MODELLING AND FORECASTING FLIGHT DELAY AT KUALA LUMPUR INTERNATIONAL AIRPORT USING HYBRID ARIMA-GARCH MODEL

ILYA FARHANA ZULKEFLEE

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DEDICATION

To my dearest husband, who has always believed in me and my beloved family, who never fail to support me.

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ABSTRACT

Flight delay has become a hot issue over the recent years since it is one of the common factors that can impact the airline companies in terms of financial cost. When a flight is delayed, it requires the consumption of extra fuels, labor and other necessary aspects in the airline production process and this may lead to higher operating cost to the airlines. Thus, this study aims to develop the hybridization between Autoregressive Integrated Moving Average (ARIMA) models and Generalised Autoregressive Conditional Heteroscedasticity (GARCH) models to predict the flight delay at Kuala Lumpur International Airport (KLIA). The weekly average minutes flight delay data were obtained from Kuala Lumpur Air Traffic Control Centre (KL ATCC) Flight Information Regions (FIR) Subang which dated from 5^{th} May 2014 until 2^{nd} July 2018. The data are divided into two parts, which 80% of the data are used as in-sample data and the rest 20% are used as out-sample data. The in-sample data are those from 5^{th} May 2014 until 28^{th} August 2017 and out-sample data will be from 4^{th} September 2017 until 2^{nd} July 2018. The data are first analysed by using GARCH models and the performance of these models is compared with hybrid ARIMA-GARCH models. The results of this study revealed that hybrid ARIMA-GARCH model is the best method for modelling and forecasting flight delay compared to GARCH models as it has a smaller value of Akaike's Information Criterion, Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE).

ABSTRAK

Kelewatan penerbangan merupakan satu isu yang hangat dibincangkan semenjak beberapa tahun ini kerana ia merupakan salah satu faktor yang menjejaskan prestasi sesebuah syarikat penerbangan terutamanya dari segi kewangan. Hal ini kerana keperluan untuk penambahan bagi penggunaan tenaga kerja serta bahan bakar akibat kelewatan penerbangan menyebabkan sesebuah syarikat penerbangan itu harus menanggung kos operasi yang lebih tinggi. Justeru, kajian ini dijalankan bagi membangunkan model penghibridan antara model Autoregresi Purata Bergerak Terkamir (ARIMA) dan model Autoregresi Teritlak Heteroskedastisiti Bersyarat (GARCH) untuk ramalan kelewatan penerbangan di Lapangan Antarabangsa Kuala Lumpur (KLIA). Data mingguan dari tempoh 5 Mei 2014 sehingga 2 Julai 2018 bagi kelewatan penerbangan mengikut purata minit diperoleh daripada Pusat Kawalan Trafik Udara Kuala Lumpur (KL ATCC) Informasi Penerbangan Kawasan (FIR) Subang. Data tersebut dibahagikan kepada dua bahagian di mana 80% daripadanya digunakan sebagai data sampel dalam dan selebihnya digunakan sebagai data sampel luar. Data yang bertarikh 5 Mei 2014 sehingga 28 Ogos 2017 digunakan sebagai data sampel dalam manakala data sampel luar diambil daripada data yang bertarikh 4 September 2017 sehingga 2 Julai 2018. Analisis data tersebut dibuat menggunakan model GARCH dan kemudiannya dibandingkan dengan hasil analisis daripada model penghibridan ARIMA-GARCH. Hasil kajian menunjukkan bahawa model penghibridan ARIMA-GARCH adalah model yang terbaik dalam permodelan dan peramalan kelewatan penerbangan kerana model ini mempunyai nilai Kriteria Informasi Akaike (AIC), MAE, MSE, RMSE dan MAPE yang kecil berbanding model GARCH.

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LIST OF ABBREVIATIONS

AAR	-	Airport Arrival Rate
ACF	-	Autocorrelation Function
ADF	-	Augmented-Dicky Fuller
AIC	-	Akaike’s Information Criterion
APMC	-	Agricultural Produce Market Committee
ARCH	-	Autoregressive Conditional Heteroscedasticity
ARIMA	-	Autoregressive Integrated Moving Average
ARMA	-	Autoregressive Moving Average
CBR	-	Case-Based Reasoning
DMT	-	Danger Model Theory
DSE	-	Dhaka Stock Exchange
FAA	-	Federal Aviation Administration
FIR	-	Flight Information Regions
GARCH	-	Generalised Autoregressive Conditional Heteroscedasticity
GDP	-	Ground Delay Programs
GMT	-	Grey Model Theory
KL ATCC	-	Kuala Lumpur Air Traffic Control Centre
KLIA	-	Kuala Lumpur International Airport
LM	-	Lagrange Multiplier
MAE	-	Mean Absolute Error
MAPE	-	Mean Absolute Percentage Error
MLE	-	Maximum Likelihood Estimation
MOM	-	Method of Moments
MSE	-	Mean Squared Error
MSM	-	Muscat Security Market
OBHI	-	Ober-House Lithuanian House Price Index
OLS	-	Ordinary Least Squares
PACF	-	Partial Autocorrelation Function
PPI	-	Producer Price Index

