RISK IN FORECASTING CORRECT DIRECTIONAL CHANGES IN
FINANCIAL TIME SERIES

by

Mohamed Ismail Shaban

A Project Presented to the Faculty of the
American University of Sharjah
College of Engineering
in Partial Fulfillment
of the Requirements
for the Degree of

Master of Science in
Engineering Systems Management

Sharjah, United Arab Emirates

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Approval Signatures

We, the undersigned, approve the Master’s Project of Mohamed Ismail Shaban

Project title: Risk in Forecasting Correct Directional Changes in Financial Time Series

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DEDICATION

I dedicate this document to my family (Father, Mother, and my lovely Brother Shadi) who were there every step of the way who were there encouraging me throughout my education and continue to be a motivating factor in my life to achieve and reach my potentials and beyond. Their unconditional love, support, and encouragement are my inspiration to achieve and reach new horizons in my life.

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Last but not least, I dedicate this document to all the ESM Graduate program students, those who I met and those who I did not have the chance to meet, for the lovely synergy that we shared and the help we offered each other.
Abstract

Forecasting future moves of financial time series is an important task. Decision makers use different forecasting approaches. Regardless of the approach used, decision makers need to confident that the forecasting approach and methodology they use is the most appropriate one for the financial time series they are analyzing and the risk associated with it. A financial risk in this research is defined as the probability that the forecasting method will not predict the Correct Directional Change of the next periods’ move. The approach of this research aims at analyzing the error in predicting the correct directional move from period to period. The accuracy will be determined by the ability of the forecasting method to predict the correct move (up or down) of the next day, week, and month. Six forecasting methods are evaluated in this research: Naïve forecast, 14 Periods Moving Average, ARIMA, Exponential Smoothing, ARRSES and Neural Network. These forecasting methods were used to predict the closing value of the Next-Period’s move as well as its direction. A new approach is also presented in this research based on which decision makers may use to compare the forecasting accuracy and associated risk of different forecasting methods to predict the Correct Directional Change of the next periods. The use of the new approach is illustrated by applying it to four financial time series, which represent different financial markets namely: Spot Oil Price, Gold Daily Price, FTSE100, and Euro to Dollar Daily Exchange Rate. The results of the four markets indicated that using any of the six forecasting methods will have a success percentage of approximately 50% with small variation form a forecasting method to another. In addition, when comparing the six forecasting methods using the new presented approach, the 14 Periods Moving Average has proved to be the least risky forecasting method in three out of the four markets which are: Brent Spot Oil Price, Gold Daily Data, and Euro to Dollar Exchange Rate while Neural Network has proven to be the least risky in forecasting the FTSE100 stock market.

Search Terms: Risk, Forecasting Methods, Correct Directional Change
# TABLE OF CONTENTS

Abstract ........................................................................................................................................... 6

Chapter 1: Introduction ................................................................................................................... 11
  1.1 Background ............................................................................................................................ 11
  1.2 Problem Statement .................................................................................................................. 13
  1.3 Project Objectives .................................................................................................................. 13
  1.4 Significance of the Project ...................................................................................................... 14
  1.5 Project Organization .............................................................................................................. 15

Chapter 2: Literature Review .......................................................................................................... 16
  2.1 Historically Used Analysis ...................................................................................................... 16
  2.2 Studied Markets and Results ................................................................................................. 22
  2.3 Traditional Risk Definition .................................................................................................... 25
  2.4 Correct Directional Change (CDC) and Market Volatility in Literature ................................. 26

Chapter 3: Methodology ................................................................................................................ 27
  3.1 Methodology Overview .......................................................................................................... 27
  3.2 Data Collection ...................................................................................................................... 29
    3.2.1 Brent Spot Oil Price .......................................................................................................... 29
    3.2.2 Gold Daily Price ............................................................................................................... 30
    3.2.3 FTSE100 Daily Price ....................................................................................................... 30
    3.2.4 Euro to Dollar Daily Exchange Rate ............................................................................... 31
  3.3 Data Processing ..................................................................................................................... 32
  3.4 Data Forecasting and Forecasting Methods .......................................................................... 33
    3.4.1 Naïve Forecast ............................................................................................................... 34
    3.4.2 14 Periods Moving Average Forecast ............................................................................ 34
    3.4.3 Exponential Smoothing Forecast ................................................................................... 35
    3.4.4 Neural Network Forecast ............................................................................................ 35
    3.4.5 ARRSES Forecast ......................................................................................................... 36
    3.4.6 ARIMA Forecast ............................................................................................................ 37
  3.5 Error Measurement ................................................................................................................ 38
  3.6 Risk Indicator Inception ........................................................................................................ 39
  3.7 Correlation Coefficient (R) .................................................................................................. 40
  3.8 Directional Change Assessment ............................................................................................. 40
  3.9 Coefficient of Variation (CV) ............................................................................................. 43

Chapter 4: Results and Discussion ................................................................................................. 44
  4.1 Brent Spot Oil Price ............................................................................................................... 44
    4.1.1 Error Distribution for Brent Oil ....................................................................................... 44
4.1.2 Correlation Coefficients for Brent Oil ................................................................. 45
4.1.3 CDC Ratios for Brent Oil ................................................................................. 46
4.1.4 Coefficient of Variations for Brent Oil ............................................................ 47
4.1.5 Risk Indicator Results for Brent Oil ................................................................. 48
4.2 Gold Daily Price ................................................................................................. 49
  4.2.1 Error Distribution for Gold Daily Price ............................................................ 49
  4.2.2 Correlation Coefficients for Gold Daily Price ............................................... 50
  4.2.3 CDC Ratios for Gold Daily Price .................................................................... 51
  4.2.4 Coefficient of Variation for Gold Daily Price ................................................. 52
  4.2.5 Risk Indicator Results for Gold Daily Prices .................................................. 52
4.3 FTSE100 Daily Price ........................................................................................ 53
  4.3.1 Error Disruption for FTSE100 Daily Prices ................................................... 53
  4.3.2 Correlation Coefficients for FTSE100 Daily Prices ....................................... 54
  4.3.3 CDC Ratios for FTSE100 Daily Prices ........................................................... 55
  4.3.4 The Coefficient of Variation for the FTSE100 Daily Prices ......................... 56
  4.3.5 Risk Indicator Results for the FTSE100 Daily Prices ....................................... 57
4.4 Euro to Dollar Daily Exchange Rate ............................................................... 57
  4.4.1 Error Distribution for the Euro to Dollar Daily Exchange Rate ..................... 57
  4.4.2 Correlation Coefficients for the Euro to Dollar Daily Exchange Rate .......... 58
  4.4.3 The CDC Ratios for the Euro to Dollar Daily Exchange Rate ...................... 59
  4.4.4 The Coefficient of Variation for the Euro to Dollar Daily Exchange Rate ...... 60
  4.4.5 Risk Indicator Results for the Euro to Dollar Daily Exchange Rate ............... 61
4.5 Markets Over-All Results ............................................................................... 62
Chapter 5: Conclusion ......................................................................................... 63
  5.1 Summary and Conclusion ............................................................................... 63
  5.2 Future Research .............................................................................................. 63
References .......................................................................................................... 65
APPENDEX A: Brent Spot Oil Price - Errors Histograms ......................................... 68
APPENDEX B: gold Daily Price - Errors Histograms ............................................. 74
APPENDEX C: ftse100 Index – Errors Histograms .................................................. 80
Appendix D: Euro to Dollar Daily Exchange Rate- Errors Histograms ..................... 86
LIST OF TABLES

Table 1: Traditional Forecasting Method per Reference .............................................................. 17
Table 2: Studied Markets per Forecasting Method per Duration .................................................. 23
Table 3: Directional Change Cases ............................................................................................. 42
Table 4: Brent Spot Oil Price - Correlation Coefficients .............................................................. 46
Table 5: Brent Spot Oil Price - CDC Ratios .................................................................................. 47
Table 6: Brent Spot Oil Price - CV Values .................................................................................... 48
Table 7: Brent Spot Oil Price - Risk Indicator (RI) Results .......................................................... 49
Table 8: Gold Daily Price - Correlation Coefficients .................................................................. 51
Table 9: Gold Daily Price - CDC Ratios ...................................................................................... 52
Table 10: Gold Daily Price - CV Values ....................................................................................... 52
Table 11: Gold Daily Price - Risk Indicator (RI) Results .............................................................. 53
Table 12: FTSE100 Daily Price - Correlation Coefficients ............................................................ 55
Table 13: FTSE100 Daily Price - CDC Ratios .............................................................................. 56
Table 14: FTSE100 Daily Price - CV Values ................................................................................ 56
Table 15: FTSE100 Daily Price - Risk Indicator (RI) Results ....................................................... 57
Table 16: Euro to Dollar Daily Exchange Rate - Correlation Coefficients .................................... 59
Table 17: Euro to Dollar Daily Exchange Rate - CDC Ratios ....................................................... 60
Table 18: Euro to Dollar Daily Exchange Rate - CV Values ......................................................... 60
Table 19: Euro to Dollar Daily Exchange Rate Data - Risk Indicator (RI) Results ....................... 61
Table 20: Over All Markets’ Summaries per Forecasting Method Results .................................... 62
LIST OF FIGURES

Figure 1: Multi Input, Single Output Neural Network Optioned [24] ......................................................... 18
Figure 2: Brent Daily Spot Prices ............................................................................................................. 29
Figure 3: Gold Daily Prices ....................................................................................................................... 30
Figure 4: Daily Index level of FTSE 100 ................................................................................................. 31
Figure 5: Euro to Dollar Daily Exchange Rate .......................................................................................... 32
Figure 6: Brent Spot Oil – Next-Period’s Forecast using 14 Days Moving - Error Histogram .......... 44
Figure 7: Brent Spot Oil – 6th Period’s Forecast using Exponential Smoothing - Error Histogram .. 45
Figure 8: Gold Daily Price – Next-Period’s Forecast using ARIMA - Error Histogram ...................... 50
Figure 9: Gold Daily Price – 6th Period’s Forecast using Naive - Error Histogram ............................. 50
Figure 10: FTSE100 Price – Next Period’s Forecast using ARRSES - Error Histogram ..................... 54
Figure 11: FTSE100 Price – 6th Period’s Forecast using Exponential Smoothing - Error Histogram .. 54
Figure 12: Euro / Dollar Daily Price – Next Period’s Forecast using NN - Error Histogram ............... 58
Figure 13: Euro / Dollar Daily Price – 6th Period’s Forecast using Naive - Error Histogram .............. 58
CHAPTER 1: INTRODUCTION

1.1 Background

In the last decade, the global financial market has witnessed its greatest rise and its greatest fall resulting in huge financial loses, high levels of unemployment, and drastic slowdowns in several economies around the world. The risk associated with this dramatic change in the global economy is undeniable and the fact that no indications or alerts were raised before the global financial crises in year 2008 can be an indicator of the inadequacy of the currently used fundamental and technical analysis for the financial markets. During the last decade the world witnessed several wars and events such as: 9/11 Terror Attacks, Afghanistan War, Iraq War, and a Tsunami each of which could singlehandedly stop the global economical growth, yet the financial forecasts during these periods indicated a positive outlook for the global financial markets. The financial markets during the last era were driven by an excessive amount of greed that manipulated traders, companies, and even countries to enter into risky financial transactions that later will be regretted.

The market efficiency hypotheses suggests that an investor cannot achieve an excessive amount of return on any investment based on his/ her knowledge of the past information, current information, or even insider information. Moreover, the random walk theory, which implies that the market cannot be forecasted or modeled also in agreement with the market efficiency hypothesis.

A financial market is a means of funds’ transactions between lenders (usually investors with an extra amount of unutilized money) and barrowers (usually companies in need of funds). Financial markets are usually split into two types of markets: Security markets and Commodity markets.

A security market is the market were part of the ownership of a company is treaded for a market price set by supply and demand, company news, market outlook, traders expectations and the economical situation surrounding the market. The majority of the transactions in the stock markets take place between traders rather than companies and traders. The recorded transactions of a market stock including the opining price, closing price, high, low, and the traded volume are the major composition of the financial time series of a stock market.
In the Commodity markets on the other hand, goods such as oil and energy, precious and industrial metals, food, serves, and several others are traded. The dynamics of the Commodity market is similar to the Security market in terms of transactions and trades yet the only major difference is the goods traded.

For analysts, professionals, and academicians, a financial market can be modeled by the financial time series representing the historical data of market transactions. Analysts who are not keen on the fundamental analysis of a company or a market consider the market’s historical information to contain all the required information including the company performance, seasonality of the data, trending of the market, and the trading cycle. They use this data to make future forecasts and required investments decisions. The period of the forecasted data (daily, weekly, or monthly) and the length of the forecasted period depend solely on the investor interest.

Fundamentalists (analysts, economists, and scholars who believe in fundamental analysis of the financial market over technical analysis or forecasting of financial markets) are more often driven towards prediction rather than forecasting. Although to many, predictions and forecasts are very similar concepts, vital differences distinguish the two. Moreover, several practitioners and economists tend to believe in prediction rather than forecasting. Prediction is the art of subjectively reading into the future after taking into consideration all the current information and the anticipated information in the near future. A prediction cannot be replicated or regenerated and it is subjective to the expert bias and judgment. On the other hand, forecasting is the formal process of analyzing the information in an objective manner depending solely on the past and using it to read into the future. A forecast can be regenerated and it is subject to human errors in calculations, noise in data selected, and several other errors that can be measured and quantified. The forecasting process also can produce ‘a tangible result’ of the forecasted market. The intention of this research is to study the forecasting methods and the risk associated with using a forecasting method over another.

