A HYBRID OF BEKK GARCH WITH NEURAL NETWORK FOR MODELLING AND FORECASTING TIME SERIES

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A HYBRID OF BEKK GARCH WITH NEURAL NETWORK FOR MODELING AND FORECASTING TIME SERIES

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To my beloved family, for your love and support.

To my friends, for your wits, intelligence and guidance in life.

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ABSTRACT

Gold prices change rapidly from time to time. The change is not only in the mean, but also in the variability of the series. The Malaysian Kijang Emas (MKE) is the official national bullion gold coin of Malaysia and it is high in demand. The purchase and resale prices of MKE are determined by the prevailing international gold market price. However, the value of Ringgit Malaysia (RM) that is used to purchase MKE is affected by United States (U.S.) dollar. Thus, the purpose of this study is to develop the best model for forecasting international gold prices, U.S. dollar index and MKE prices by investigating their co-movement. In an attempt to find the best model, fifteen years of data for MKE prices, international gold prices in U.S. dollar and U.S. dollar index were used. This study initially considered three standard methods namely bivariate generalized autoregressive conditional heteroskedasticity (GARCH), trivariate GARCH and multilayer feed-forward neural network (MFFNN). Bivariate and trivariate GARCH are from Baba-Engle-Kraft-Kroner (BEKK) GARCH. The current study further hybridized these methods to improve forecasting accuracy. Bivariate and trivariate GARCH were used to examine the relationship between gold prices and U.S. dollar. The trivariate GARCH was modified to develop GARCH-in-mean model due to the existence risk that was expected in the data. Analysis was done by using E-Views software. However, analysis using MFFNN model and hybridized models were carried out using MATLAB software. Analyses of performances were evaluated using mean absolute percentage error (MAPE) and mean square error (MSE). The MAPE for all in and out sample forecasts were less than 1%. The lowest values of MAPE were 0.8% for gold prices and 0.2% for U.S. dollar index. These low values were produced by using trivariate GARCH-in-mean model that was developed by the current study either as a single or hybdridized model with MFFNN. MSE recorded the lowest values when trivariate GARCH-in-mean model was hybridized with MFFNN using 15 hidden nodes.

ABSTRAK

Harga emas berubah dengan cepat dari semasa ke semasa. Perubahan ini bukan sahaja dalam purata, tetapi juga dalam kebolehubahan siri tersebut. Kijang Emas Malaysia (KEM) adalah wang syiling emas rasmi Malaysia dan mempunyai permintaan yang tinggi. Harga belian dan jualan semula KEM ditentukan oleh harga pasaran emas antarabangsa. Walau bagaimanapun, nilai Ringgit Malaysia (RM) yang digunakan untuk membeli KEM dipengaruhi oleh dolar Amerika. Oleh itu, tujuan kajian ini adalah untuk membangunkan model terbaik untuk meramal harga emas antarabangsa, indeks dolar Amerika dan KEM dengan mengkaji gerakan bersama. Dalam usaha untuk mencari model terbaik, data lima belas tahun untuk harga KEM, harga emas antarabangsa dalam dolar Amerika, dan indeks dolar Amerika telah digunakan. Kajian ini pada awalnya menggunakan tiga kaedah piawai iaitu heteroskedastisiti bersyarat autoregresif teritlak (GARCH) bivariat, GARCH trivariat dan rangkaian neural ke hadapan (MFFNN). GARCH bivariat dam trivariat adalah dari GARCH Baba-Engle-Kraft-Kroner (BEKK). Kajian ini seterusnya menggabungkan kaedah tersebut untuk membaiki kejituan ramalan. GARCH bivariat dan trivariat digunakan untuk meneliti hubungan antara harga emas dan dolar Amerika. GARCH trivariat telah diubahsuai untuk membangunkan model GARCH-dalam-min disebabkan kewujudan risiko yang dijangkakan dalam data. Analisis dilakukan dengan menggunakan perisian E-Views. Walau bagaimanapun, analisis menggunakan model MFFNN dan model gabungan telah dijalankan dengan perisian MATLAB. Kejituan analisis telah dinilai dengan menggunakan min ralat peratusan mutlak (MAPE) and ralat kuasa dua (MSE). MAPE untuk semua ramalan sampel dalam dan luar adalah kurang daripada 1%. Nilai MAPE yang terendah adalah 0.8% untuk harga emas dan 0.2% untuk indeks dolar Amerika. Nilai rendah ini dihasilkan dengan menggunakan model GARCH-dalam-min trivariat yang telah dibangunkan oleh kajian ini samada sebagai model univariat atau digabungkan dengan MFFNN. MSE mencatatkan nilai terendah apabila model *GARCH-dalam-min* trivariat digabungkan dengan MFFNN dengan menggunakan 15 nod tersembunyi.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF APPENDICES

