if we compare our results with previous researches and methods that we talked about in chapter two, we can conclude that our ANN model gave better and more accurate results concerning exchange rate prediction and determination. We think that our model can be taken as a starting point to reach a more accurate and global exchange rate prediction model based on ANN. We are convinced at this stage that ANNs, when used correctly and with the right parameters and variables, can be a good approximate for exchange rates, especially because exchange rate is related to its dependent variables with a complex, non-linear, relation; and ANNs are good approximates for non-linear relations.

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APPENDICES

Appendix A: List of Abbreviations

AI: Artificial Intelligence

APR: Annual Percentage Rate

APY: Annual Percentage Yield

ANN: Artificial Neural Network

BOP: Balance Of Payments

CA: Current Account

ECB: European Central Bank

EU: European Union

GA: Genetic Algorithms

IMF: International Monetary Fund

MLP: Multilayer Perceptron

Appendix B: Monthly Rates, Regression Rates, and ANN Rates (2002-2013)

Date	Euro/Dollar	EuroCoreInf. %	USCoreInf. %	Euribor1Year %	USDLibor1Year %	Oil Price $	Regr.	ANN
Jan-02	0.88	2.6	1.1	3.48	2.36	19.15	0.96	0.87
Feb-02	0.87	2.5	1.1	3.59	2.45	19.98	0.98	0.87
Mar-02	0.88	2.5	1.5	3.82	2.85	23.64	1.02	0.89
Apr-02	0.89	2.3	1.6	3.86	2.79	25.43	1.07	0.92
May-02	0.92	2	1.2	3.96	2.65	25.69	1.11	0.95
Jun-02	0.96	1.9	1.1	3.87	2.42	24.49	1.11	0.96
Jul-02	0.99	2	1.5	3.64	2.14	25.75	1.12	0.97
Aug-02	0.98	2.1	1.8	3.44	1.88	26.78	1.12	0.97
Sep-02	0.98	2.1	1.5	3.24	1.87	28.28	1.10	1.02
Oct-02	0.98	2.3	2	3.13	1.81	27.53	1.09	0.98
Nov-02	1.00	2.3	2.2	3.02	1.63	24.79	1.09	0.95
Dec-02	1.02	2.3	2.4	2.87	1.58	27.89	1.11	1.01
Jan-03	1.06	2.1	2.6	2.70	1.48	30.77	1.16	1.10
Feb-03	1.08	2.4	3	2.50	1.41	32.88	1.13	1.10
Mar-03	1.08	2.5	3	2.41	1.33	30.36	1.10	1.07
Apr-03	1.09	2.1	2.2	2.45	1.36	25.49	1.10	1.07
May-03	1.16	1.8	2.1	2.25	1.25	26.06	1.14	1.15
Jun-03	1.17	1.9	2.1	2.01	1.09	27.91	1.12	1.18
Jul-03	1.14	1.9	2.1	2.08	1.20	28.59	1.13	1.19
Aug-03	1.11	2.1	2.2	2.28	1.41	29.68	1.11	1.16
Sep-03	1.12	2.2	2.3	2.26	1.35	26.88	1.09	1.12
Oct-03	1.17	2	2	2.30	1.40	29.01	1.11	1.16
Nov-03	1.17	2.2	1.8	2.41	1.51	29.12	1.07	1.14
Dec-03	1.23	2	1.9	2.38	1.50	29.95	1.11	1.17
Jan-04	1.26	1.9	1.9	2.22	1.41	31.40	1.13	1.21
Feb-04	1.26	1.6	1.7	2.16	1.40	31.32	1.17	1.24
Mar-04	1.23	1.7	1.7	2.06	1.33	33.67	1.16	1.25
Apr-04	1.20	2	2.3	2.16	1.62	33.71	1.14	1.22
May-04	1.20	2.5	3.1	2.30	2.02	37.63	1.12	1.21
Jun-04	1.22	2.4	3.3	2.40	2.35	35.54	1.14	1.20
Jul-04	1.23	2.3	3	2.36	2.33	37.93	1.15	1.23
Aug-04	1.22	2.3	2.7	2.30	2.29	42.08	1.15	1.25
Sep-04	1.22	2.1	2.5	2.38	2.37	41.65	1.17	1.25
Oct-04	1.25	2.4	3.2	2.32	2.47	46.87	1.18	1.26
Nov-04	1.30	2.2	3.5	2.33	2.80	42.23	1.20	1.25