The concept of risk in financial markets has been traditionally measured by the value at risk concept (VaR). This concept can be defined as a specific expectancy percentage of value loss of an asset or portfolio for a specific period of time. Although VaR is a simple risk
indicator, it remains unimmunized to sudden market movements and volatility of data. A simpler more generic approach based on the used forecasting method is still required.

Although a financial time series can be analyzed by tick, day, week, month, quarter, or year, the period to forecast and its importance depend mainly on the investor and his /her requirements to make his/ her investment decisions. Investors who are interested in short term investments would be concerned mainly with the tick, day, and week forecasts. For investors who are interested in long term investments they would be concerned with the monthly, quarter, and yearly forecasts. In this research the daily, weekly, and monthly financial time series of several markets are analyzed and future forecasts are generated. In addition, the forecasted outputs of each method are compared to the actual closing value and the errors of each method are used to calculate the risk associated with each market in predicting the correct direction of the next period movement.

1.2 Problem Statement

The need for a risk measurement method associated with the market directional changes has presented itself. It is required to have a measuring tool for the market volatility in association with the expected (forecasted) return to assist decision makers in making a decision on the utilized forecasting methods in his / her markets.

The inconvenience of utilizing complex mathematical models and the required time to generate a satisfactory result while forecasting a financial time series is another problem that is required to be eliminated. Any forecasting method or risk evaluation method should be simple to use, easy to generate, and requires a short period of time to generate acceptable results.

1.3 Project Objectives

This research has two major objectives, which are:

1. Evaluate the accuracy of forecasting methods in predicting Correct Directional Changes of a financial time series.
2. Develop a new risk index that may be used to compare forecasting methods accuracy in predicting Correct Directional Change
1.4 Significance of the Project

Investors, traders, and financial managers of individual funds as well as corporate funds make decisions on daily basis on long term and short term investments that affects the capital of the investing party. Financial decisions such as to invest or not to invest in a company or a commodity depend mainly on analyzing the historical financial time series of a company or a commodity and forecast the expected return in the future. The expected high returns are often coupled with high risk if the odds are not in the favor of the investing party.

In this research, a new light is shed on the traditional concepts and evaluation techniques of forecasting methods. The risk in this research is defined as the probability that the forecasting method will not predict the Correct Directional Change of Next-Period’s move.

Each market is essentially unique and it has a set of characteristics that identifies it. This concept of market uniqueness is exposed in this research. In addition, measuring the risk of utilizing a forecasting method over another is a new concept especially since that the major element of the measurement is the forecasting method ability to correctly predict the directional change of the market.

This new approach can be used in evaluating forecasting methods to choose the most adequate method to forecast a specific market. This new risk indicator is expected to assist financial managers and decision makers to make decisions not driven only by expected returns but also by the associated risk with the used forecasting methods. Moreover, the new risk indicator can be utilized in association with any other evaluation method required.
1.5 Project Organization

This project is divided into 5 chapters. Each chapter contains the following:

**Chapter 1: Introduction**
- Provides an introduction to the project and it sets the expectations for the rest of the research. This chapter includes a brief background about the topic, the problem studied in this research, the research objectives, and the importance and significance of the research.

**Chapter 2: Literature Review**
- Highlights the historically used forecasting methods to forecast the financial markets.
- Demonstrates some of the results of previously studied markets.
- Examine the historical definition of risk.
- Introduces the Correct Direction Change concept.

**Chapter 3: Methodology**
- Explains the data collection process and identifies the examined markets, namely: Brent Spot Oil, Gold, FTSE100, and Euro to Dollar Daily Exchange Rate.
- Identifies the data processing steps and the related importance of this stage.
- Demonstrated the forecasting methods used in this research including the related mathematical models.
- Explains the error measurement method used in this research and its importance to synthesize the new Risk indicator.
- Explore the inception of the new Risk Indicator and the involved factors of the forming it.

**Chapter 4: Results and Discussion**
- Highlights the findings per market per forecasting method per period in terms of error, Correlation Coefficient value, Directional Change value, and the Coefficient of Variation value.
- Suggests the least risky method to use per market and display the ranking of the forecasting methods riskiness compared to each other per market.

**Chapter 5: Conclusion**
- Provides conclusion notes, remarks, and highlights about the research.
- Proposes thoughts and ideas for further research.
2.1 Historically Used Analysis

Historically, the fundamental analysis and the technical analysis were widely used in financial markets; however, other researchers have tended to use traditional forecasting methods as well. The fundamental analysis is the analysis of the overall wellbeing of the company (in terms of performance, market share, resources utilization, and several other elements) and the economy surrounding the company (in terms of GDP growth, stability, prosperity, employment level, inflation, and currency exchange rates). On the other hand, the technical analysis depends mainly on analyzing the prices of stocks and indexes, trading volume, open and close values, and high and lows of the trading period. Technical analysis depends mainly on technical indicators and data patterns. The technical indicators are a formulated set of indicators (leading or lagging indicators) used by analysts to predict the movement of the market and to form a trading strategy (usually identifying the levels of the call or put options). The technical analysis is a quantitative approach where the end result of a technical analysis is a number or set of numbers that can be recalculated by different analysts given the same set of information. For fundamental analysis, each analyst can have a different view of the same company. Technical analysts assume that any significant financial information about the company or the economy would be reflected in the stock’s behavior in all of its aspects hence a fundamental analysis is not really required to analyze and forecast the future of the company’s stock movement. The other part of the technical analysis is the identification of the data patterns and the associated implications of these patterns on the future of the stock. Nevertheless, technical indicators have an essential fault, which is the lack of predictive capability as technical indicators usually recognize and follow a trend after it starts.

Some of the traditional forecasting methods utilized in several previous research are: Naïve forecast, ARIMA/ARMA, GARCH/ARCH, Neural Network, Support Vector Regression, Moving Average Variance (MAV), and Ordinary Least-Squares (OLS). Table (1) summarizes the scientific articles, researches, books, journals, and resources used in this research per traditional forecasting method used.
A few of the thoroughly examined forecasting methods in the literature are: Neural Networks (NN), ARCH/ GARCH, ARIMA/ ARMA, and Exponential Something.

Neural Network is a mathematical model that has the capability to model and predict any relationship between a set of input data to generate an output result that is considered to be an expected continuation of the data pattern and an expected output of the system. The construction of a Neural Network consists of several stages, which are: selection of input data, data processing, sensitivity analysis, model construction, and training algorithm [21]. In addition, building a neural network is based on a lot of experimentation and a trial and error approach. A Neural Network is a combination of three layers: The input layer, the hidden layer, and the output layer. The processing and the relay of data in the neural network is mainly carried by neurons or nodes by means of nonlinear transfer functions while the majority of the computation is taking part in the hidden layer or layers , called the processing unit [22].
Neural Networks have different designs based on the requirements of the user and such diversification in requirements result in different number of inputs neurons, hidden layers’ number, weights and specifications of transfer functions and several others. The average recorded number of hidden layers within a network is between one or two while the maximum-recorded amount of used hidden layers is 42 layers [1]. The main concern when the number of inputs and the number of hidden layers in a Neural Network increases is the over fitting and over training errors.

As the designs of Neural Networks differ from one case to another, the type of Neural Network also changes. Some of the available identified types of Neural Networks are: Feed Forward Neural Network, Fully Recurrent Neural Network, Hierarchical Neural Network and several others. It is claimed that 60% of the researchers have used Feed Forward Neural Networks (FFNN) and Recurrent Networks [23]. Figure 1 represents a simple visualization of a Neural Network with multi inputs, single output model.

![Figure 1: Multi Input, Single Output Neural Network Optioned](image)

The Artificial Neural Networks were considered widely due to its suitability to forecast nonlinear time series, which is according to [14] the nature of the financial time series. The perception of nonlinearity of financial data time series was also adopted by [24] who claims that the stock markets follow non-linear behavior and the usage a Neural Network model that follows a nonlinear learning and smooth interpolation would have a competitive edge over the rest of computer forecasting based systems.

The expected high performance of Neural Networks is anther reason behind its wide usage in the academic world where sometimes the performance of Neural Networks is over
estimated. In his analysis, [1] has indicated that several researchers have overestimated the Neural Network capabilities and some others have underestimated the Neural Network performance in financial markets, yet a more satisfactory conclusion was archived by non-biased researchers who suggested that a Neural Network outperforms traditional forecasting models in particular situations and markets implies that no single forecasting method dominates all others.

Another reason for researchers to use Neural Network models is the absence of needs or requirements to know the relationship between the inputted variables. This is mainly due to the Neural Network ability to identify the independent and dependent variables to create the required output of the network [1].

On the other hand, it was pointed out that the potentials of Neural Networks are not reached yet and Neural Networks output needed to be used in combination with other methods as per previous studies. However, several researchers have used Neural Networks in combination with other forecasting methods or with other Neural Networks. Neural Networks have their own drawbacks and it has been suggested that a nonlinear combination of forecasts will provide a great improvement for the forecast [9].

The second forecasting method that is used is the ARCH / GARCH family of linear forecasting. ARCH is an abbreviation for Auto-regressive Conditional Heteroscedasticity while GARCH is an abbreviation for Generalized Auto-regressive Conditional Heteroscedasticity. The inception of the ARCH/GARCH forecasting methods started in 1982 with the introduction of ARCH by Engle who is considered the father of this forecasting model and all its subsequent modifications and improvements. The assumption of the initial model of ARCH is that: time series and financial series are of constant variance, which helped in simplifying the modeling of these markets. The ARCH model was received well among researchers as it has a combination of desired attributes such as: a linear model that can handle nonlinearity of the data, a simple mathematical model that can be used, and a model that can eliminate the clustering of errors [12].

The fundamental assumption that times series are of constant variance was challenged with the introduction of GARCH model that used the conditional variance as a function of the past error and a conditional variance that changes overtime [11]. The newly modified concept has allowed the model to be utilized further in measuring the volatility of financial markets as
the interest of financial markets have shifted to also question about the error according to [12].

Another advantage of the GARCH/ARCH model is the model flexibility to determine the best weights for its objective function to achieve the forests [12]. As volatile times trend to cluster with high autocorrelation between the data, having equal weights among past events is irrational and it is more logical that more recent events must have higher weight.

Although the ARCH and the GARCH methods are part of the same family of forecasting, researchers believe that these two models should be separated as the introduction of GARCH came to improve the ARCH model [8]. The GARCH model is basically a weighted average of past squared residuals and it has proven to be successful in predicting conditional variances. GARCH (1, 2) means the following: the 1st number (1) refers to the number of autoregressive lags and the 2nd number (2) refers to the number of moving average lags [12].

Although GARCH model came to correct the ARCH model, yet this model has its own drawbacks, which are:

1. The model depends mainly on the magnitude, and positivity or negativity of unanticipated excess returns determines the feature of volatility while it was noted that the tendency for negative innovations to generate volatility in future periods compared with positive innovations has the same magnitude (leverage effect).
2. The limitation on the model parameters that forces the estimated variance to remain non-negative.
3. The interpretation of the “persistence” of the stocks to the conditional variance [8]. Also it is indicated that the ARCH/ GARCH models have ignored any related information on the direction of returns and these models have focused only on the magnitude of the returns.

The third commonly mentioned forecasting method in the literature is the ARMA/ARIMA forecasting family. ARMA is an abbreviation for Autoregressive Moving Average model while ARIMA is an abbreviation for Auto Regressive Integrated Moving Average model. As the names indicate, this family is based mainly on two fundamental linear concepts, which are: auto regression and moving average. It is notices that this model is a
linear combination of several other forecasting methods and ARIMA is the generalized and the most outer band of linear forecasting methods.

One of the ARIMA model characteristics is its dependency on last periods’ values and past periods’ errors as well in a linear formulation. It was observed by [25] that any ARIMA model is shaped by the inputted data to that model and each model will have a different structure accordingly. Another characteristic of the ARIMA model is its ability to model nonlinear models such as Random Walk theory [26] and several other models. Moreover, ARIMA model can be a short memory or a long memory model based on the data structure and the inputted objective function parameters [5]. The ARIMA model came to complement and correct to the ARMA model to count for nonlinearity and seasonality effect [5].

The fourth forecasting family is the Exponential Smoothing family, which is a special case of the ARIMA family. The sudden movement of the market is recorded and reflected in a smoothing factor that affects the next period forecasting [18] [19]. The logic behind this family is simple as it behaves as a tracking signal to the market where the error of the previously forecasted period is reflected in the new forecast. A major drawback for this family is the reaction to sudden sharp drops or peaks in the market forecasted as the entire system will require a period of time to re-establish its balance [18] [19].

Few researchers have observed that each forecasting family had several strength and weakness, due to that they have suggested to use a combination of forecasting models to overcome weakness and drawbacks of single forecasting method. The type of the combination of forecasting methods (linear or non linear combination) was also studied and it has been suggested that the basic evaluation of a combination methodology should take into consideration:

1- The ability of a model to handle and produce broad features of data
2- The combination methodology should not do worse than individual forecasting methods used in terms of Root Mean Squared Forecast Error (RMSFE) and Mean Absolute Forecast Error (MAFE) [9].

Therefore, Artificial Neural Network (ANN) has several advantages over the linear combination methods, few of them are: ANN has the capability to predict the relationship between the different forecasting methodologies whether linear or non-linear relationships
and ANN has the capabilities to turn-off one of the forecasting methods in favor of the other which is undoable by any “linear combination methodology [9]. It has been suggested that a nonlinear combination of forecasts using ANN can be a great improvement over traditional linear combination methods.