CHAPTER 1

INTRODUCTION

This chapter provides an introduction to the study and a statement of the problem. Then, it describes objectives of the study, significance of the study and scopes of the study. The contributions of the study and thesis organization conclude this chapter.

1.1 Introduction

Gold is a popular precious metal for investment and is considered to be a hedge against inflation (Baur and Lucey, 2010; Ciner et al., 2013; O'Connor et al., 2015; Hoang et al., 2016; Bekiros et al., 2017; Junttila et al., 2018; Tronzano, 2021). Gold has historically been used as currency remains a safe haven for investors. There is an inherent correlation between gold prices and the United States dollar (U.S. dollar) (Gilroy, 2014). The U.S. dollar was tied to gold when the gold standard came into use from 1900 (Craig, 2011). Gold moved to floating exchange rates after 1971, making gold prices vulnerable to the external effects of the U.S. dollar. The International Monetary Fund (IMF) reported in 2008 that 40-50 percent of moves in the international gold prices were related to the U.S. dollar since 2002. It was mentioned that one percent change in the external value of U.S. dollar led to more than one percent change in gold prices. When the demand for the US dollar falls, banks and investors around the world invest more in gold to protect their money. This makes the value of gold increase. Therefore, many central banks around the world invest more in gold to preserve their assets during unstable economic conditions. Likewise, when the U.S. dollar rises, investors will shift their investments from gold to the U.S. dollar. This causes the demand for gold to fall. This behavior causes an inverse relationship between gold and the U.S. dollar (Shafiee and Topal, 2010). In other words, the higher the value of the U.S. dollar, the weaker the price of international gold. Conversely, the lower the value of the U.S. dollar, the stronger the price of international gold. Thus, researchers are interested in the relationship between gold and the U.S. dollar.

However, it cannot be concluded that the price of gold and the U.S. dollar have always moved in opposite directions. There have been times in which gold prices and the U.S. dollar have risen together. This may be caused by other external factors, even though the U.S. dollar is the benchmark for gold trading worldwide. However, it is important to understand that there is a possibility for the U.S. dollar and gold prices to rise at the same time. This might be caused by the crisis in some other countries. Moreover, the U.S. dollar is motivated by many factors such as economic prospects, monetary policy and inflation in the U.S. with other countries. All of these should be investigated. However, in this study, the U.S. dollar index and not the U.S. dollar itself is considered. The US Dollar Index is a measure or an index of the value of the U.S. dollar relative to the value of a basket of foreign currencies. This is often in reference to the majority of the U.S. most significant trading partners' currencies. The U.S. dollar index is a weighted geometric mean of the dollar's value relative to other selected currencies. It uses exchange rates from the major same trading partners' currencies, including the Euro (EUR) at 57.6% weight, Japanese yen (JPY) at 13.6% weight, Pound sterling (GBP) at 11.9% weight, Canadian dollar (CAD) at 9.1% weight, Swedish krona (SEK) at 4.2% weight, and Swiss franc (CHF) at 3.6% weight.