RMSE	-	Root Mean Square Error
SPL	-	Square Pharmaceuticals Limited
SSE	-	Sum of Squared Errors
TOTP	-	Total Daily Punctuality
WITI	-	Weather Impacted Traffic Index
WTI	-	West Texas Intermediate
WTM	-	Weather Translation Model

LIST OF SYMBOLS

$\hat{\rho}_k^2$	-	Squared sample autocorrelations at lag k
$\emptyset_p$	-	AR polynomial
A_t	-	actual values
F_t	-	forecasted values
H_0	-	null hypothesis
H_1	-	alternative hypothesis
x_t	-	optional exogenous regressor
z_t	-	series of independent identically distributed random variables
α_i	-	coefficient of ARCH parameters
β_i	-	coefficients of the lag difference
β_j	-	coefficient of GARCH parameters
$\hat{\gamma}$	-	tested time series
ε_t	-	error at time t
ε_{t-i}^2	-	past squared return
$\hat{\varepsilon}(k)$	-	McLeod-Li test
θ_q	-	MA polynomial
σ_t^2	-	estimated conditional variance
σ_{t-j}^2	-	past conditional variance
$\psi_\tau(0,1)$	-	probability density function of residuals with 0 mean and variance 1
Δy_t	-	differenced series
B	-	backward shift operator
EK	-	excess kurtosis
h	-	number of tested lags
K	-	sample kurtosis
n	-	sample size
N	-	sample size
p	-	autoregressive order
q	-	moving average order

S	-	sample skewness
δ	-	estimated parameters
λ	-	minimum residual mean square error value
τ	-	distributional parameter

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CHAPTER 1

INTRODUCTION

1.1 Introduction

Flights can be delayed due to the airline maintenance and services, security issues, extreme events such as heavy floods, volcano eruption, thunderstorm and tsunami. According to the *Federal Aviation Administration* (FAA), flights are considered to be delayed when it is 15 minutes later than its scheduled time. These flight delays can cause so much inconvenience to people who travel back and forth for businesses and also leisure activities. On top of that, when flights are delayed, the passengers who are on a multi-plane trips could miss the connecting flights and arrive late at the destinations. If flights are cancelled, most airlines will rebook the tickets for the affected passengers at no additional charge but it is totally a different case when flights are delayed.

Flights can also be affected by reactionary delays, in which this delays are caused by the late arrival of previous flights. These type of delays can worsen the schedule operation. Flight schedules are often subjected to irregularity. Due to tight connections among airlines resources, flight delays could grow immensely over time and space unless the proper actions are taken (Oza et al. 2015). It can be costly to airline companies if the flights are delayed as this involves all aspects of aerodrome operations such as extra consumptions of aircraft fuelling and aircraft maintenance. Ryersen et al. (2014) also claimed that flight delays will usually lead to massive amount of fuel burnt. This sometimes will urge the airlines to increase the price of the flight tickets just to cover the costs of extra consumptions of fuel and other necessities.

1.2 Background of the Study

According to Cheng (2014), flight delays prediction has been one of the hot issues over the past few years. Many factors can lead to flight delays such as adverse weather conditions, the reactionary delays, mechanical and maintenance problems. There have been a lot of researches conducted previously regarding the flight delays. In a research done by Mueller and Chatterji (2002), the departure and arrivals delay were modelled by using Normal or Poisson distributions and its purpose is to improve the airlines traffic management systems. Kalliguddi and Leboulluec (2017) proposed a predictive modelling engine using machine learning techniques and developed some statistical models to predict flight delays. The aim of developing the predictive model for flight delay is to have better management decisions for the airlines.

In addition, Oza et al. (2015) in their study managed to develop the models which can help to predict the flight delay using OneR Algorithm. Cheng (2014) on the other hand, used weighted spline combined with ARIMA model as a tool to predict flight departure delay. The model is able to predict delays for each flight in terms of specific day and hour. The study involved several contributing factors such as school and public holidays, weather and hourly pattern which lead to flight delay. In another study done by Lee and Zhong (2016), the correlation between flight delay and duration of rainfall as well as thunderstorms were investigated using multiple regression model namely linear model and square root model. It turns out that square root model produced a better accuracy in determining the correlation between weather and the flight delay compared to the linear model.

These past researches prove that it is crucial to predict flight delay as it will help in enhancing the accuracy of flight schedules and more importantly, provide convenience for the passengers. Therefore, in this study, GARCH and hybrid ARIMA-GARCH models will be proposed to predict flight delays at Kuala Lumpur International Airport. Weekly average minutes will be considered since daily data is not appropriate due to massive missing values. This study only focuses on the delay between 15 minutes up to 60 minutes as more than one hour delay will be considered as outliers.

At the end of the study, modelling and forecasting performance between the best models of GARCH and hybrid ARIMA-GARCH will be compared. The smaller value of Akaike's Information Criterion (AIC) indicates that the model is better than the other model in terms of modelling performance. Meanwhile, in terms of forecasting performance, the smaller values of Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) will be concluded as the best forecasting method.