Dec-04	1.34	2.4	3.3	2.30	3.02	39.09	1.14	1.24
Jan-05	1.31	1.9	3	2.31	3.22	42.89	1.22	1.26
Feb-05	1.30	2.1	3	2.31	3.38	44.56	1.19	1.26
Mar-05	1.32	2.1	3.1	2.33	3.68	50.93	1.22	1.27
Apr-05	1.29	2.1	3.5	2.27	3.73	50.64	1.24	1.27
May-05	1.27	2	2.8	2.19	3.75	47.81	1.19	1.26
Jun-05	1.22	2.1	2.5	2.10	3.81	53.89	1.18	1.26
Jul-05	1.20	2.2	3.2	2.17	4.05	56.37	1.21	1.26
Aug-05	1.23	2.2	3.6	2.22	4.27	61.87	1.26	1.27
Sep-05	1.22	2.6	4.7	2.22	4.21	61.65	1.26	1.26
Oct-05	1.20	2.5	4.3	2.41	4.57	58.19	1.24	1.26
Nov-05	1.18	2.3	3.5	2.68	4.78	54.98	1.22	1.26
Dec-05	1.19	2.2	3.4	2.78	4.84	56.47	1.24	1.27
Jan-06	1.21	2.4	4	2.83	4.84	62.36	1.27	1.27
Feb-06	1.19	2.3	3.6	2.91	5.08	59.71	1.25	1.27
Mar-06	1.20	2.2	3.4	3.11	5.19	60.93	1.27	1.27
Apr-06	1.23	2.5	3.5	3.22	5.33	68.00	1.26	1.27
May-06	1.28	2.5	4.2	3.31	5.40	68.61	1.31	1.27
Jun-06	1.27	2.5	4.3	3.40	5.60	68.29	1.31	1.27
Jul-06	1.27	2.4	4.1	3.54	5.66	72.51	1.34	1.28
Aug-06	1.28	2.3	3.8	3.62	5.50	71.81	1.34	1.29
Sep-06	1.27	1.7	2.1	3.72	5.38	61.97	1.31	1.29
Oct-06	1.26	1.6	1.3	3.80	5.36	57.95	1.26	1.29
Nov-06	1.29	1.9	2	3.86	5.30	58.13	1.26	1.28
Dec-06	1.32	1.9	2.5	3.92	5.24	61.00	1.31	1.30
Jan-07	1.30	1.8	2.1	4.06	5.37	53.40	1.27	1.29
Feb-07	1.31	1.8	2.4	4.09	5.38	57.58	1.31	1.30
Mar-07	1.32	1.9	2.8	4.11	5.20	60.60	1.33	1.32
Apr-07	1.35	1.9	2.6	4.25	5.28	65.10	1.34	1.34
May-07	1.35	1.9	2.7	4.37	5.33	65.10	1.36	1.35
Jun-07	1.34	1.9	2.7	4.51	5.45	68.19	1.37	1.37
Jul-07	1.37	1.8	2.4	4.56	5.38	73.67	1.40	1.41
Aug-07	1.36	1.7	2	4.67	5.19	70.13	1.39	1.43
Sep-07	1.39	2.1	2.8	4.72	5.06	76.91	1.40	1.44
Oct-07	1.42	2.6	3.5	4.65	4.88	82.15	1.39	1.41
Nov-07	1.47	3.1	4.3	4.61	4.52	91.27	1.40	1.42
Dec-07	1.46	3.1	4.1	4.79	4.42	89.43	1.39	1.44
Jan-08	1.47	3.2	4.3	4.50	3.44	90.82	1.40	1.47
Feb-08	1.47	3.3	4	4.35	2.80	93.75	1.38	1.48
Mar-08	1.55	3.6	4	4.59	2.51	101.84	1.38	1.50
Apr-08	1.57	3.3	3.9	4.82	2.83	109.05	1.47	1.55