2.2 Studied Markets and Results

Several markets were studied covering both Security markets and Equity markets as well. The markets were studied in different periods of time and occasionally different studies have overlapped and analyzed the same market in the same period or in a part of the same period. The duration of recorded periods varied from as little as 5 months [25], 3 years [8], 5 years [7], 9 years [4], 18 years [9][10], up to a maximum of 26 years [25]. Also the type of selected data varied from 15 minutes data [5] to daily data (majority of reviewed researches and papers). It was noted that the majority of the papers observed under this literature review did not utilize the data as is and some data processing took place before inputting the data into the forecasting methods. These processes varied from eliminating non-trading days, elimination of seasonality effect, removal of trends, and removal of outliers’ data.

Table 2 summarizes the studied markets under this review of literature per forecasting method per duration.
<table>
<thead>
<tr>
<th>Markets / Stock/ Industry</th>
<th>Reference</th>
<th>Forecasting Method</th>
<th>Duration</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>[14]</td>
<td>Feed Forward Neural Network</td>
<td>(9 Years)</td>
</tr>
<tr>
<td></td>
<td>[16]</td>
<td>Neural Network</td>
<td>January 1982- December 1993 (12 Years)</td>
</tr>
<tr>
<td>SMI</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DJIA</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DAI</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>FTSE100</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>NASDAQ</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>BES</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Stock Exchange of Singapore (SES)</td>
<td>[15]</td>
<td>Feed Forward Neural Network, Genetic Algorithm</td>
<td>August 1998- January 2000 (1.5 Years)</td>
</tr>
<tr>
<td>Canadian Stock Market</td>
<td>[1]</td>
<td>Neural Network, Ordinary Least Squares (OLS), and Logistic</td>
<td>1983- 1993 (10 Years)</td>
</tr>
<tr>
<td>Markets / Stock/ Industry</td>
<td>Reference</td>
<td>Forecasting Method</td>
<td>Duration</td>
</tr>
<tr>
<td>---------------------------</td>
<td>-----------</td>
<td>--------------------</td>
<td>----------</td>
</tr>
<tr>
<td>German Market</td>
<td>[27]</td>
<td>Structural Vector Autoregressive models</td>
<td>1963-1999 (36 Years)</td>
</tr>
<tr>
<td>Saudi Market</td>
<td>[28]</td>
<td>GARCH</td>
<td>February 1985- April 2000 (15 Years)</td>
</tr>
<tr>
<td>U.S. Dollar Versus British Pound, the German Mark, the Japanese Yen, and the Swiss Franc</td>
<td>[13]</td>
<td>Neural Networks</td>
<td>(32 Months)</td>
</tr>
<tr>
<td>West Texas Intermediate Crude Oil Spot Prices (WTI)</td>
<td>[29]</td>
<td>OECD</td>
<td>January 1992- April 2003 (11 Years)</td>
</tr>
<tr>
<td>Industry Production in Germany</td>
<td>[30]</td>
<td>Leading Indicators</td>
<td>208-2009 (1 Year)</td>
</tr>
<tr>
<td>IBM Stock</td>
<td>[31]</td>
<td>Loss Function/ Volatility</td>
<td>1993-2003 (10 Years)</td>
</tr>
</tbody>
</table>
Some of the completely contradicting observations recorded on the examined markets in table 2 came from the Canadian and the Singaporean stock markets were:

- For the Canadian Stock Market [1]
  - Neural Network has under performed against Naïve forecast for short period of time.
  - Neural Network has outperformed the Naïve forecast on the long horizon of time.
  - Fundamental Analysis also adds a value to the forecasting process while using Neural Network.
  - It was also observed that the Neural Network did not reach its maximum potentials and a combination with other methods is highly recommended.

- For the Stock Exchange of Singapore (SES)
  - Neural Network had a forecasting accuracy as high as 81%
  - The best time horizon to use a Neural Network was for a 1-Day period forecast

Such contradiction is clear proof that no single forecasting method can have the same performance and the same accuracy in all markets studied. It is also shows that no single forecasting method outperforms all other forecasting methods and the performance of a forecasting method is mainly based on the forecasted market.

2.3 Traditional Risk Definition

Risk, in its most basic and general definition can be defined as a measurable uncertain event that may have a positive or a negative effect on achieving an objective [34]. For financial markets and portfolios, risk can be defined as losses or reduction of expected returns of a financial transaction. The risk in financial markets ignores the possibility of positive outcomes and ‘pleasant surprises’ as it only focus on losses.

The risk in financial markets has been usually quantified by Value at Risk (VaR) model. The unique intertwine between risk and the monetary value is an important characteristic and a main drive to create methods to quantify and calculate risk. To calculate the VaR, several methods are available such as: Monte Carlo, Variance- Covariance, and Historical Simulation [3]. Although VaR is a widely utilized risk measurement method, its performance and ability to apprehend sudden and volatile movements is questionable at best [3].
Another method to calculate the financial risk is to identify a loss function for the financial transaction. Loss function identifies mainly how much a loss would be expected and on what period. This loss is measured per forecasting model as different forecasting models provides different forecasting results. The errors of this loss function is often measured and analyzed using the Mean Squared Error (MSE) to further improve the loss function prediction capabilities [35].

A third measure of financial risk is the Beta (β). Beta is a relative risk indicator that measures the riskiness of a stock in a market to the entire market using the entire market as a benchmark. In the measurements of Beta, the covariance and the variance are calculated for the stock compared to the market. The value of Beta can be less than 1 or greater than one (that depends mainly on the volatility of the stock examined against the volatility of the market). If the stock has a higher volatility than the market then the calculated Beta will be higher than one and vice versa.

As the concept of Beta depends on relevancy, a violet stock in a violet market will have a similar Beta of a stable stock in a stable market. It is clear that such a risk measurement method cannot be a real representative of risk and will not provide an absolute risk rating of an investment [36].

2.4 **Correct Directional Change (CDC) and Market Volatility in Literature**

The Correct Directional Change (CDC) has several definitions some of which are related to volatility while other are related to profitability. As defined by [18], Correct Directional Change is a method used to examine if the direction of the forecast and the actual change matches. For [22] the CDC is used mainly as a statistical tool to measure the accuracy of a forecasting method.

The Correct Directional Change concept is important as several future contracts of commodities and currencies are being traded on expectations of market movements and the same applies to the stocks and company shares. A major disadvantage of the Correct Directional Change was highlighted with the low correct percentages [40%- 60%] recorded while forecasting currency exchange rates in [22].
CHAPTER 3: METHODOLOGY

3.1 Methodology Overview

In this research, six forecasting methods are analyzed, these forecasting methods are: Naïve forecast, 14 Periods Moving Average, Exponential Smoothing, Neural Network, Adaptive-Response-Rate Single Exponential Smoothing (ARRSES), and Auto Regressive Integrated Moving Average (ARIMA). Four different markets were also analyzed in this research, which are: Brent Spot Oil, Gold Daily, FTSE100, and Euro to Dollar Daily Exchange Rate. These four markets were selected as samples form the Security market and the Commodity market.

The daily, weekly, and monthly closing data of each market was obtained and the Next-Period forecasts as well as the 6th Period forecasts were generated. The errors of these forecasts were compared to the actual closing value changes and these results were used later in creating the new Risk Indicator. The Correct Directional Changes of the forecasted closing values and the actual closing values were identified. The Correct Directional Change concept is used to include the movement of the market and the volatility of the data in the newly proposed Risk Indicator. The Coefficient of Correlation of each forecasted data was measured as well against the actual closing values. The Coefficient of Variation was used in this research as part of the newly formulated Risk Indicator. The Coefficient of Variation had been used before in formatting many risk concepts and equations yet the use of the Coefficient of Variation was modified for the purpose of this research. The last stage of this research was to measure the riskiness of each forecasting method per market per period and rank them accordingly.
The research methodology followed in this research can be displayed and summarized as follow:

**Data Collection**
- Brent Spot Oil
- Gold Daily Price
- FTSE100 Daily Price
- Euro to Dollar Daily Exchange Rate

**Data Processing**
- Elimination of Non Trading days
- Identification of weekly and monthly data

**Closing Values Forecast**
- Naive
- 14 Periods Moving Average
- Exponential Smoothing
- Neural Network
- ARRES
- ARIMA

**Error Measurement**
- Delta of Actual
- Delta of Forecasted

**Risk Indicator Inception**
- Correlation Coefficient (R)
- Directional Change Assessment
- Coefficient of Variation (CV)
3.2 Data Collection

For the purpose of this research, data from the Commodity market as well as the Security market were selected. The selected data samples from the Commodity market and the Security markets are: Brent Spot Oil price, Gold Daily price, FTSE100, and Euro to Dollar Exchange Rate.

The data was captured and analyzed for the period of late year 2000 till early 2012; however, 2920 trading days (365 Days *8 Years) were selected to perform the forecasting and the related analysis. The data reflects the closing prices of the trading periods.

3.2.1 Brent Spot Oil Price

Oil prices have been increasing over the last 8 years. Nevertheless, the oil prices did not increase linearly; they witnessed a rapid incline in the years 2006-2007 till it peaked during the early 2008. By the end of 2008, as the financial crisis hit the world’s economy, the oil prices dropped sharply. By the early 2009, the oil prices have started to recover yet it did not fully recover to reach the peak it achieved on year 2008. Figure 2 demonstrates the daily Brent Oil Spot prices.

![Brent Spot Price Data](image-url)
3.2.2 Gold Daily Price

In addition to oil market, gold market will also be studied as a part of the Commodity market. Gold Daily price’s trend indicates that the gold market has sustained an up trending pattern over the last 8 years. Also, the data reveal that the global recession in year 2008 had a limited effect on the gold prices. Moreover, the recovery time for the gold market was remarkable as it resumed its previous incremental trend in less than 6 months after the economical crises. Figure 3 demonstrates the Daily Gold prices.

![Figure 3: Gold Daily Prices](image)

3.2.3 FTSE100 Daily Price

The FTSE 100, is an index of the biggest 100 companies in London Stock Exchange Market in terms of capitalization. Its data is used as a sample of the Security markets. The data obtained show that the market had reached its lowest on the 3rd of March 2009 under the effect of the global economical crises. The market fluctuated between a lower band of 3000 index points and an upper band of 7000 index points. Figure 4 shows the daily index point level of FTSE100.
3.2.4 Euro to Dollar Daily Exchange Rate

The Euro to Dollar Daily Exchange rate is the last sample of data collected for the purpose of this research. The exchange rate of the Euro to Dollar fluctuates between 0.8 USD and 1.6 USD. A more volatile trend presents itself in the years follow the Global Economical Crises as both currencies were considered the most traded and used world wide. The data obtained from the European Central Bank. Figure 5 shows the Daily Exchange Rate between Euro and Dollar.

Figure 4: Daily Index level of FTSE 100
The selected samples of the four different markets represent the daily closing value of the selected markets. These markets had 5 days trading and 2 days weekend in addition to several holidays that may differ from a market to another, therefore a data processing step was required to unify the data structure of the selected markets. The data collected from the four markets went through 2 main stages of processing: the first one is eliminating the non-trade days and the second one is grouping of weekly and monthly data.

The non-trading days were eliminated (including weekends, holidays, public holidays, missing data, and non recorded days). The purposes of such elimination are: to guarantee the continuity of data flow, unifying the number of trading days, elimination of undesired interruption to forecasting methods, and increasing the accuracy of the forecasting methods. The elimination on non-trading days has resulted in obtaining 2920 trading days for each of the four selected markets.

The second stage of data processing was: identifying the weekly and monthly data out of the daily data for each market. This stage was performed after the first stage, which may
result in mismatches between the reported weekly and monthly closing prices by other researchers and the obtained weekly and monthly closing prices in this research. A trading week is defined in this research by 5 days of trading. The weekly price of a market is the fifth day’s closing price. A trading month is defined by 25 trading days. The monthly price of the market is the twenty-fifth day’s closing price.

3.4 Data Forecasting and Forecasting Methods

Six forecasting methods were used for the purpose of this research. These forecasting methods are a combination of traditional forecasting methods and computer based forecasting method. The selection of these forecasting methods was a direct result of the extensive literature review. The traditional forecasting methods used are: Naïve, 14 Periods Moving Average, Exponential Smoothing, Adaptive-Response-Rate Single Exponential Smoothing (ARRSES), and Auto Regressive Integrated Moving Average (ARIMA). The computer based forecasting and modeling method used in this research is the Neural Network (NN). The selected forecasting methods cover linear and nonlinear forecasting mathematical models.

The previously mentioned selected forecasting methods were used to forecast the Next-Period closing price and the 6th Period closing price for the daily data, weekly data, and the monthly data. The total number of forecasts for each market is 36 forecasts. The final count of forecasts for this research is 144 forecasts.

The purpose of forecasting the next period is to examine the forecasting methods’ capabilities to adjust and modify forecasts in the presence of a sudden change in the market or if the market experienced a volatile behavior. In addition, forecasting the Next-Period is used to serve the short-term traders who are interested in short term investments. Forecasting short-term periods is considered as a popular choice among researchers as it is widely believed that the longer the forecasted period the poorer the accuracy and the higher the error of the forecast.

The 6th Period forecasts were generated to examine if the market behavior/ reaction would change or adjust if a 5 trading periods would pass on an event. The generated forecasts are also used to identify which of the forecasting methods can react and forecast changes on a longer period of trading periods.
The models of the forecasting methods used in this research are explained in the following sections.