1.3 Problem Statement

Flight delay is one of the common factors that lead to high cost impact to airline companies. When a flight is delayed, it requires the consumption of extra fuel, labor and other necessary in the airline production process, resulting in higher operating cost to the airlines. It is also inconvenience to the passengers when flights are delayed as this could affect their schedules and activities. Therefore, it is vital to carry a study which is able to improve the accuracy of flight arrivals and departures.

Since there is no similar studies exist in Malaysia yet, modelling and forecasting flight delays at Kuala Lumpur International Airport (KLIA) can be considered to overcome the problem. Time series model are used in the current study. However, volatility which exist in the flight delay data can be a tough issue in modelling and forecasting the time series. Hence, it is crucial to perform an analysis that can comprehend the entire behavior of the delay data as well as provide more accurate result at the end of the study.

Even though Autoregressive Integrated Moving Average (ARIMA) is known as a flexible model, it is unfortunately unable to handle volatility. Thus, this study aims to find the best method which can model and forecast the volatile flight delay data. Furthermore, the presence of Autoregressive Conditional Heteroscedasticity (ARCH) effect is another problem which needs to be taken care of. Hence, a more appropriate model is chosen in order to remove the ARCH effect that exists in the data. Hopefully this study will produce better accuracy of flight schedules and reduce the number of flight delays.

1.4 Objectives of the Study

The objectives of the research are:

1) To develop the best GARCH model for flight delay at Kuala Lumpur International Airport (KLIA).

2) To develop the best hybrid ARIMA-GARCH model for flight delay at Kuala Lumpur International Airport (KLIA).

3) To compare the modelling as well as forecasting performances between GARCH and hybrid ARIMA-GARCH models for flight delay data.

1.5 Scopes and Limitations

This study involves weekly average minutes flight delay data at Kuala Lumpur International Airport (KLIA) which are obtained from Kuala Lumpur Air Traffic Control Centre (KL ATCC) Flight Information Regions (FIR) Subang dated from 8th October 2013 until 13th July 2018. In this study, the flight delay data cover both KLIA and KLIA 2. The reason why this study used weekly data instead of daily data is because there are massive missing values for the whole consecutive three weeks from 29th January 2017 until 17th February 2017. Mean imputation method can be used to overcome the missing values but it is still considered inappropriate for replacing the three weeks missing values with the imputed mean of average minutes flight delay.

Moreover, the research only focuses on the data after KLIA2 has been fully operated, which is on 2nd May 2014 onwards. It is impossible to consider the whole data prior and after the opening of KLIA2 since there are huge difference between the delay records among these two events. Obviously, there was quite a large delay which had been recorded prior to the opening of KLIA2 since there are only two runways operated. It is a weekly data and every new week will start on Mondays, therefore the data will begin on Monday (5^{th} May 2014). There are a total of 218 observations indicating that there are 218 weekly data involve in this research. The data in this study were analysed by using EViews and RStudio softwares.

GARCH models will be proposed in this study since the data are very volatile. In a study done by Miswan et al. (2014), GARCH models need to be applied only to a volatile data and if it happens otherwise, it will not produce a good modelling and forecasting results. Hybridization between ARIMA and GARCH models will be proposed later to compare the modelling and forecasting performance. In most cases, hybridization models will increase the accuracy performance since it is able to complement the weakness of each model components. Therefore, in this research two methods of modelling and forecasting will be compared at the end of the study which are GARCH models and hybrid ARIMA-GARCH models.

1.6 Significance of the Study

In this study, flight delay will be modelled and forecasted by using GARCH and hybrid ARIMA-GARCH models. ARIMA model has the ability to handle nonstationary data while GARCH model is able to capture the volatility which exists in the conditional variance of the time series. Hybridization between these two models will improve the accuracy and forecasting performance since it carries both qualities in ARIMA and GARCH models.

Flight delays can be costly to airline companies as it requires the consumptions of extra fuel, labor and other necessary production process. According to Abdullah et al. (2007), even though promotions for flight tickets are widely held, it is still not enough to satisfy the airline customers. This is because not all customers are willing to accommodate unnecessary delays in their travel plans. Therefore, it is crucial to predict the flight delays as it can be beneficial for airlines.

1.7 Organizations of the Report

This research consists of five chapters, which in the first chapter includes the introduction, background of the study, problem statement, scopes and limitations in the study, significance of study and lastly the organizations of the report. Chapter 2 describes in detail the reviewed literature made in the past by other researchers. The methodology of this research will be discussed in Chapter 3 which includes volatility testing for GARCH models, stationary testing, model identification, parameter estimation, diagnostic checking and forecasting. Meanwhile, the analysis of this research will be done in Chapter 4. This chapter is the most important chapter as it will conclude the best method for modelling and forecasting. The best modelling performance will be assessed by using the smallest value of Akaike's Information Criterion (AIC). On the other hand, the best forecasting performance will be assessed by using the smallest value of Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE). Finally, chapter 5 consists of summary and conclusions of the study as well as suggestions for future research.

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