May-08	1.56	3.7	4.2	4.99	3.03	122.77	1.48	1.56
Jun-08	1.56	4	5	5.36	3.42	131.52	1.53	1.57
Jul-08	1.57	4	5.6	5.39	3.28	132.55	1.58	1.57
Aug-08	1.49	3.8	5.4	5.32	3.24	114.57	1.51	1.54
Sep-08	1.43	3.6	4.9	5.38	3.37	99.29	1.45	1.47
Oct-08	1.33	3.2	3.7	5.25	3.79	72.69	1.31	1.26
Nov-08	1.27	2.1	1.1	4.35	2.82	54.04	1.23	1.30
Dec-08	1.34	1.6	0.1	3.45	2.38	41.53	1.16	1.27
Jan-09	1.32	1.1	0	2.62	1.90	43.91	1.22	1.33
Feb-09	1.28	1.2	0.2	2.14	2.06	41.76	1.17	1.28
Mar-09	1.30	0.6	-0.4	1.91	2.12	46.95	1.25	1.30
Apr-09	1.32	0.6	-0.7	1.77	1.94	50.28	1.24	1.30
May-09	1.37	0	-1.3	1.64	1.68	58.10	1.34	1.36
Jun-09	1.40	-0.1	-1.4	1.61	1.68	69.13	1.40	1.39
Jul-09	1.41	-0.6	-2.1	1.41	1.50	64.65	1.41	1.41
Aug-09	1.43	-0.2	-1.5	1.33	1.42	71.63	1.41	1.39
Sep-09	1.46	-0.3	-1.3	1.26	1.27	68.38	1.42	1.41
Oct-09	1.48	-0.1	-0.2	1.24	1.23	74.08	1.48	1.44
Nov-09	1.49	0.5	1.8	1.23	1.08	77.56	1.52	1.45
Dec-09	1.46	0.9	2.7	1.24	1.00	74.88	1.50	1.43
Jan-10	1.43	0.9	2.6	1.23	0.90	77.12	1.51	1.44
Feb-10	1.37	0.8	2.1	1.23	0.85	74.72	1.48	1.43
Mar-10	1.36	1.6	2.3	1.22	0.87	79.30	1.38	1.34
Apr-10	1.34	1.6	2.2	1.23	0.96	84.14	1.40	1.34
May-10	1.26	1.7	2	1.25	1.13	75.54	1.33	1.30
Jun-10	1.22	1.5	1.1	1.28	1.19	74.73	1.30	1.30
Jul-10	1.28	1.7	1.2	1.37	1.12	74.52	1.28	1.30
Aug-10	1.29	1.6	1.1	1.42	0.94	75.88	1.30	1.32
Sep-10	1.31	1.9	1.1	1.42	0.80	76.11	1.26	1.30
Oct-10	1.39	1.9	1.2	1.50	0.77	81.72	1.29	1.32
Nov-10	1.36	1.9	1.1	1.54	0.77	84.53	1.30	1.33
Dec-10	1.32	2.2	1.5	1.53	0.78	90.07	1.30	1.32
Jan-11	1.34	2.3	1.6	1.55	0.78	92.66	1.30	1.32
Feb-11	1.37	2.4	2.1	1.71	0.79	97.73	1.34	1.35
Mar-11	1.40	2.7	2.7	1.92	0.78	108.65	1.39	1.39
Apr-11	1.45	2.8	3.2	2.09	0.77	116.32	1.45	1.44
May-11	1.43	2.7	3.6	2.15	0.74	108.18	1.45	1.46
Jun-11	1.44	2.7	3.6	2.14	0.73	105.85	1.44	1.45
Jul-11	1.43	2.6	3.6	2.18	0.75	107.88	1.47	1.48
Aug-11	1.43	2.5	3.8	2.10	0.78	100.45	1.46	1.46
Sep-11	1.38	3	3.9	2.07	0.83	100.83	1.38	1.38