In Malaysia, one of the highest gold investment demands is for its own gold bullion coins called Kijang Emas. The Malaysian Kijang Emas is the official gold bullion coin of Malaysia and was first issued by the Royal Mint of Malaysia on 17 July 2001. The coins come in three different weights of 1 oz., ½ oz. and ¼ oz., respectively. The buying and selling price of Kijang Emas is determined by the prevailing international gold market price. However, the price of Kijang Emas is tied to and driven by Malaysian ringgit (RM). The daily selling and buying prices of these coins are important to investors in order to make an investment decision. Although gold coins serve primarily as a store of value or an alternative financial asset for investment, the gold investment performance for Kijang Emas in Malaysia has received little empirical attention. However, the forecasting of its prices is used for investment purposes in Malaysia. So, in this study, investigation of the investment role of gold from a domestic market perspective is undertaken.

Hashim et al. (2017) conducted a study on macroeconomic factors against the change in the price of gold. They studied 20 years annual data, from 1996 to 2015 of gold-related countries such as India, United States, China, Turkey and Saudi Arabia. They found that there was a positive correlation between oil prices and gold prices but a negative relationship between exchange rates, inflation and interest rates and gold prices. Only the exchange rate did not significantly affect the price of gold. The same study was also conducted by Zakaria et al. (2015). They used monthly data of 14 years from 2000 to 2013. The study was about the factors that caused the change in the prices of gold in Malaysia. Based on the results of their study, it was found that the exchange rates, interest rates and inflation rates had a significant relationship with the prices of gold in Malaysia according to the difference in magnitude and direction. Empirical evidence also showed that any changes in the three variables would cause the prices of gold to change.

Sukri, Mohd Zain and Zainal Abidin (2015) also conducted a study to determine the relationship between macroeconomic factors and the prices of gold, Kijang Emas in Malaysia. The data used were the data of each macroeconomic factor (inflation rates, crude oil prices, ringgit exchange rates, real GDP and inflation rates) during the 9th quarter of 2005 to 2014. Multiple Linear Regression Methods were used to get their findings, from which it was discovered that the Ringgit exchange rate showed a negative correlation with the prices of gold, Kijang Emas.

Gold prices and U.S. dollar index are volatile and clustering, making them difficult to predict (Wang et al., 2011; Chang et al., 2013; Beckmann et al., 2015; Ayele et al., 2017; Liu and Li, 2017; Ameer et al., 2018; Anis et al., 2019; Pierzioch and Risse, 2020). The data series display periods of high volatility followed by periods of relative tranquility. Volatility refers to the rate where the values change. Such volatility behavior is important in financial activities such as forecasting. Volatile data series typically change rapidly from period to period and are not constant over time. This makes gold prices and U.S. dollar index data difficult for management to predict in terms of future value changes. The determination of stability and instability of the volatility in the financial markets are significant, especially when risk is involved. Such time series are not easily modeled using common methods.

Some financial time series do not have a constant mean, while some of them display periods of high volatility, followed by periods of relative tranquility. The characteristics are that large returns will be followed by large returns while small returns will be followed by small returns. This implies that future volatility can be predicted by past and current volatilities (Aleye et al., 2017; Ameer et al., 2018; Anis et al., 2019; Perry, 2021). The volatility of a particular variable refers to the rate at which the values of that variable change. For a financial series, it is said to be volatile if and only if it is random; it is not constant over time; it undergoes rapid changes over time; and the values cluster. In the financial area, modeling volatility in asset returns, also called asset prices, is of great concern. The asset prices move slowly when the condition is in equilibrium and move fast when there are news and trading. In the literature, researchers are likely to use standard deviations or the logarithmic forms of returns in an asset. This is because if the series are converted to log forms before estimating and modeling, they tend to converge to steady states (Bala and Takimoto, 2017). These series in log forms are called returns. This form of data is easier to handle than price series data.

Modeling volatility in time series has attracted attention since the introduction of the Autoregressive Conditional Heteroscedasticity (ARCH) model in a seminal paper by Engle (1982). As a consequence, several variants and extensions of ARCH models such as Generalized ARCH (GARCH) model introduced by Bollerslev (1986) have been proposed to capture volatility clustering or the periods of fluctuations, measure and predict volatilities in the future. GARCH models have been used intensively and widely in educational studies. Many variations of GARCH models exist and numerous studies have examined the extended estimation of the development.