3.4.1 Naïve Forecast

The Naïve forecast is considered the simplest forecasting method chosen for this research. The forecast depends mainly on the previous period’s actual closing value. The Naïve forecast follows the previous period’s actual closing value regardless of the market volatility, sudden changes, droops, fluctuation, and trending. This model uniqueness comes as a result of its simplicity and exotic behavior where it considers the market data as random and the best way to forecast the market is to assume that the market will behave the same in the current period as it did in the last period. Also, the Naive forecast is usually done for a short period of time. It is believed that the Naïve forecast performance output increases as the market stability increases.

3.4.2 14 Periods Moving Average Forecast

The 14 Periods Moving Average is a simple moving average of the last 14 periods actual closing prices with out modification or weight factors of the previous periods’ data. The 14 Periods Moving Average is a sample of a linear model of a forecasting technique. The result of the averaging of the last 14 periods is a mean value that serves as a forecast for the next period. The forecasting method can be easily represented in the following formula:

\[
14 \text{ Periodes Moving Average} = \frac{P1 + P2 + P3 + \ldots + P14}{14}
\]

The closing prices of the previous periods are captured in the new forecast of the coming period, which may result in a negative or a positive effect on the forecast. The negative effect may rise from the fact that the model will not adjust its forecast result as rapid as required if the market experienced changes. An example of the negative effect would be the process of forecasting the beginning of an up trending period following a down trending period. The down trending period will affect the forecast and it will indicate that the market is experiencing a down term while it is actually experiencing an up trend.

On the other hand, the 14 Periods Moving Average can minimize the effect of periodic changes if the pattern represented itself in the data. The 14 Periods Moving Average is a commonly used tool in the financial forecasting in addition to the 3 days moving average, and the 5 days moving average.
3.4.3 Exponential Smoothing Forecast

The Exponential Smoothing depends mainly on the previous period closing price and the previous period forecast with a weight factor for each to generate the next period forecast. The forecasting method can be represented by the following formula:

\[ ES = \alpha \times \text{Previous Period Closing Value} + [(1 - \alpha) \times \text{Previous Period Forecast}] \]  \hspace{1cm} (2)

where:

\(\alpha\) is a smoothing factor

and \(0 < \alpha < 1\).

Two important factors affect the accuracy of the forecast, which are: the initial forecast value and the smoothing factor. The initial forecast value was considered to be the same as the previous period actual closing value which categorizes this model as Brown's Simple Exponential Smoothing model [20]. On the other hand, the smoothing factor was chosen to be 0.8 based on trial and error where factors of 0.2, 0.3, 0.5, and 0.8 where examined however the 0.8 factor had given the best accuracy of them all. A smoothing factor of 0.8 means that 80% of the new forecast depends mainly on the previous period’s closing value and 20% of the new forecast depends on the previous period forecast.

The method is called exponential due to the fact that the forecast results dependence will be greater on historical data every time the forecast process is performed. Nevertheless, the Exponential Smoothing is considered as a linear model of a forecasting technique. Exponential Smoothing was historically used in different forms, some of them are even more advance than the simple exponential smoothing such as the double exponential smoothing and the triple exponential smoothing [20].

As a forecasting method that depends mainly on historical data, Exponential Smoothing is still countering the problem of proper time reaction to changes in the market and this problem remains a vital threat to the model’s forecasting capabilities.

3.4.4 Neural Network Forecast

Neural Network, commonly called Artificial Neural Network to differentiate between the mathematical model and the human based system, is a forecasting and modeling computer based method that adapts the input data and identifies the relationships between them. In
general a Neural Network consists of 3 layers: the input layer, the hidden layer and the output layer. The noise associated with the input data can reduce the effectiveness of the Neural Network capability to predict the relationships and identify the patterns between the input data, therefore the input data will go through a normalization process before modeling and training the neural network. The number of hidden layers, the number of inputs to the Neural Network, and the objective function of the network also play important factors in the accuracy of produced forecasts. The purpose of this research is not to create the optimum neural network to predict each market movement rather the purpose of it is to examine the effectiveness and simplicity of using a Neural Network in forecasting a market movement and the associated risk with using such method.

For the purpose of this research, a Feed Forward Neural Network is created and utilized. The first step in the process is to input the data into the Neural Network and to choose the amount of the data specified for training and the amount of data specified for testing and forecasting. The generally recommended split of 70:30 will be applied in this research (70% of the data for training and 30% of the data for testing, a different split of the data may result in overfitting or poor training for the Neural Network). For the training phase, the back propagation method will be applied where an error from the output layer will be injected back to the input layer during the training period to improve the accuracy of the forecasted results. The testing phase comes after the training phase where the Neural Network examines the pattern it recognized during the training period and applies them during the testing period. The Neural Network design and operation is considered as a nonlinear model and it is mainly a computer-based method that involves high volume of mathematical calculation.

### 3.4.5 ARRSES Forecast

Adaptive-Response-Rate Single Exponential Smoothing (ARRSES) model depends mainly on the previous period closing value, the previous period forecast, the error between the forecasted value and the actual value, a smoothing factor, and error correction factor (tracking signal). The major advantage of this forecasting method is its capability to modify the error correction factor (tracking signal) based on the produced error in the previous period forecast. ARRSES model can be presented by the following formulas [20]:

\[ y_t = \alpha \cdot \text{Close}_{t-1} + (1-\alpha) \cdot y_{t-1} + \delta_t \]

\[ \delta_t = y_t - \text{Close}_{t-1} \]

\[ y_t = y_t - \delta_t \]
ARRSES = α × Previous Period Closing Value + (1 − α) × Previous Period Forecast

where:

Error (Ei) = Period Closing Value − Forecast Closing Value
(4)
Smoothed Error(Et) = β × Ei + (1 − β) × Previous Period (Et)
(5)
Absolute Smoothed Error (Mt) = β × ABS(Ei) + (1 − β) × Previous Period (Mt)
(6)
α = ABS (Previous Period $\frac{E_t}{M_t}$)
(7)

And:

β is a smoothing factor = 0.8 (selected by trial and error)

α is a weight factor / error correction factor / tracking signal

The ARRSES is an advanced form of the Single Exponential Smoothing with the capability to adapt to the market changes in a timely adequate manner. The majority of the researchers overruled this method and it was considered as an inferior forecasting method to others; however, this method was selected for this research due to the simplicity of the model and adoptive capabilities.

3.4.6 ARIMA Forecast

The Auto Regressive Integrated Moving Average (ARIMA) model depends on combination of previous period closing prices as well as the errors between forecasted and actual previous period closing prices. In general the model is referred to as ARIMA $(p,d,q)$ where $p$ represent the autoregressive term, $d$ represent the integrated term, and $q$ represent the moving average part of the model. Different combinations of the three previous elements create different models; however, the selection of each term depends mainly on the data. Also, the results obtained from the ARIMA model depends on the confidence interval required of the forecast. For the purpose of this research the ARIMA model used is the ARIMA $(8, 1, 10)$ with a confidence interval of 95%.

Different authors have different mathematical models for the ARIMA, yet the used mathematical model for this research is obtained from [37] and it is as follow:

\[ Y_t = (1 - B)^d (1 - B^e)^p X_t - \mu \]  
(8)

\[ \phi(B)\Phi(B^e)Y_t = \theta(B)\Theta(B^e)Z_t, \quad Z_t \sim N(0, \sigma^2) \]  
(9)

\[ \phi(z) = 1 - \sum_{i=1}^{p} \phi_i z^i, \quad \Phi(z) = 1 - \sum_{i=1}^{p} \Phi_i z^i \]  
(10)

\[ \theta(z) = 1 + \sum_{i=1}^{q} \theta_i z^i, \quad \Theta(z) = 1 + \sum_{i=1}^{q} \Theta_i z^i \]  
(11)
where:

\[ p \] is the order of the autoregressive part of the model.
\[ q \] is the order of the moving average part of the model.
\[ d \] is the differencing order of the model.
\[ D \] is the differencing order of the seasonal part of the model.
\[ s \] is the period of the model.
\[ P \] is the order of the autoregressive seasonal part of the model.
\[ Q \] is the order of the moving average seasonal part of the model.

The purpose of this research is not to choose the optimum ARIMA model to forecast the examined markets. The purpose of this research is to examine the capability of the forecasting method in predicting the changes of the market direction and its riskiness. The ARIMA model is an example of linear model forecasting technique.

### 3.5 Error Measurement

The error measurement is an essential part of measuring the accuracy of a forecasting method. Traditionally, researchers tended to use error measurements such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), the Mean Squared Prediction Error (MSPE) and several others; however, for the purpose of this research a different error measurement method was used. The forecasting error in this research is defined as the difference between the delta of actual and delta of forecast over the delta of actual. This forecasting error is modeled in the following equation:

\[
\text{Forecasting Error (Fe)} = \frac{(\Delta \text{Actual} - \Delta \text{Forecast})}{\Delta \text{Actual}} \tag{14}
\]

where:

\[ \Delta \text{Actual}: \text{The difference between the Actual Current Closing value and the Actual Closing Value of the required period (previous period or the 6th period values)} \]

\[ \Delta \text{Forecast}: \text{The difference between the Forecasted Current Closing value and the Forecasted Closing Value of the required period (previous period or the 6th period values)} \]

The purpose of using the difference between the actual closing value and the forecasts is to examine the proportion of change between the actual and the forecast. This error formula examines
the forecasting method reaction to sudden changes in the market and the proportion of which an adjustment takes place in the forecasting results.

The resulting Forecasting Error (Fe) will be utilized in forming a new proposed Risk Indicator that is built around the market movement and the Directional Change of the actual closing prices compared to the forecasted closing prices.

### 3.6 Risk Indicator Inception

The new proposed risk indicator in this research is a combination of three terms that determine the riskiness of a forecasting method compared to another in forecasting a certain market. This indicator is a comparative indicator and it has no unit to quantify it. The new Risk Indicator can be summarized in the following mathematical model:

\[
\text{Risk Indicator (RI)} = \left( \frac{1}{R} \right) \times \left[ (P \times CV_{+1}) + ((1 - P) \times CV_{-1}) \right]
\]  

(15)

where:

- **R**: The Correlation Coefficient between actual and forecasted closing prices
- **P**: The Probability of Correct Directional Change
- **1-P**: The Probability of Wrong Directional Change
- **CV+1**: The Coefficient of Variation for Correct Directional Changes
- **CV-1**: The Coefficient of Variation for Wrong Directional Changes

The New Risk Indicator depends mainly on studying the direction of the forecast against actual closing values that can be identified from using the Correlation Coefficient (R) and the Probability of Correct Directional Change (P). In addition, the concept of the Coefficient of Variation (CV) in identifying the risk is modified for the purpose of this research as the Coefficient of Variation for correctly identified directional movement days were measured separately from wrongly forecasted directional movement days.

The New Risk Indicator is a combination of three terms. The combination of these three terms that results in the lowest value on the Risk Indicator is the favorable combination. These three terms are:
1/R: The higher the positive Correlation between the forecasted closing prices and the actual closing prices, the lower the risk indicator.

P*CV: The higher the probability of CDC and the smaller the CV, the lower the risk indicator.

(1- P)*CV: The lower the probability of WDC and the smaller the CV, the lower the risk indicator.

In general, a forecasting method is less risky than others if it scores lower than them using the proposed risk indicator. The elements of this risk indicator are explained in details in the following sections.

It is worth noticing that this new Risk Indicator takes values greater than zero and negative values indicate high risk of the forecasted method.

3.7 Correlation Coefficient (R)

The Correlation Coefficient (R) is used to indicate the strength of the relationship between the movement of the actual and forecasted closing prices of a market. The Correlation of Coefficient ranges from 1 to -1 with 1 being the preferred result as it indicates that both the forecasted closing value and the actual closing value have perfect positive relationship in terms of direction and value. While -1 indicates that the forecasted value and the actual value have a negative relationship in terms of direction and value. A correlation coefficient value of 0 is also not preferred in this research as it indicates that the relationship between the actual closing value and the forecasted closing value is indeterminate.

The Correlation Coefficients for each of the six forecasting methods results and the actual closing values for all of the 4 markets were calculated for each of the examined cases (the Next-Period forecast and the 6th Period forecast).

3.8 Directional Change Assessment

The directional change assessment is usually used to describe the volatility of a market; however, the concept of directional change will be modified for the purposes of this research to measure the probability of right forecasted directions by each of the forecasting methods. The concept used in this research focuses on identifying the directional change between the
current actual closing price and the pervious period closing price as well as the current forecasted closing price and the previous period closing price.