Oct-11	1.37	3	3.5	2.11	0.91	99.92	1.36	1.37
Nov-11	1.36	3	3.4	2.04	1.00	105.36	1.37	1.36
Dec-11	1.31	2.7	3	2.00	1.10	104.26	1.39	1.37
Jan-12	1.29	2.7	2.9	1.84	1.11	106.89	1.38	1.35
Feb-12	1.32	2.7	2.9	1.68	1.07	112.70	1.40	1.35
Mar-12	1.32	2.7	2.7	1.50	1.05	117.79	1.41	1.33
Apr-12	1.32	2.6	2.3	1.37	1.05	113.75	1.37	1.31
May-12	1.28	2.4	1.7	1.27	1.06	104.16	1.32	1.29
Jun-12	1.25	2.4	1.7	1.22	1.07	90.73	1.26	1.28
Jul-12	1.23	2.4	1.4	1.06	1.07	96.75	1.26	1.28
Aug-12	1.24	2.6	1.7	0.88	1.04	105.28	1.28	1.27
Sep-12	1.29	2.6	2	0.74	1.00	106.32	1.29	1.27
Oct-12	1.30	2.5	2.2	0.65	0.92	103.39	1.31	1.27
Nov-12	1.28	2.2	1.8	0.59	0.86	101.17	1.32	1.28
Dec-12	1.31	2.2	1.7	0.55	0.85	101.17	1.31	1.28
Jan-13	1.33	1.97	1.6	0.58	0.81	105.04	1.31	1.29
Feb-13	1.34	1.84	2	0.59	0.76	107.66	1.37	1.31
Mar-13	1.30	1.73	1.5	0.55	0.74	102.61	1.34	1.30
Apr-13	1.30	1.18	1.1	0.53	0.72	98.85	1.39	1.32
May-13	1.30	1.42	1.4	0.48	0.69	99.35	1.37	1.31
Jun-13	1.32	1.6	1.8	0.51	0.68	99.74	1.36	1.31
Jul-13	1.31	1.61	2	0.53	0.68	105.21	1.40	1.32
Aug-13	1.33	1.34	1.5	0.54	0.67	108.06	1.42	1.34

Appendix C: Regression Unstandardized Residuals (2002-2013)

The unstandardized residual is the actual difference between the real value of the exchange rate and the predicted value using regression.

Date	Exchange Rate	Predicted Exchange Rate	Unstandardized Residuals
Jan-02	0.88261	0.95511	-0.07250
Feb-02	0.87032	0.97896	-0.10864
Mar-02	0.87642	1.02201	-0.14559
Apr-02	0.88652	1.07242	-0.18589
May-02	0.91827	1.10724	-0.18897
Jun-02	0.95694	1.11250	-0.15556
Jul-02	0.99206	1.12019	-0.12812
Aug-02	0.97752	1.12153	-0.14402
Sep-02	0.98135	1.10044	-0.11909
Oct-02	0.98135	1.08977	-0.10841
Nov-02	1.00200	1.08788	-0.08587
Dec-02	1.01833	1.10765	-0.08932
Jan-03	1.06383	1.15940	-0.09557
Feb-03	1.07759	1.13474	-0.05715
Mar-03	1.07875	1.10400	-0.02525
Apr-03	1.08696	1.10163	-0.01467
May-03	1.15741	1.14067	0.01674
Jun-03	1.16686	1.12378	0.04308
Jul-03	1.13636	1.12771	0.00865
Aug-03	1.11483	1.11120	0.00363
Sep-03	1.12486	1.08819	0.03667
Oct-03	1.16959	1.11402	0.05557
Nov-03	1.17233	1.07260	0.09974
Dec-03	1.23001	1.11419	0.11582
Jan-04	1.26103	1.13099	0.13004
Feb-04	1.26422	1.16581	0.09842
Mar-04	1.22549	1.15604	0.06945
Apr-04	1.19904	1.14188	0.05716
May-04	1.20192	1.12289	0.07904
Jun-04	1.21507	1.14072	0.07435
Jul-04	1.22699	1.14820	0.07879
Aug-04	1.21951	1.14685	0.07266
Sep-04	1.22249	1.16808	0.05442
Oct-04	1.24844	1.17866	0.06978