ARCH and GARCH have proven successful in modeling asset price second-moment movements. Bollerslev (1987), Bailie and Bollerslev (1989) and Diebold (1988) have shown that the GARCH (1,1) model is effective in explaining the distribution of exchange rate changes. When conditional volatilities vary over time, ARCH and GARCH models may be used to capture dynamic clustering behavior. Several extensions of ARCH have been developed in recent years to capture time-varying conditional variances and covariances, including work by Sentana and Wadhwani (1992), Kim and Kon (1994), Kearney and Daly (1998), Floros (2007), Teräsvirta (2009), Jensen and Maheu (2013), Boussama and Stelzer (2011), Rasmus and Anders (2014), Abdullah et al. (2016), Ayele et al. (2017), Shetty et al. (2018). Sentana and Wadhwani (1992), Kim and Kon (1994), and Kearney and Daly (1998) used daily data from Middle East stock markets as tested using GARCH models. Floros (2008) examined the use of GARCH models for modeling volatility and evaluated their performance in explaining financial market risk.

Even though the ARCH and GARCH models may be applied in many time series, they suffer from two major deficiencies, (Huynh et al., 2013). Both ARCH and GARCH assume symmetric impacts of unconditional shocks, such that a positive shock has the same impact on conditional volatility as a negative shock. This restriction is contradictory, as negative shocks tend to have larger impacts on volatility than positive shocks of the stylized facts of financial returns. The second deficiency is that they are a univariate specification which does not permit independencies across different asset. They do not test for an interdependent relationship between the conditional volatilities of different asset and non-zero conditional correlations.

To address the deficiencies of the ARCH and GARCH, multivariate GARCH models (MGARCH) have been introduced. Multivariate GARCH (MGARCH) models present a natural investigative framework for possible relations within the conditional mean and time-varying conditional variance of two or more financial series. These models have become well-known in the empirical financial economics and econometrics literature in recent years, such as Lu and Dong (2016), Bala and Takimoto (2017), Shettty et al. (2018), Canh et al. (2019). MGARCH is an extension of the well-known univariate GARCH model. It is one of the most useful methods for modeling the co-movement of multivariate time series with time fluctuating covariance matrix. The co-movements of returns have been shown to be important when modeling volatility of the returns. MGARCH models, which allow the conditional covariance matrix of the dependent variables to follow a flexible dynamic structure, have been shown to be successful in modeling and forecasting volatilities of the dependent variable. For example, asset pricing depends on the covariance of the assets in a portfolio, while risk management and asset allocation relate for instance to finding and updating optimal hedging positions.

MGARCH models have been used to investigate volatility, correlation transmission, and spillover effects (Bala and Takimoto, 2017). They may also be used to investigate the relationships among some macroeconomic variables such as interest rate, stock market prices, and the exchange rate. The MGARCH model can represent the dynamics of the conditional variances and covariances. (Watcher et al., 2013) As the number of parameters in an MGARCH model often increases rapidly with the dimension of the model, the specification should be parsimonious enough to allow for relatively easy estimation of the model and interpretation of the model parameters. Models with only a few parameters may not be able to capture the related dynamics in the covariance structure (Canh et al., 2019). The specification must also consider the imposition of positive definiteness. An alternative way to formulate the model is positive definiteness which is implied by the model structure, in addition to some simple constraints. These are the difficulties in the MGARCH.

The first MGARCH is called VEC GARCH model. It is the model for the conditional covariance matrices which was proposed by Bollerslev et al. (1988). This model is general and allows for a flexible modeling of the conditional variance matrix. However, these models suffer from two disadvantages. First, it is not ensured that the estimated conditional variance matrices are positive definite. Second, the numbers of functionally independent parameters have to be estimated. To overcome these problems, Engle and Kroner (1995) developed a restricted version of VEC model called Baba-Engle-Kraft-Kroner (BEKK) GARCH. The conditional covariance matrices of BEKK are positive definite by construction. Each BEKK model implies a unique VEC model that can generate positive definite conditional covariance matrices.