A Correct Directional Change (CDC) is recorded if the current actual closing price directional change compared to the previous period’s actual closing price matched the current forecasted closing price directional change compared to the previous period forecasted closing price. A Wrong Directional Change (WDC) would be a mismatch between the compared actual closing prices directional change and the forecasted closing prices directional change. Table 3 summarizes all the possible cases of directional changes.
Table 3: Directional Change Cases

<table>
<thead>
<tr>
<th>Actual</th>
<th>Forecast</th>
<th>Results</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="#" alt="Diagram 1" /></td>
<td><img src="#" alt="Diagram 2" /></td>
<td>CDC</td>
</tr>
<tr>
<td><img src="#" alt="Diagram 3" /></td>
<td><img src="#" alt="Diagram 4" /></td>
<td>WDC</td>
</tr>
<tr>
<td><img src="#" alt="Diagram 5" /></td>
<td><img src="#" alt="Diagram 6" /></td>
<td>WDC</td>
</tr>
</tbody>
</table>

The probability of Correct Directional Changes and Wrong Directional Changes per forecasting method is calculated by the following formula:

\[
\text{Probability of CDC (P)} = \frac{\text{Number of CDC Observations}}{\text{Total Number of Observations}} \tag{16}
\]

The probability of WDC is the complement probability of the CDC:

\[
\text{Probability of WDC} = 1 - \text{Probability of CDC} \tag{17}
\]

The forecasting method with the highest probability of CDC is considered to be the best forecasting method to forecast the future directional movement of the market.
3.9 Coefficient of Variation (CV)

The Coefficient of Variation is widely used in identifying the risk related to a financial time series or a financial transaction. It measures the distribution of the data around the mean using the standard deviation of the data. It is calculated by the following formula:

\[ CV = \frac{\sigma}{\mu} \]  

(18)

where:

- \( \sigma \): The standard deviation of the selected data sample
- \( \mu \): The mean of the selected data sample (also known as the expected return)

For the purposes of this project, the coefficient of Variation was calculated for the previously defined forecasting error (Fe). The absolute of the forecasting error (Fe) was obtained and the errors corresponded to CDC was separated from the errors corresponded to WDC. The mean and standard deviation of each group was calculated separately as this research is shedding new light on the previously used definition of Coefficient of Variation.
CHAPTER 4: RESULTS AND DISCUSSION

4.1 Brent Spot Oil Price

4.1.1 Error Distribution for Brent Oil

Several methods were used to forecast the Next-Period and the 6th Period closing value of Brent Spot Oil market for the daily, weekly, and monthly data; these forecasting methods are: Naïve, 14 Periods Moving Average, Exponential Smoothing, ARRSES, ARIMA, and Neural Network. The forecasting error of each method was then calculated and the histogram of each was created. The error histograms help identifying the spread of the error compared to the data mean. Figure 6 and 7 below represent a sample of the error histograms obtained for the market, while the entire errors’ histograms are available in Appendix A.

The error distribution of the Next Day’s 14 Days Moving Average forecast, presented in figure 6, is centered on the mean with more of the errors are on the left side of the mean indicating more negative error values (forecasting results were higher than actual results). On the other hand, the error distribution of the 6th Day Exponential Smoothing forecast, presented in figure 7, has more results gathered on the mean’s right side indicating that the forecasting results were less in value than the actual closing prices.

![Error Histogram](image)

Figure 6: Brent Spot Oil – Next-Period’s Forecast using 14 Days Moving - Error Histogram
It is also worth noticing that the presented error in the shown histograms is defined as delta actual minus delta forecast and it is used for demonstration purposes only while the error definition used in the new Risk Indicator remains as per detailed in section 3.5.

4.1.2 Correlation Coefficients for Brent Oil

The Correlation Coefficient (R) indicates the type (positive or negative) and the strength (strong or weak) of the relationship between the forecast and the actual closing prices. The majority of the R results for the Brent Spot Oil market indicate strong positive relationship between the forecasted data and the actual data for all the periods (daily, weekly, and monthly). This R result indicates that the correlation factor has a limited impact on the value of the risk indicator as the majority of the results is approximately 1.

A single point that stands from the different correlation coefficient results is the Neural Network forecast Correlation Coefficient for the monthly period. This result is attributed to the lack of training of the Neural Network as it had a limited data set (116 data points) for the training and testing. Table 4 summarizes the Correlation Coefficient results. The indicated Rs vary from a forecasting method to another while it remains unaffected by the tested periods (Next-Period forecast and 6th Period forecast).
Table 4: Brent Spot Oil Price - Correlation Coefficients

<table>
<thead>
<tr>
<th>Forecasting Methods</th>
<th>Daily</th>
<th>Weekly</th>
<th>Monthly</th>
</tr>
</thead>
<tbody>
<tr>
<td>Naïve</td>
<td>0.999</td>
<td>0.995</td>
<td>0.969</td>
</tr>
<tr>
<td>14 Periods Moving Average</td>
<td>0.994</td>
<td>0.961</td>
<td>0.809</td>
</tr>
<tr>
<td>Exponential Smoothing</td>
<td>0.999</td>
<td>0.995</td>
<td>0.965</td>
</tr>
<tr>
<td>Neural Network</td>
<td>0.987</td>
<td>0.952</td>
<td>0.148</td>
</tr>
<tr>
<td>ARRES</td>
<td>0.999</td>
<td>0.994</td>
<td>0.967</td>
</tr>
<tr>
<td>ARIMA</td>
<td>0.999</td>
<td>0.995</td>
<td>0.978</td>
</tr>
</tbody>
</table>

4.1.3 CDC Ratios for Brent Oil

The capability of forecasting methods to predict the next movement of the Brent Spot Oil market was assessed as well, and the results indicate that the highest accuracy achievable in predicting the next period movement (daily, weekly, or monthly) ranges from 52% to 57%. This low accuracy in predicting the movement is not a satisfactory result and it indicates that predicting the next period movement is not advisable. On the other hand, the highest achievable accuracy in predicting the 6th Period movement ranges from 76% to 82%, which is an acceptable result. This result means that if the forecast for the 6th Period is known and the directional change between the 6th Period and the initial period is known then there is a 76%-82% chance that the next period actual will have the same direction as the indicated direction between the 6th period forecast and the initial period forecast.

The best direction prediction method for the Next-Period case is the 14 Periods Moving Average. None of the used methods indicated a higher capability in predicting the direction change of the 6th Period case although the majority of them have shown a great improvement in the prediction accuracy. Table 5 below presents the Correct Directional Changes ratios for the Brent Spot Oil market.
Table 5: Brent Spot Oil Price - CDC Ratios

<table>
<thead>
<tr>
<th>Forecasting Methods</th>
<th>Daily</th>
<th>6th Period CDC%</th>
<th>Weekly</th>
<th>6th Period CDC%</th>
<th>Monthly</th>
<th>6th Period CDC%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Naïve</td>
<td>51.47%</td>
<td>81.64%</td>
<td>53.09%</td>
<td><strong>81.00%</strong></td>
<td>51.75%</td>
<td>75.45%</td>
</tr>
<tr>
<td>14 Periods Moving Average</td>
<td>52.81%</td>
<td>60.19%</td>
<td>52.72%</td>
<td>59.82%</td>
<td><strong>57.43%</strong></td>
<td>59.79%</td>
</tr>
<tr>
<td>Exponential Smoothing</td>
<td>51.51%</td>
<td>80.27%</td>
<td><strong>56.01%</strong></td>
<td>79.24%</td>
<td>50.00%</td>
<td><strong>76.36%</strong></td>
</tr>
<tr>
<td>Neural Network</td>
<td>51.20%</td>
<td>64.98%</td>
<td>47.13%</td>
<td>64.71%</td>
<td>39.39%</td>
<td>37.93%</td>
</tr>
<tr>
<td>ARRESSES</td>
<td>50.89%</td>
<td>79.34%</td>
<td>54.81%</td>
<td>79.07%</td>
<td>49.12%</td>
<td>73.64%</td>
</tr>
<tr>
<td>ARIMA</td>
<td>51.58%</td>
<td><strong>81.67%</strong></td>
<td>55.50%</td>
<td>80.31%</td>
<td>56.14%</td>
<td>75.45%</td>
</tr>
</tbody>
</table>

4.1.4 Coefficient of Variations for Brent Oil

The data points of the Brent Spot Oil Prices were split into two sets based on the result of the Directional Change. The calculated Forecast Error (Fe) of data points corresponded to CDC were grouped and the Coefficient of Variation was calculated for selected data. The calculated error data points corresponded to WDC were grouped and the Coefficient of Variation was calculated for the set of selected data. The smaller the Coefficient of Variation the better the fit between the forecasting method and the actual closing value data. The Coefficient of Variation measures the scatter of the data around the error mean and the more scattered the data, the more volatile the error results.

The CV’s results range from 0.38 to 5.35 with the highest CV found in the weekly data and the lowest was counted for the monthly data. Table 6 summarizes the values of CVs per period per forecasting method.
4.1.5 Risk Indicator Results for Brent Oil

The new Risk Indicator (RI) was calculated based on the above results of the Correlation Coefficient, the Directional Change test, and the Coefficient of Variation. The new RI identified that the 14 Periods Moving Average is the least risky forecasting method to use while predicting the Brent Spot Oil market for the daily forecasts in both cases (the Next-Period forecast and the 6th Period forecast). The Neural Network was identified as the least risky forecasting method in forecasting the market movement of the Brent Spot Oil market for weekly data. A firm decision on the best method to predict the market monthly movement could not be achieved. The least risky forecasting method to predict the movement and the value of the market for the Brent Spot Oil market is the 14 Periods Moving Average. The results of each of the forecasting methods per period (daily, weekly, monthly) per case (Next-Period, 6th period) are tabulated and ranked based on its riskiness in table 7. The forecasting methods results ranked from 1 to 6 with the lower the rank the less risky the forecasting method and the higher the rank the more risky the forecasting method.
Table 7: Brent Spot Oil Price - Risk Indicator (RI) Results

<table>
<thead>
<tr>
<th>Forecasting Methods</th>
<th>Daily</th>
<th>Weekly</th>
<th>Monthly</th>
</tr>
</thead>
<tbody>
<tr>
<td>Naïve</td>
<td>(5)</td>
<td>(4)</td>
<td>(5)</td>
</tr>
<tr>
<td></td>
<td>3.75</td>
<td>4.15</td>
<td>3.05</td>
</tr>
<tr>
<td>14 Periods Moving Average</td>
<td>(1)</td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td></td>
<td>2.29</td>
<td>2.45</td>
<td>2.53</td>
</tr>
<tr>
<td>Exponential Smoothing</td>
<td>(3)</td>
<td>(5)</td>
<td>(4)</td>
</tr>
<tr>
<td></td>
<td>2.68</td>
<td>4.22</td>
<td>2.94</td>
</tr>
<tr>
<td>Neural Network</td>
<td>(2)</td>
<td>(2)</td>
<td>(1)</td>
</tr>
<tr>
<td></td>
<td>2.62</td>
<td>3.19</td>
<td>1.88</td>
</tr>
<tr>
<td>ARRSAES</td>
<td>(6)</td>
<td>(3)</td>
<td>(6)</td>
</tr>
<tr>
<td></td>
<td>3.86</td>
<td>4.01</td>
<td>3.83</td>
</tr>
<tr>
<td>ARIMA</td>
<td>(4)</td>
<td>(6)</td>
<td>(3)</td>
</tr>
<tr>
<td></td>
<td>3.71</td>
<td>4.29</td>
<td>2.69</td>
</tr>
</tbody>
</table>

4.2 Gold Daily Price

4.2.1 Error Distribution for Gold Daily Price

The Gold Daily market’s price was also forecasted using the Naïve, 14 Days Moving Average, Exponential Smoothing, ARRSAES, ARIMA, and Neural Network forecasting methods. The forecasting error of each method was calculated and measured. The error histograms help identify the spread of the error compared to the data mean. Figure 8 and 9 below represent a sample of the error histograms obtained for the market, while the entire errors’ histograms are available in Appendix B.
The error distribution of the Next Day ARIMA forecast errors, presented in figure 8, is centered on the mean with a long tail on the right side of the mean indicating a tendency to positive errors (the Actual value is higher than the forecasted value).

On the other hand, the error distributions of the 6th Day Naïve forecast error, presented in figure 9, has an even distribution and relatively similar tails.

![Figure 8: Gold Daily Price – Next-Period’s Forecast using ARIMA - Error Histogram](image)

![Figure 9: Gold Daily Price – 6th Period’s Forecast using Naive - Error Histogram](image)

It is also worth noting that the presented error in the shown histograms is defined as delta actual minus delta forecast and it is used for demonstration purposes only while the error definition used in the new Risk Indicator remains as per detailed in section 3.5.

4.2.2 Correlation Coefficients for Gold Daily Price

The majority of the R results for the Gold market indicate strong positive relationship between the forecasted data and the actual data for all the periods (daily, weekly, and
monthly). This R result indicates that the correlation factor has a limited impact on the value of the risk indicator, as the majority of the results is approximately 1. The indicated R vary from a forecasting method to another while it remains unaffected by the tested periods.

Table 8: Gold Daily Price - Correlation Coefficients

<table>
<thead>
<tr>
<th>Forecasting Methods</th>
<th>Gold Daily Price - R</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Daily</td>
</tr>
<tr>
<td>Naïve</td>
<td>1.000</td>
</tr>
<tr>
<td>14 Periods Moving Average</td>
<td>0.998</td>
</tr>
<tr>
<td>Exponential Smoothing</td>
<td>1.000</td>
</tr>
<tr>
<td>Neural Network</td>
<td>0.993</td>
</tr>
<tr>
<td>ARRSES</td>
<td>1.000</td>
</tr>
<tr>
<td>ARIMA</td>
<td>1.000</td>
</tr>
</tbody>
</table>

4.2.3 CDC Ratios for Gold Daily Price

The capability of forecasting methods to predict the next movement of the Gold market was measured as well, and the results indicate that the highest accuracy achievable in predicting the Next-Period movement (daily, weekly, or monthly) ranges from 49% to 69%. This low accuracy in predicting the movement indicates that predicting the Next-Period movement is not advisable. On the other hand, the highest achievable accuracy in predicting the 6th Period movement ranges from 80% to 84%, which is an acceptable result.