Nov-04	1.30039	1.20278	0.09761
Dec-04	1.34228	1.13800	0.20428
Jan-05	1.31062	1.21622	0.09439
Feb-05	1.30208	1.18724	0.11484
Mar-05	1.31752	1.21674	0.10078
Apr-05	1.29366	1.23516	0.05850
May-05	1.26743	1.19303	0.07439
Jun-05	1.21507	1.18005	0.03502
Jul-05	1.20482	1.21490	-0.01008
Aug-05	1.23001	1.26179	-0.03178
Sep-05	1.22399	1.26157	-0.03758
Oct-05	1.20337	1.24071	-0.03734
Nov-05	1.17925	1.22054	-0.04129
Dec-05	1.18624	1.24154	-0.05530
Jan-06	1.21212	1.27306	-0.06094
Feb-06	1.19332	1.25295	-0.05963
Mar-06	1.20337	1.27014	-0.06677
Apr-06	1.22850	1.26090	-0.03240
May-06	1.27714	1.30832	-0.03118
Jun-06	1.26582	1.31344	-0.04761
Jul-06	1.26904	1.34238	-0.07335
Aug-06	1.28041	1.34495	-0.06454
Sep-06	1.27389	1.30567	-0.03178
Oct-06	1.26263	1.26077	0.00185
Nov-06	1.28866	1.25815	0.03051
Dec-06	1.31926	1.30508	0.01418
Jan-07	1.30039	1.26799	0.03240
Feb-07	1.30890	1.30589	0.00301
Mar-07	1.32450	1.33107	-0.00657
Apr-07	1.35135	1.34482	0.00653
May-07	1.35135	1.35563	-0.00428
Jun-07	1.34228	1.37363	-0.03135
Jul-07	1.37174	1.40090	-0.02916
Aug-07	1.36240	1.38668	-0.02428
Sep-07	1.39082	1.40410	-0.01328
Oct-07	1.42248	1.38666	0.03582
Nov-07	1.46843	1.39792	0.07051
Dec-07	1.45560	1.38881	0.06680
Jan-08	1.47059	1.39594	0.07465
Feb-08	1.47275	1.38017	0.09258
Mar-08	1.55280	1.38443	0.16837

Apr-08	1.57480	1.46522	0.10959
May-08	1.55521	1.48275	0.07246
Jun-08	1.55521	1.53034	0.02487
Jul-08	1.57480	1.57523	-0.00043
Aug-08	1.49477	1.51339	-0.01862
Sep-08	1.43472	1.44841	-0.01369
Oct-08	1.32802	1.30850	0.01952
Nov-08	1.27226	1.22702	0.04524
Dec-08	1.34228	1.15880	0.18348
Jan-09	1.31926	1.21536	0.10390
Feb-09	1.28041	1.17406	0.10635
Mar-09	1.30378	1.24851	0.05527
Apr-09	1.32100	1.24238	0.07862
May-09	1.36612	1.33979	0.02633
Jun-09	1.40056	1.39806	0.00250
Jul-09	1.40845	1.41273	-0.00428
Aug-09	1.42653	1.41146	0.01508
Sep-09	1.45560	1.42499	0.03061
Oct-09	1.48148	1.48325	-0.00177
Nov-09	1.49254	1.52166	-0.02912
Dec-09	1.45773	1.49968	-0.04195
Jan-10	1.42857	1.50526	-0.07669
Feb-10	1.36799	1.48172	-0.11373
Mar-10	1.35685	1.38081	-0.02396
Apr-10	1.33869	1.39522	-0.05653
May-10	1.25786	1.32591	-0.06805
Jun-10	1.22100	1.30186	-0.08086
Jul-10	1.27877	1.27973	-0.00096
Aug-10	1.29032	1.30225	-0.01193
Sep-10	1.30890	1.25642	0.05248
Oct-10	1.38889	1.29192	0.09697
Nov-10	1.36240	1.30078	0.06162
Dec-10	1.32100	1.29878	0.02222
Jan-11	1.33690	1.30102	0.03587
Feb-11	1.36612	1.34492	0.02120
Mar-11	1.40056	1.39065	0.00991
Apr-11	1.44509	1.44649	-0.00140
May-11	1.43062	1.45422	-0.02361
Jun-11	1.44092	1.44390	-0.00298
Jul-11	1.42857	1.47106	-0.04249
Aug-11	1.43266	1.46147	-0.02881

Sep-11	1.37552	1.38380	-0.00828
Oct-11	1.37174	1.35634	0.01540
Nov-11	1.35685	1.36959	-0.01274
Dec-11	1.31406	1.38635	-0.07229
Jan-12	1.29032	1.38367	-0.09335
Feb-12	1.32275	1.40280	-0.08005
Mar-12	1.32100	1.40515	-0.08414
Apr-12	1.31579	1.37335	-0.05756
May-12	1.27877	1.32234	-0.04357
Jun-12	1.25313	1.25977	-0.00664
Jul-12	1.22850	1.26107	-0.03257
Aug-12	1.24069	1.27555	-0.03485
Sep-12	1.28700	1.29235	-0.00535
Oct-12	1.29702	1.30504	-0.00802
Nov-12	1.28370	1.31888	-0.03518
Dec-12	1.31234	1.31130	0.00104