The number of parameters in the MGARCH model usually increases rapidly with the size of the model. The specification should be concise enough so that the model can be estimated relatively easily and the model parameters can be easily explained. However, simplification usually means simplification, and a model with only a few parameters may not be able to capture the relevant dynamics in the covariance structure (Watcher et al., 2013, Chaudhuri et al., 2016). In addition, although modeling the volatility of returns has become the main focus of attention, understanding the linkage of financial returns has important practical significance. Therefore, it is important to extend the considerations to the MGARCH model. For example, asset pricing depends on the covariance of the assets in the investment portfolio, while risk management and asset allocation are, for example, related to finding and updating the best hedging positions (Gencer and Musoglu, 2014). Therefore, in the current study, BEKK parameterizations for the bivariate and trivariate GARCH model are used to investigate the relationships between gold prices and U.S. dollar index. The models define linkages, if any, between gold prices and U.S. dollar index. This information provides important implications for investors and traders in carrying out trading strategies and portfolio managers in risk management. In addition, a hybrid method of artificial neural network (ANN) with MGARCH is proposed to obtain more efficient models to estimate the time series data.

The current study proposes the hybridization of ANN with MGARCH because ANN has attracted a great deal of attention and widely used in many studies. This suggests an alternative approach to computing and understanding of the human brain. ANN processes information in a way which mimics the human brain. The network is making up by of a large number of highly interrelated processing elements called neurons which work in parallel to solve a specific problem. Neural networks cannot be programmed to implement a specific task. For that reason, the examples must be selected carefully. Otherwise, the network might function incorrectly.

ANN has been often hybridized from different perspectives. In the current study, ANN analysis addresses problems caused by the implicit limitations of BEKK models. The rapid increase in the number of parameters to be estimated in the BEKK GARCH equation limits the number of assets that can be included. Besides, the large number of parameters in BEKK and local maxima in the likelihood function often lead to overfitting. Financial markets are dynamic, and market conditions change with time. However, BEKK does not naturally capture these shifts in market conditions. Furthermore, the maximum likelihood fit of the BEKK parameters involves solving a non-linear optimization process, which is computationally expensive and infeasible in high dimensions (Watcher et al., 2013). This is because ANN is suitable for evaluating the reliability of many variables. ANN is non-parametric and non-linear and can therefore handle such problems in BEKK. This may theoretically provide a better and more accurate classification tool.

1.2 Statement of the Problem

Volatility analysis of financial time series is a crucial aspect of many financial decisions. Volatility forecasts are important in order to either construct less risky portfolios, asset allocation or obtain higher profits. Hence, good analysis and forecasting of volatility become an important aspect in recent years. In recent years, multivariate GARCH models have been used extensively to analyze the co-movements of stock markets and volatility spillovers. It is due to financial return series exhibit many non-normal characteristics that cannot be captured by the standard GARCH model.

In the current study, a set of gold prices and U.S. dollar index are modelled by using multivariate GARCH models. Multivariate GARCH models are able to capture volatility, observe the relationship between long-term/short-term time series data where periods of volatility clustering. However, sometimes the series do not move in the same direction. As a consequence, this relationship might not be embedded in a model that is developed based on the co-movement of three time series. Therefore, it is important to extend the considerations to multivariate GARCH (MGARCH) models. For example, asset pricing depends on the covariance of the assets in a portfolio, and risk management and asset allocation relate for instance to finding and updating optimal hedging positions.

The specification of an MGARCH model should be flexible enough to be able to represent the dynamics of the conditional variances and covariances. The number of parameters in an MGARCH model should often increases rapidly with the dimension of the model, the specification should be parsimonious enough to allow for relatively easy estimation of the model and also allow for easy interpretation of the model parameters. For examples, see Bollerslev, Engle, and Wooldridge (1988), Ng (1991), and Hansson and Hordahl (1998). Thus, trivariate GARCH model gas been proposed to improve these problems. However, parsimony often means simplification, and models with only a few parameters may not be able to capture the relevant dynamics in the covariance structure.