The best direction prediction method for the Next-Period case cannot be identified based on the current information. On the other hand, the Naïve forecast has proven to be the best direction prediction method for the 6th Period Case. Table 9 below presents the Correct Directional Changes ratios for the Gold Daily market.
Table 9: Gold Daily Price - CDC Ratios

<table>
<thead>
<tr>
<th>Forecasting Methods</th>
<th>Gold Daily Price - CDC Ratios</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Daily</td>
</tr>
<tr>
<td></td>
<td>Next Period CDC%</td>
</tr>
<tr>
<td>Naïve</td>
<td>48.12%</td>
</tr>
<tr>
<td>14 Periods Moving Average</td>
<td>49.40%</td>
</tr>
<tr>
<td>Exponential Smoothing</td>
<td>48.22%</td>
</tr>
<tr>
<td>Neural Network</td>
<td>47.66%</td>
</tr>
<tr>
<td>ARRSSES</td>
<td>49.21%</td>
</tr>
<tr>
<td>ARIMA</td>
<td>48.66%</td>
</tr>
</tbody>
</table>

4.2.4 Coefficient of Variation for Gold Daily Price

The CV’s results for the Gold Market ranges from 0.61 to 6.88 with the highest CV found in the weekly data and the lowest was counted for the monthly data. Table 10 summarizes the values of CVs per period per forecasting method.

Table 10: Gold Daily Price- CV Values

<table>
<thead>
<tr>
<th>Forecasting Methods</th>
<th>Gold Daily Price - CV Values</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Daily</td>
</tr>
<tr>
<td></td>
<td>Next Period CV</td>
</tr>
<tr>
<td>Naïve</td>
<td>2.97</td>
</tr>
<tr>
<td>14 Periods Moving Average</td>
<td>1.71</td>
</tr>
<tr>
<td>Exponential Smoothing</td>
<td>3.02</td>
</tr>
<tr>
<td>Neural Network</td>
<td>2.59</td>
</tr>
<tr>
<td>ARRSSES</td>
<td>3.29</td>
</tr>
<tr>
<td>ARIMA</td>
<td>3.04</td>
</tr>
</tbody>
</table>

4.2.5 Risk Indicator Results for Gold Daily Prices

The new risk indicator (RI) was calculated based on the above results of the Correlation Coefficient, the directional change test, and the Coefficient of Variation. The
new RI indicated that the 14 Periods Moving Average is the least risky forecasting method to use while predicting the Gold Daily market for the Next-Period case for all periods (daily, weekly, and monthly). The least risky method to predict the Gold market for the 6th Period case is the Neural Network. The results of each of the forecasting methods per period (daily, weekly, monthly) per case (Next-Period, 6th period) are tabulated and ranked based on its riskiness in table 11. The forecasting methods results ranked from 1 to 6 with the lower the rank the less risky the forecasting method and the higher the rank the more risky the forecasting method.

Table 11: Gold Daily Price - Risk Indicator (RI) Results

<table>
<thead>
<tr>
<th>Forecasting Methods</th>
<th>Gold Daily Price - Risk Indicator (RI) Results</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Gold Daily Price - Risk Indicator (RI) Results</td>
<td>Daily</td>
<td>Weekly</td>
<td>Monthly</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Naïve</td>
<td></td>
<td>(3)</td>
<td>(5)</td>
<td>(2)</td>
<td>(1)</td>
<td>(4)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2.46</td>
<td>3.50</td>
<td>2.72</td>
<td>2.55</td>
<td>1.86</td>
</tr>
<tr>
<td>14 Periods Moving Average</td>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(1)</td>
<td>(5)</td>
<td>(1)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1.31</td>
<td>2.70</td>
<td>1.72</td>
<td>4.08</td>
<td>0.96</td>
</tr>
<tr>
<td>Exponential Smoothing</td>
<td></td>
<td>(4)</td>
<td>(4)</td>
<td>(4)</td>
<td>(3)</td>
<td>(3)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2.51</td>
<td>3.42</td>
<td>2.78</td>
<td>2.73</td>
<td>1.84</td>
</tr>
<tr>
<td>Neural Network</td>
<td></td>
<td>(2)</td>
<td>(1)</td>
<td>(5)</td>
<td>(6)</td>
<td>(2)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2.45</td>
<td>2.28</td>
<td>2.96</td>
<td>5.55</td>
<td>1.40</td>
</tr>
<tr>
<td>ARRSES</td>
<td></td>
<td>(6)</td>
<td>(3)</td>
<td>(6)</td>
<td>(4)</td>
<td>(6)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2.88</td>
<td>2.83</td>
<td>3.43</td>
<td>3.57</td>
<td>1.91</td>
</tr>
<tr>
<td>ARIMA</td>
<td></td>
<td>(5)</td>
<td>(6)</td>
<td>(3)</td>
<td>(2)</td>
<td>(5)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2.52</td>
<td>3.59</td>
<td>2.76</td>
<td>2.66</td>
<td>1.87</td>
</tr>
</tbody>
</table>

4.3 FTSE100 Daily Price

4.3.1 Error Disruption for FTSE100 Daily Prices

The FTSE100 Daily market’s price was also forecasted using the Naïve, 14 Days Moving Average, Exponential Smoothing, ARRSES, ARIMA, and Neural Network forecasting methods. The forecasting error of each method was calculated and measured. Figure 10 and 11 below represent a sample of the error histograms obtained for the market, while the entire errors’ histograms are available in Appendix C.

The error distribution of the Next Day ARRSES forecast errors, presented in figure 10, is centered on the mean with a high portion of the errors located on the right side of
the mean. A long tail on the right side presents itself in the histogram indicating a tendency toward positive errors (the Actual value is higher than the forecasted value).

On the other hand, the error distribution of the 6th Day Exponential Smoothing forecast error, presented in figure 11, has an even distribution and relatively equal sized tails. It also can also be noticed that the highest error frequency for the 6th Day forecast is lower than the error frequency of the Next-Day’s forecast.

It is also worth noting that the presented error in the shown histograms is defined as delta actual minus delta forecast and it is used for demonstration purposes only while the error definition used in the new Risk Indicator remains as per detailed in section 3.5.

4.3.2 Correlation Coefficients for FTSE100 Daily Prices

The majority of the R results for the FTSE100 market indicate strong positive relationship between the forecasted data and the actual data for all the periods (daily,
weekly, and monthly). This R results indicate that the Correlation Factor has a limited impact on the value of the Risk Indicator, as the majority of the results is approximately 1.

A single result that stands out from the different correlation coefficient results is the Neural Network forecast Correlation Coefficient for the monthly period. This result is not close to 1 and it is attributed to the lack of training of the Neural Network. It can be observed that the correlation factor between the Neural Network forecasting results and the actual closing values decreases as the number of data sets decreases. This observation can be witnessed also in all the tested markets. Table 12 summarizes the Correlation Coefficient results for the FTSE100.

Table 12: FTSE100 Daily Price- Correlation Coefficients

<table>
<thead>
<tr>
<th>Forecasting Methods</th>
<th>FTSE100 Daily Price - R</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Daily</td>
</tr>
<tr>
<td>Naïve</td>
<td>0.997</td>
</tr>
<tr>
<td>14 Periods Moving Average</td>
<td>0.986</td>
</tr>
<tr>
<td>Exponential Smoothing</td>
<td>0.997</td>
</tr>
<tr>
<td>Neural Network</td>
<td>0.976</td>
</tr>
<tr>
<td>ARRSES</td>
<td>0.996</td>
</tr>
<tr>
<td>ARIMA</td>
<td>0.997</td>
</tr>
</tbody>
</table>

4.3.3 CDC Ratios for FTSE100 Daily Prices

The capability of forecasting methods to predict the next movement of the FTSE100 market was considered as well and the results indicate that the highest accuracy achievable in predicting the Next-Period movement (daily, weekly, or monthly) ranges from 50% to 58%. This low accuracy in predicting the movement is not a satisfactory result. On the other hand, the highest achievable accuracy in predicting the 6th Period movement ranges from 78% to 86%, which is an acceptable result.

The best direction prediction method for the Next-Period case cannot be identified based on the current results. The Naïve forecast has proven superiority in predicting the direction change of the 6th Period case. Table 13 below presents the correct directional changes ratios for the FTSE100 market.
Table 13: FTSE100 Daily Price - CDC Ratios

<table>
<thead>
<tr>
<th>Forecasting Methods</th>
<th>FTSE100 Daily Price - CDC Ratios</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Daily</td>
<td>Weekly</td>
<td>Monthly</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Next Period CDC%</td>
<td>6th Period CDC%</td>
<td>Next Period CDC%</td>
<td>6th Period CDC%</td>
<td>Next Period CDC%</td>
<td>6th Period CDC%</td>
</tr>
<tr>
<td>Naïve</td>
<td>48.42%</td>
<td><strong>78.93%</strong></td>
<td>50.52%</td>
<td><strong>78.24%</strong></td>
<td>44.74%</td>
<td>83.64%</td>
</tr>
<tr>
<td>14 Periods Moving Average</td>
<td>48.88%</td>
<td>59.53%</td>
<td>50.26%</td>
<td>59.65%</td>
<td>55.45%</td>
<td>61.86%</td>
</tr>
<tr>
<td>Exponential Smoothing</td>
<td>47.81%</td>
<td>77.56%</td>
<td><strong>51.03%</strong></td>
<td>77.34%</td>
<td>45.61%</td>
<td>82.73%</td>
</tr>
<tr>
<td>Neural Network</td>
<td><strong>50.40%</strong></td>
<td>59.59%</td>
<td>47.13%</td>
<td>62.94%</td>
<td>47.06%</td>
<td>70.00%</td>
</tr>
<tr>
<td>ARRTSES</td>
<td>48.12%</td>
<td>77.21%</td>
<td>50.69%</td>
<td>76.12%</td>
<td>45.61%</td>
<td>81.82%</td>
</tr>
<tr>
<td>ARIMA</td>
<td>48.46%</td>
<td>78.86%</td>
<td>51.03%</td>
<td>77.72%</td>
<td><strong>58.77%</strong></td>
<td><strong>86.36%</strong></td>
</tr>
</tbody>
</table>

4.3.4 The Coefficient of Variation for the FTSE100 Daily Prices

The CV’s results range from 0.53 to 7.65 with the highest CV found in the daily data and the lowest was counted for the monthly data. The FTSE100 market has shown the widest distribution among all the other markets. Table 14 summarizes the values of CVs per period per forecasting method.

Table 14: FTSE100 Daily Price - CV Values

<table>
<thead>
<tr>
<th>Forecasting Methods</th>
<th>FTSE100 Daily Price - CV Values</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Daily</td>
<td>Weekly</td>
<td>Monthly</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Next Period</td>
<td>6th Period</td>
<td>Next Period</td>
<td>6th Period</td>
<td>Next Period</td>
<td>6th Period</td>
</tr>
<tr>
<td></td>
<td>CV +1</td>
<td>CV -1</td>
<td>CV +1</td>
<td>CV -1</td>
<td>CV +1</td>
<td>CV -1</td>
</tr>
<tr>
<td>Naïve</td>
<td>5.06</td>
<td>3.45</td>
<td>7.57</td>
<td>2.20</td>
<td>6.26</td>
<td>6.11</td>
</tr>
<tr>
<td>15 Periods Moving Average</td>
<td>4.16</td>
<td>2.75</td>
<td>7.14</td>
<td>4.76</td>
<td>2.77</td>
<td>7.42</td>
</tr>
<tr>
<td>Exponential Smoothing</td>
<td>5.05</td>
<td>3.49</td>
<td>7.82</td>
<td>2.42</td>
<td>6.32</td>
<td>6.15</td>
</tr>
<tr>
<td>Neural Network</td>
<td>2.13</td>
<td>4.50</td>
<td>5.09</td>
<td>5.16</td>
<td>4.50</td>
<td>5.62</td>
</tr>
<tr>
<td>ARRTSES</td>
<td>4.33</td>
<td>3.74</td>
<td>7.65</td>
<td>2.26</td>
<td>7.51</td>
<td>6.48</td>
</tr>
<tr>
<td>ARIMA</td>
<td>5.15</td>
<td>3.35</td>
<td>7.40</td>
<td>2.22</td>
<td>5.68</td>
<td>7.10</td>
</tr>
</tbody>
</table>
4.3.5  Risk Indicator Results for the FTSE100 Daily Prices

The new risk indicator (RI) was calculated based on the above results of the Correlation Coefficient, the Directional Change test, and the Coefficient of Variation. The new RI identified that the Neural Network is the least risky forecasting method to use while predicting the FTSE100 market for the Next-Period forecast. A conclusion could not been made on the least risky forecasting method to predict the 6th period case for the FTSE100 market. The results of each of the forecasting methods per period (daily, weekly, monthly) per case (Next-Period, 6th period) are tabulated and ranked based on their riskiness in table 15. The forecasting methods results ranked from 1 to 6 with the lower the rank the less risky the forecasting method and the higher the rank the more risky the forecasting method.