Another feature that needs to be considered in the specification is imposing positive definiteness, such as covariance matrices need, by definition, to be positive definite. Thus, to improve on the Multivariate GARCH model, it will be hybridized with neural network model. The models proposed in this study are trivariate GARCH and hybrid trivariate GARCH with neural network model. Multivariate GARCH models have been used widely for forecasting different types of time series to capture the long term trend while in the case of financial time series that have been shown to have volatility clustering, ARCH based models have been used.

In this study, the following question will be explored: Between trivariate GARCH and hybrid trivariate GARCH with neural network model, which model is more accurate in modelling volatile data.

1.3 Objectives of the Study

The purpose of this study is to develop the best model for forecasting gold prices and U.S. dollar index by studying co-movement. In the attempt to find the best model, specific objectives have been established as follows:

a) To develop a new trivariate GARCH model and improve the forecasting accuracies of the single model.
b) To hybrid the new trivariate GARCH model with the neutral network.
c) To compare the forecast ability of the new trivariate GARCH model with hybrid neutral network and new trivariate GARCH model.

1.4 Significance of the Study

When two or more volatile financial time series are verified as related, that is having co-movement, a multivariate GARCH model is developed based on such a relationship can be used to forecast a series, even if only one of the series is present. In other words, looking at the movement of a related time series, we can still predict future values of the other series with an acceptable level of confidence and accuracy.

The current study aims to investigate the potential of hybridizing trivariate GARCH model with the neural network to model and forecast the variance of financial and economic time series over time. It aims to do so by analyzing the co-movement relationship between financial series in handling volatility. For the purpose of the study, the prices of the gold market (Malaysian Kijang Emas and international gold prices) and the U.S. dollar index over the period 2001 to 2016 will be used as case studies. Gold prices and the U.S. dollar index are not easy to model using common methods. Gold prices have ranged widely since 1968. The price of gold as of every traded asset is subject to the ups and downs of the market. The rate of gold also fluctuates. In the past, when the USD went down, the gold prices remained. It has been found that the gold prices are always moving in the opposite direction to the US dollar. The relationship of the co-movement and covariance between two time series data have not been investigated by other researchers. The current study aims to address this research gap.

The Malaysian Kijang Emas is the official gold bullion coin of Malaysia and is minted by the Royal Mint of Malaysia. It was first issued on 17 July, 2001. It is not in high demand compared to currencies from countries such as China, Saudi Arabia and India. For that reason, it is not certain whether it has been affected by the international price of gold or the U.S. index. For the benefit of local investors, trivariate GARCH is applied to study the time-varying volatility relationship between international gold markets, Malaysian Kijang Emas and U.S. index. In this study, an investigation is carried out to determine whether there are interactions, unidirectional and spillover effects among these three markets. Such information can be used as reference and guidance for investors, commercial banks, and researchers to take measures at the policy level, to safeguard against and prevent adverse impacts of fluctuations in gold prices. Moreover, stakeholders can take actions to maintain gold prices and economic development stability.

1.5 Scope of the Study

The U.S. financial crisis had an impact on the international gold market via certain transmission channels. By comparing the degree of change of spillover effects before and after the crisis, the impact of U.S. index during the financial crisis on the international gold market and Malaysian gold prices through spillover effects is analyzed. Taking the volatility of gold prices after the year of 2001 as the sample data, bivariate GARCH and trivariate GARCH models were established to analyze the correlation between three markets studied. They are U.S. index, international gold prices and the Malaysian Kijang Emas (official gold bullion coin of Malaysia). The bivariate GARCH model is used to analyze U.S. index and international gold prices. The trivariate GARCH model is applied to study the time-varying volatility relationship between international gold markets, Malaysian Kijang Emas and U.S. index. An investigation is carried out to determine whether there are interactions and unidirectional and spillover effects among these three markets studied.

1.6 Contribution of the Study

In the attempt to find the best model for forecasting U.S. index and gold prices, the following are the contributions of this study.

The first contribution is the new trivariate GARCH model. This model is useful in capture multivariate volatile time series data. It may give more accurate forecasts than the original model. Details are provided in Chapter 3.

The second contribution is to verify the best-selected model is the best model for this study. First, we examined the data by using MGARCH models. Unlike previous studies, the current study divides all three data sets into four sub-periods (four economic cycles). The output (forecasts) of new trivariate GARCH model will be trained by ANN. Results showed that the hybrid model of new trivariate GARCH with ANN is the best model for this study. Details of the third contribution are found in Chapter 5 and Chapter 6.

The third contribution is the hybrid model, which has been shown to outperform the single model. Mean square error (MSE) of the hybrid model is smaller than the single model. Details are found in Chapter 6.

The forth contribution is the data used for analysis. The data include the prices of gold market (Malaysian Kijang Emas and international gold prices) and the U.S. dollar index over the period of 2001 to 2016. The data are divided into four different economic cycles, to represent a real period of market turmoil and a normal situation. This is because volatility forecasting is usually considered for long periods, such as five years, ten years, or more. It will lead to insufficiently in capturing volatility in different economic situations. Additionally, the buying and selling price of Kijang Emas is determined by the prevailing international gold market price. It is found that the time of volatility of Kijang Emas is different with international gold prices. This may be affected by the international price of gold or the U.S. dollar index. The ways and procedures cannot be found in any literature. Details are provided in Chapter 4.

1.7 Thesis Organization

This thesis consists of seven chapters. Chapter 1 is an introduction to the current study. It introduces the current study, followed by the statement of the problem. Next, it describes objectives of the study, significance of the study and scopes of the study, as well as its contributions. A description of the thesis organization ends this chapter.

Chapter 2 is a literature review of the current study. The purpose of the chapter is to review previous studies related to the current study. Basically, this study focuses on modeling volatility data by using multivariate GARCH model. The multivariate GARCH models are bivariate GARCH and trivariate GARCH models. We are also interested in hybridization method which combines trivariate GARCH and artificial neural network model. Therefore, for the purposes of this study, we reviewed literature concerning multivariate GARCH, artificial neural networks and hybrid models. This chapter concludes with a table summarizing relevant studies in GARCH.

Chapter 3 is the research methodology for the current study. This chapter describes three approaches for forecasting gold prices and U.S. dollar index data which are multivariate GARCH models, neural network model and hybrid model. Forecasting evaluation method will be presented and this is followed by a concluding remark which ends this chapter.

Chapter 4 describes three things. First, the results of bivariate and trivariate GARCH models when applied to U.S. index, international gold prices and the Malaysian Kijang Emas (official gold bullion coin of Malaysia). Second, it describes the results of the trivariate GARCH-in-mean model when applied to the U.S. index, international gold prices and the Malaysian Kijang Emas (official gold bullion coin of Malaysia), and describes the time-varying volatility relationship between them in terms of whether these three markets interact or experience unidirectional and spillover effects. Third, it describes the results of a hybrid model which combines the multilayer feedforward neural network and trivariate GARCH-in-mean models when applied to Malaysian Kijang Emas, international gold prices, and the U.S. dollar index. Next, it discusses the best hybrid model of this current study. The performances of the hybrid model, followed by a conclusion of hybrid model analysis, end this chapter.

Chapter 5 describes the results of the trivariate GARCH and trivariate GARCH-in-mean model when applied to the daily exchange rate for the Japanese Yen (JPY), daily exchange rate for the U.S. dollar (USD), NASDAQ stock market (American stock exchange), spot prices for crude oil and petroleum products (FOB) price, current West Texas intermediate crude oil prices (OIL) and American stock market index – Standard & Poor's 500 (SP500) and describes the time-varying volatility relationship between them in terms of whether these markets interact or experience unidirectional and spillover effects. The results are used to compare with trivariate GARCH model and proved that trivariate GARCH-in-mean model is better than trivariate GARCH model.

Chapter 6 is the summary and conclusions of this current study. This chapter summarizes the materials presented in the previous six chapters and discusses in further detail certain results and findings. Based on the results and findings, conclusions and suggestions are made.

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