Table 15: FTSE100 Daily Price - Risk Indicator (RI) Results

<table>
<thead>
<tr>
<th>Forecasting Methods</th>
<th>FTSE100 Daily Price - Risk Indicator (RI) Results</th>
<th>Daily</th>
<th>Weekly</th>
<th>Monthly</th>
</tr>
</thead>
<tbody>
<tr>
<td>Naïve</td>
<td>(5)</td>
<td>(5)</td>
<td>(3)</td>
<td>(2)</td>
</tr>
<tr>
<td></td>
<td>4.25</td>
<td>6.46</td>
<td>6.28</td>
<td>2.33</td>
</tr>
<tr>
<td>14 Periods Moving Average</td>
<td>(2)</td>
<td>(2)</td>
<td>(1)</td>
<td>(4)</td>
</tr>
<tr>
<td></td>
<td>3.49</td>
<td>6.26</td>
<td>5.40</td>
<td>3.60</td>
</tr>
<tr>
<td>Exponential Smoothing</td>
<td>(6)</td>
<td>(6)</td>
<td>(4)</td>
<td>(3)</td>
</tr>
<tr>
<td></td>
<td>4.25</td>
<td>6.63</td>
<td>6.33</td>
<td>3.08</td>
</tr>
<tr>
<td>Neural Network</td>
<td>(1)</td>
<td>(1)</td>
<td>(2)</td>
<td>(5)</td>
</tr>
<tr>
<td></td>
<td>3.39</td>
<td>5.24</td>
<td>5.46</td>
<td>4.01</td>
</tr>
<tr>
<td>ARRTSES</td>
<td>(3)</td>
<td>(4)</td>
<td>(6)</td>
<td>(6)</td>
</tr>
<tr>
<td></td>
<td>4.03</td>
<td>6.44</td>
<td>7.11</td>
<td>5.24</td>
</tr>
<tr>
<td>ARIMA</td>
<td>(4)</td>
<td>(3)</td>
<td>(5)</td>
<td>(1)</td>
</tr>
<tr>
<td></td>
<td>4.24</td>
<td>6.32</td>
<td>6.47</td>
<td>2.20</td>
</tr>
</tbody>
</table>

4.4  Euro to Dollar Daily Exchange Rate

4.4.1  Error Distribution for the Euro to Dollar Daily Exchange Rate

The Euro to Dollar Daily Exchange market’s price was forecasted. The forecasting error of each method was calculated and measured. The error histograms help in identifying the spread of the error compared to the data mean. Figure 12 and 13 below...
represent a sample of the error histograms obtained for the market, while the entire errors’ histograms are available in Appendix D.

The error distribution for the Next Day Neural Network forecast’s errors, presented in figure 12, is centered on the mean with even distribution among the errors value without favoring a value over another. On the other hand, the error distribution of the 6th Day Naïve forecast error, presented in figure 13, is centered around the mean with a high volume of errors placed on the right-side of the mean indicating that the actual values were higher than the forecasted values for the 6th Period’s case using the Naïve forecast.

4.4.2 Correlation Coefficients for the Euro to Dollar Daily Exchange Rate

The majority of the R results for the Euro to Dollar Daily Exchange market indicate strong positive relationship between the forecasted data and the actual data for all the
periods (daily, weekly, and monthly). This R results indicate that the Correlation factor has a limited impact on the value of the risk indicator, as the majority of the results is approximately 1.

A single result of a negative correlation that stands from the different Correlation Coefficient results is the Neural Network forecast Correlation Coefficient for the monthly period. This result is a direct indication that using this method to forecast the monthly period is not advisable and using this method has the highest risk. Table 16 summarizes the correlation coefficient results.

Table 16: Euro to Dollar Daily Exchange Rate - Correlation Coefficients

<table>
<thead>
<tr>
<th>Forecasting Methods</th>
<th>Euro to Dollar Daily Exchange Rate - R</th>
<th>Daily</th>
<th>Weekly</th>
<th>Monthly</th>
</tr>
</thead>
<tbody>
<tr>
<td>Naïve</td>
<td>0.999</td>
<td>0.995</td>
<td>0.973</td>
<td></td>
</tr>
<tr>
<td>14 Periods Moving Average</td>
<td>0.995</td>
<td>0.972</td>
<td>0.840</td>
<td></td>
</tr>
<tr>
<td>Exponential Smoothing</td>
<td>0.999</td>
<td>0.995</td>
<td>0.971</td>
<td></td>
</tr>
<tr>
<td>Neural Network</td>
<td>0.949</td>
<td>0.848</td>
<td>-0.596</td>
<td></td>
</tr>
<tr>
<td>ARRES</td>
<td>0.999</td>
<td>0.995</td>
<td>0.969</td>
<td></td>
</tr>
<tr>
<td>ARIMA</td>
<td>0.999</td>
<td>0.995</td>
<td>0.979</td>
<td></td>
</tr>
</tbody>
</table>

4.4.3 The CDC Ratios for the Euro to Dollar Daily Exchange Rate

The capability of forecasting methods to predict the next movement of the Euro to Dollar Daily Exchange market was assessed as well, and the results indicate that the highest accuracy achievable in predicting the Next-Period movement (daily, weekly, or monthly) ranges from 49% to 66%. This low accuracy in predicting the movement is not a satisfactory result. On the other hand, the highest achievable accuracy in predicting the 6th Period movement ranges from 80% to 88%, which is an acceptable result.

The best direction prediction method for the Next-Period case can not be identified from the available results. On the other hand, the ARIMA method is the best used method to predict the movement of the market for the 6th Period case. Table 17 below presents the Correct Directional Changes ratios for the Euro to Dollar Daily Exchange Rate market.
### Table 17: Euro to Dollar Daily Exchange Rate - CDC Ratios

<table>
<thead>
<tr>
<th>Forecasting Methods</th>
<th>Euro to Dollar Daily Exchange Rate - CDC Ratios</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Daily</td>
<td>Weekly</td>
<td>Monthly</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Next Period CDC%</td>
<td>6th Period CDC%</td>
<td>Next Period CDC%</td>
<td>6th Period CDC%</td>
<td>Next Period CDC%</td>
<td>6th Period CDC%</td>
<td></td>
</tr>
<tr>
<td>Naïve</td>
<td>49.11%</td>
<td>80.69%</td>
<td>53.26%</td>
<td>81.35%</td>
<td>54.39%</td>
<td>82.88%</td>
<td></td>
</tr>
<tr>
<td>15 Periods Moving Average</td>
<td>49.67%</td>
<td>60.08%</td>
<td>54.66%</td>
<td>60.35%</td>
<td>47.52%</td>
<td>55.67%</td>
<td></td>
</tr>
<tr>
<td>Exponential Smoothing</td>
<td>49.14%</td>
<td>80.16%</td>
<td>53.44%</td>
<td>81.14%</td>
<td>56.14%</td>
<td>84.55%</td>
<td></td>
</tr>
<tr>
<td>Neural Network</td>
<td>49.71%</td>
<td>59.47%</td>
<td>52.30%</td>
<td>69.41%</td>
<td>23.53%</td>
<td>20.00%</td>
<td></td>
</tr>
<tr>
<td>ARRES</td>
<td>48.63%</td>
<td>79.17%</td>
<td>52.75%</td>
<td>79.58%</td>
<td>55.26%</td>
<td>81.82%</td>
<td></td>
</tr>
<tr>
<td>ARIMA</td>
<td>49.55%</td>
<td>80.41%</td>
<td>52.75%</td>
<td>82.38%</td>
<td>66.67%</td>
<td>88.29%</td>
<td></td>
</tr>
</tbody>
</table>

#### 4.4.4 The Coefficient of Variation for the Euro to Dollar Daily Exchange Rate

The CV’s results range from 0.38 to 5.35 with the highest CV found in the weekly data and the lowest was counted for the monthly data. Table 18 summarizes the values of CVs per period per forecasting method.

### Table 18: Euro to Dollar Daily Exchange Rate - CV Values

<table>
<thead>
<tr>
<th>Forecasting Methods</th>
<th>Euro to Dollar Daily Exchange Rate - CV Values</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Daily</td>
<td>Weekly</td>
<td>Monthly</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Next Period</td>
<td>6th Period</td>
<td>Next Period</td>
<td>6th Period</td>
<td>Next Period</td>
<td>6th Period</td>
<td></td>
</tr>
<tr>
<td>Naïve</td>
<td>CV+1</td>
<td>CV-1</td>
<td>CV+1</td>
<td>CV-1</td>
<td>CV+1</td>
<td>CV-1</td>
<td>CV+1</td>
</tr>
<tr>
<td>15 Periods Moving Average</td>
<td>2.32</td>
<td>1.26</td>
<td>4.04</td>
<td>1.31</td>
<td>1.69</td>
<td>1.51</td>
<td>6.68</td>
</tr>
<tr>
<td>Exponential Smoothing</td>
<td>3.62</td>
<td>2.05</td>
<td>4.44</td>
<td>1.27</td>
<td>3.52</td>
<td>1.97</td>
<td>6.35</td>
</tr>
<tr>
<td>Neural Network</td>
<td>3.40</td>
<td>2.39</td>
<td>2.37</td>
<td>2.46</td>
<td>4.11</td>
<td>2.00</td>
<td>4.23</td>
</tr>
<tr>
<td>ARRES</td>
<td>3.49</td>
<td>2.04</td>
<td>4.82</td>
<td>1.32</td>
<td>3.48</td>
<td>1.43</td>
<td>6.23</td>
</tr>
<tr>
<td>ARIMA</td>
<td>3.68</td>
<td>2.14</td>
<td>4.95</td>
<td>1.17</td>
<td>3.08</td>
<td>2.34</td>
<td>6.10</td>
</tr>
</tbody>
</table>
4.4.5 Risk Indicator Results for the Euro to Dollar Daily Exchange Rate

The new risk indicator (RI) was calculated based on the above results of the Correlation Coefficient, the Directional Change test, and the Coefficient of Variation. The new RI identified that the 14 Periods Moving Average is the least risky forecasting method to use while predicting the Euro to Dollar Daily Exchange Rate market for the Next-Period forecasts. Meanwhile, the Neural Network was identified as the least risky forecasting method in forecasting the market movement of the 6th Period case for the Euro to Dollar Exchange Rate Market. The results of each of the forecasting methods per period (daily, weekly, monthly) per case (Next Period, 6th period) was tabulated and ranked based on its riskiness in table 19. The forecasting methods results ranked from 1 to 6 with the lower the rank the less risky the forecasting method and the higher the rank the more risky the forecasting method.

<table>
<thead>
<tr>
<th>Forecasting Methods</th>
<th>Daily</th>
<th>Weekly</th>
<th>Monthly</th>
</tr>
</thead>
<tbody>
<tr>
<td>Naïve</td>
<td>(5)</td>
<td>(6)</td>
<td>(2)</td>
</tr>
<tr>
<td></td>
<td>2.92</td>
<td>4.34</td>
<td>1.84</td>
</tr>
<tr>
<td>14 Periods Moving Average</td>
<td>(1)</td>
<td>(2)</td>
<td>(1)</td>
</tr>
<tr>
<td></td>
<td>1.80</td>
<td>2.97</td>
<td>1.66</td>
</tr>
<tr>
<td>Exponential Smoothing</td>
<td>(3)</td>
<td>(3)</td>
<td>(5)</td>
</tr>
<tr>
<td></td>
<td>2.82</td>
<td>3.82</td>
<td>2.81</td>
</tr>
<tr>
<td>Neural Network</td>
<td>(6)</td>
<td>(1)</td>
<td>(6)</td>
</tr>
<tr>
<td></td>
<td>3.05</td>
<td>2.54</td>
<td>3.66</td>
</tr>
<tr>
<td>ARRSES</td>
<td>(2)</td>
<td>(4)</td>
<td>(3)</td>
</tr>
<tr>
<td></td>
<td>2.75</td>
<td>4.10</td>
<td>2.52</td>
</tr>
<tr>
<td>ARIMA</td>
<td>(4)</td>
<td>(5)</td>
<td>(4)</td>
</tr>
<tr>
<td></td>
<td>2.90</td>
<td>4.21</td>
<td>2.75</td>
</tr>
</tbody>
</table>
4.5 Markets Over-All Results

The results, based on the proposed index, indicate that the 14 Periods Moving Average is the least risky forecasting method to use while forecasting the Brent Spot Oil Prices, the Gold Daily Prices, and the Euro to Dollar Exchange rate. Meanwhile, Neural Network had proven to be the least risky method to use while forecasting the FTSE100 Daily Price.

On the other hand, determining the most risky forecasting method to use for any of these markets remains vague. The Neural Network and the ARRSES methods has ranked the worst forecasting methods using the proposed risk indicator when used for the Brent Spot Oil Market while ARRSES ranked the most risky when used to predict the Gold Daily market. Moreover, the Exponential Smoothing and ARRSES had ranked the most risky forecasting methods when used to predict the FTSE100 market and Neural Network is considered the most risky to predict the Euro to Dollar Daily Exchange Rate. The detailed results of each market are verified in the following sections. Table 20 summarizes the markets’ overall results.

Table 20: Over All Markets’ Summaries per Forecasting Method Results

<table>
<thead>
<tr>
<th>Over All Markets’ Summaries per Forecasting Method Results</th>
</tr>
</thead>
<tbody>
<tr>
<td>Naïve</td>
</tr>
<tr>
<td>-----------------------------------</td>
</tr>
<tr>
<td>Brent Spot Oil Price</td>
</tr>
<tr>
<td>Gold Daily Price</td>
</tr>
<tr>
<td>FTSE100 Daily Price</td>
</tr>
<tr>
<td>Euro to Dollar Daily Exchange Rate</td>
</tr>
</tbody>
</table>

It is worth noticing that obtained results are applicable only for the tested markets during the tested periods and no generalization can be applied to the different markets.
CHAPTER 5: CONCLUSION

5.1 Summary and Conclusion

This research had two main objectives to deliver; first, the research aimed at evaluating the accuracy of forecasting methods based on their capability to correctly predict the Next-Period’s Correct Directional Change. The second objective was to present a new approach by which forecasting methods may be compared. The decision makers will be able then to properly evaluate the risk in using any of the methods to predict the Correct Directional Change of the Next-Period.

To satisfy these objectives, six common forecasting methods were used (Naïve Forecast, 14 Periods Moving Average, Exponential Smoothing, Neural Network, ARRSES, and ARIMA) to forecast the next period’s movements of four financial markets (Brent Spot Oil Price, Gold Daily Data, FTSE100 Daily Data, and Euro to Dollar Daily Exchange Rate). The results suggest that the accuracy of any of the forecasting methods in predicting the market movement is approximately 50%. When the same approach was used to forecast the directional move of six days ahead, the results improved for all the forecasting methods. Financial markets move randomly from day to day and the randomness may be dampened if a group of days such as five days are used. When randomness decreases, prediction becomes more efficient and, hence, forecasting the directional move will be more accurate.

For the forecasting methods used and the financial markets investigated, the new approach not only distinguished between the ability of the forecasting method to correlate with the actual values but also added a new dimension to evaluate the risk if the method is used to forecast the directional move of the Next-Period of the time series. The next period definition depends on the time frame used. If daily data is used then the Next-Period means the next day and if the weekly or monthly data are used then the Next-Period move means next week and next moth respectively. This is important for those decision makers who are interested in forecasting very-short time frames.

5.2 Future Research

Forecasting the correct directional move of a financial time series has not received much attention from previous research. The inherent random behavior of financial markets causes researchers to focus on the overall accuracy of forecasting methods and the resulting financial return in the short, medium, and long-term time horizons. Forecasting market moves in the
very short-term time deserves more attention from researchers. New mathematical models or approaches need to be applied to solve the problems in predicting the Correct Directional Change for the financial time series.
REFERENCES


APPENDIX A: BRENT SPOT OIL PRICE - ERRORS
HISTOGRAMS

A1. Daily Next-Period Forecasting Errors Per Forecasting Method

App A-Figure 1: Next-Period - Naïve Forecast Error Histogram
App A-Figure 2: Next-Period – 14 Periods Average Error Histogram
App A-Figure 3: Next-Period – Exponential Smoothing Error Histogram
App A-Figure 4: Next-Period – NN Error Histogram
App A-Figure 5: Next-Period – ARRSES Error Histogram
App A-Figure 6: Next-Period – ARIMA Error Histogram
A2. Daily 6th Period Forecasting Errors Per Forecasting Method

App A-Figure 7: 6th Period – Naive Forecast Error Histogram

App A-Figure 8: 6th Period – 14 Periods Average Error Histogram

App A-Figure 9: 6th Period – Exponential Smoothing Error Histogram

App A-Figure 10: 6th Period – NN Error Histogram

App A-Figure 11: 6th Period – ARRSES Error Histogram

App A-Figure 12: 6th Period – ARIMA Error Histogram
A3. Weekly Next-Period Forecasting Errors Per Forecasting Method

App A-Figure 13: Next-Period - Naïve Forecast Error Histogram

App A-Figure 14: Next-Period –14 Periods Average Error Histogram

App A-Figure 15: Next-Period -Exponential Smoothing Error Histogram

App A-Figure 16: Next-Period –NN Error Histogram

App A-Figure 17: Next-Period –ARRSES Error Histogram

App A-Figure 18: Next-Period –ARIMA Error Histogram
A4. Weekly 6th Period Forecasting Errors Per Forecasting Method

App A-Figure 19: 6th Period - Naïve Forecast Error Histogram

App A-Figure 20: 6th Period – 14 Periods Average Error Histogram

App A-Figure 21: 6th Period - Exponential Smoothing Error Histogram

App A-Figure 22: 6th Period – NN Error Histogram

App A-Figure 23: 6th Period – ARRSES Error Histogram

App A-Figure 24: 6th Period – ARIMA Error Histogram
A5. Monthly Next-Period Forecasting Errors Per Forecasting Method

- App A-Figure 25: Next-Period - Naïve Forecast Error Histogram
- App A-Figure 26: Next-Period –14 Periods Average Error Histogram
- App A-Figure 27: Next-Period -Exponential Smoothing Error Histogram
- App A-Figure 28: Next-Period –NN Error Histogram
- App A-Figure 29: Next-Period –ARRSES Error Histogram
- App A-Figure 30: Next-Period –ARIMA Error Histogram
A6. Monthly 6th Period Forecasting Errors Per Forecasting Method

App A-Figure 31: 6th Period - Naïve Forecast Error Histogram

App A-Figure 32: 6th Period –14 Periods Average Error Histogram

App A-Figure 33: 6th Period -Exponential Smoothing Error Histogram

App A-Figure 34: 6th Period –NN Error Histogram

App A-Figure35: 6th Period –ARRSES Error Histogram

App A-Figure36: 6th Period –ARIMA Error Histogram
APPENDIX B: GOLD DAILY PRICE - ERRORS HISTOGRAMS

B1. Daily Next-Period Forecasting Errors Per Forecasting Method

![App B-Figure 1: Next-Period - Naïve Forecast Error Histogram](image1)

![App B-Figure 1: Next-Period –14 Periods Average Error Histogram](image2)

![App B-Figure 3: Next-Period –Exponential Smoothing Error Histogram](image3)

![App B-Figure 4: Next-Period –NN Error Histogram](image4)

![App B-Figure 5: Next-Period –ARRSES Error Histogram](image5)

![App B-Figure 6: Next-Period –ARIMA Error Histogram](image6)
B2. Daily 6th Period Forecasting Errors Per Forecasting Method

App B-Figure 7: 6th Period - Naïve Forecast Error Histogram

App B-Figure 8: 6th Period –14 Periods Average Error Histogram

App B-Figure 9: 6th Period -Exponential Smoothing Error Histogram

App B-Figure 10: 6th Period –NN Error Histogram

App B-Figure 11: 6th Period –ARRSES Error Histogram

App B-Figure 12: 6th Period –ARIMA Error Histogram
B3. Weekly Next-Period Forecasting Errors Per Forecasting Method

App B-Figure 13: Next-Period - Naive Forecast Error Histogram

App B-Figure 14: Next-Period - 14 Periods Average Error Histogram

App B-Figure 15: Next-Period - Exponential Smoothing Error Histogram

App B-Figure 16: Next-Period - NN Error Histogram

App B-Figure 17: Next-Period - ARRES Error Histogram

App B-Figure 18: Next-Period - ARIMA Error Histogram
B4. Weekly 6\textsuperscript{th} Period Forecasting Errors Per Forecasting Method

App B-Figure 19: 6\textsuperscript{th} Period - Naïve Forecast Error Histogram

App B-Figure 20: 6\textsuperscript{th} Period –14 Periods Average Error Histogram

App B-Figure 21: 6\textsuperscript{th} Period - Exponential Smoothing Error Histogram

App B-Figure 22: 6\textsuperscript{th} Period -NN Error Histogram

App B-Figure 23: 6\textsuperscript{th} -Period –ARRSE Error Histogram

App B-Figure 24: 6\textsuperscript{th} Period –ARIMA Error Histogram

77
B5. Monthly Next-Period Forecasting Errors Per Forecasting Method

App B-Figure 25: Next-Period - Naïve Forecast Error Histogram

App B-Figure 26: Next-Period –14 Periods Average Error Histogram

App B-Figure 27: Next-Period –Exponential Smoothing Error Histogram

App B-Figure 28: Next-Period –NN Error Histogram

App B-Figure 29: Next-Period –ARRSES Error Histogram

App B-Figure 30: Next-Period –ARIMA Error Histogram
B6. Monthly 6th Period Forecasting Errors Per Forecasting Method

App B-Figure 31: 6th Period - Naïve Forecast Error Histogram

App B-Figure 32: 6th Period - 14 Periods Average Error Histogram

App B-Figure 33: 6th Period - Exponential Smoothing Error Histogram

App B-Figure 34: 6th Period - NN Error Histogram

App B-Figure 35: 6th Period - ARRSES Error Histogram

App B-Figure 36: 6th Period - ARIMA Error Histogram
APPENDIX C: FTSE100 INDEX – ERRORS HISTOGRAMS

C1. Daily Next-Period Forecasting Errors Per Forecasting Method

- App C-Figure 1: Next-Period - Naïve Forecast Error Histogram
- App C-Figure 2: Next-Period – 14 Periods Average Error Histogram
- App C-Figure 3: Next-Period – Exponential Smoothing Error Histogram
- App C-Figure 4: Next-Period – NN Error Histogram
- App C-Figure 5: Next-Period – ARRES Error Histogram
- App C-Figure 6: Next-Period – ARIMA Error Histogram
C2.  Daily 6\textsuperscript{th} Period Forecasting Errors Per Forecasting Method

App C-Figure 7: 6\textsuperscript{th} Period - Naïve Forecast Error Histogram

App C-Figure 8: 6\textsuperscript{th} Period - 14 Periods Average Error Histogram

App C-Figure 9: 6\textsuperscript{th} Period - Exponential Smoothing Error Histogram

App C-Figure 10: 6\textsuperscript{th} Period - NN Error Histogram

App C-Figure 11: 6\textsuperscript{th} Period - ARRSES Error Histogram

App C-Figure 12: 6\textsuperscript{th} Period - ARIMA Error Histogram
C3. Weekly Next-Period Forecasting Errors Per Forecasting Method

App C-Figure 13: Next-Period - Naive Forecast Error Histogram

App C-Figure 14: Next-Period –14 Periods Average Error Histogram

App C-Figure 15: Next-Period -Exponential Smoothing Error Histogram

App C-Figure 16: Next-Period –NN Error Histogram

App C-Figure 17: Next-Period –ARRSES Error Histogram

App C-Figure 18: Next-Period –ARIMA Error Histogram
C4. Weekly 6\textsuperscript{th} Period Forecasting Errors Per Forecasting Method

App C-Figure 19: 6\textsuperscript{th} Period - Naïve Forecast Error Histogram

App C-Figure 20: 6\textsuperscript{th} Period - 14 Periods Average Error Histogram

App C-Figure 21: 6\textsuperscript{th} Period - Exponential Smoothing Error Histogram

App C-Figure 22: 6\textsuperscript{th} Period - NN Error Histogram

App C-Figure 23: 6\textsuperscript{th} Period - ARRES Error Histogram

App C-Figure 24: 6\textsuperscript{th} Period - ARIMA Error Histogram
C5. Monthly Next-Period Forecasting Errors Per Forecasting Method

App C-Figure 25: Next-Period - Naïve Forecast Error Histogram

App C-Figure 26: Next-Period –14 Periods Average Error Histogram

App C-Figure 27: Next-Period –Exponential Smoothing Error Histogram

App C-Figure 28: Next-Period –NN Error Histogram

App C-Figure 29: Next-Period –ARRSES Error Histogram

App C-Figure 30: Next-Period –ARIMA Error Histogram
C6. Monthly 6th Period Forecasting Errors Per Forecasting Method

App C-Figure 31: 6th Period - Naïve Forecast Error Histogram

App C-Figure 32: 6th Period -14 Periods Average Error Histogram

App C-Figure 33: 6th Period -Exponential Smoothing Error Histogram

App C-Figure 34: 6th Period -NN Error Histogram

App C-Figure35: 6th Period -ARRSES Error Histogram

App C-Figure36: 6th Period -ARIMA Error Histogram
APPENDIX D: EURO TO DOLLAR DAILY EXCHANGE RATE-ERRORS HISTOGRAMS

D1. Daily Next-Period Forecasting Errors Per Forecasting Method

App D-Figure 1: Next-Period - Naïve Forecast Error Histogram

App D-Figure 3: Next-Period - Exponential Smoothing Error Histogram

App D-Figure 5: Next-Period –ARRSES Error Histogram

App D-Figure 2: Next-Period –14 Periods Average Error Histogram

App D-Figure 4: Next-Period –NN Error Histogram

App D-Figure 6: Next-Period –ARIMA Error Histogram
D2. Daily 6th Period Forecasting Errors Per Forecasting Method

App D-Figure 7: 6th Period - Naïve Forecast Error Histogram

App D-Figure 8: 6th Period – 14 Periods Average Error Histogram

App D-Figure 9: 6th Period - Exponential Smoothing Error Histogram

App D-Figure 10: 6th Period – NN Error Histogram

App D-Figure 11: 6th Period – ARRSES Error Histogram

App D-Figure 12: 6th Period – ARIMA Error Histogram
D3. Weekly Next-Period Forecasting Errors Per Forecasting Method

App D-Figure 13: Next-Period - Naïve Forecast Error Histogram

App D-Figure 14: Next-Period –14 Periods Average Error Histogram

App D-Figure 15: Next-Period - Exponential Smoothing Error Histogram

App D-Figure 16: Next-Period –NN Error Histogram

App D-Figure 17: Next-Period –ARRSES Error Histogram

App D-Figure 18: Next-Period –ARIMA Error Histogram
D4. Weekly 6th Period Forecasting Errors Per Forecasting Method

- App D-Figure 19: 6th Period -Naive Forecast Error Histogram
- App D-Figure 20: 6th Period –14 Periods Average Error Histogram
- App D-Figure 21: 6th Period -Exponential Smoothing Error Histogram
- App D-Figure 22: 6th Period –NN Error Histogram
- App D-Figure 23: 6th Period –ARRSES Error Histogram
- App D-Figure 24: 6th Period –ARIMA Error Histogram
D5. Monthly Next-Period Forecasting Errors Per Forecasting Method

App D-Figure 25: Next-Period - Naïve Forecast Error Histogram

App D-Figure 26: Next-Period - 14 Periods Average Error Histogram

App D-Figure 27: Next-Period - Exponential Smoothing Error Histogram

App D-Figure 28: Next-Period - NN Error Histogram

App D-Figure 29: Next-Period - Arrses Error Histogram

App D-Figure 30: Next-Period - Arima Error Histogram
D6. Monthly 6th Period Forecasting Errors Per Forecasting Method

App D-Figure 31: 6th Period - Naïve Forecast Error Histogram

App D-Figure 32: 6th Period - 14 Periods Average Error Histogram

App D-Figure 33: 6th Period - Exponential Smoothing Error Histogram

App D-Figure 34: 6th Period - NN Error Histogram

App D-Figure 35: 6th Period - ARRSES Error Histogram

App D-Figure 36: 6th Period - ARIMA Error Histogram
VITA

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