A HYBRID MULTIVARIATE TIME SERIES MODEL FOR FORECASTING METEOROLOGICAL DATA IN PENINSULAR MALAYSIA

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ABSTRACT

An extreme rainfall event, high temperature, haze, glacier melting, rises of sea level, and droughts are as a result of climate change. The impact of climate change may result to the devastation of the earth and life. For early preparations to face the challenges of climate change, a model that can forecast future weather variables is needed. There exist several weather models that forecast the future atmospheric data; however, the existing models which are not station-based models, hence will have an incomplete understanding of climate system of a particular case study area. To improve on the climatic modelling, this study developed a new model where the model used data collected from Alor Setar weather stations in Peninsular Malaysia by taking into consideration all the identified dynamic features of the variables. The model is an extension of multivariate time series method, namely vector autoregressive (VAR) model. Dynamic conditional correlation (DCC) model from generalised autoregressive conditional heteroscedasticity (GARCH) model was applied in this study since weather variable has high volatility and DCC model is able to capture the volatility of the model. However, because of the high persistence in the volatility, DCC model alone is not able to capture the structural changes in the volatility. To improve on the model, a joint model with hidden Markov model (HMM) is proposed whereby HMM method will consider the structural changes in the volatility that experienced high, moderate and low volatility. The findings presented that, due to neglected of structural change in volatility, the VAR multivariate time series with the hybrid of DCC model was not able to capture closely the volatility of the weather data. Nevertheless, the proposed joint model that uses the HMM to consider the structural changes in the volatility was able to capture the degree of persistence in the weather data. The out-sample forecasting accuracy gives less than ten percent of the mean absolute percentage error (MAPE) for the proposed joint model. Simulation study proves that the VAR-HMM-DCC proposed model has better result as compare to the hybrid of the conventional VAR-DCC model. The newly joint VAR-HMM-DCC model is the contribution that provides strategies for the future forecasting weather data.

ABSTRAK

Kejadian hujan yang melampau, suhu tinggi, jerebu, pencairan glasier, kenaikan paras laut, dan kemarau adalah akibat daripada perubahan iklim. Kesan daripada perubahan iklim boleh mengakibatkan kehancuran bumi dan hidupan. Untuk persiapan awal bagi menghadapi cabaran perubahan iklim, satu model yang boleh meramal pembolehubah cuaca pada masa hadapan diperlukan. Terdapat beberapa model cuaca yang meramalkan data atmosfera, akan tetapi, model-model yang sedia ada merupakan model yang bukan asas stesen, dengan itu tidak mempunyai pemahaman yang lengkap tentang sistem iklim kawasan kajian kes tertentu. Bagi memperbaiki pemodelan iklim, kajian ini membangunkan model baharu di mana ia menggunakan data yang dikumpulkan dari stesen cuaca Alor Setar di Semenanjung Malaysia dengan mengambil kira semua ciri dinamik yang dikenal pasti bagi pembolehubah. Model ini adalah lanjutan kaedah siri masa multivariat, iaitu model autoregresi vektor (VAR). Model korelasi bersyarat dinamik (DCC) dari model heteroskedastik bersyarat autoregresi menyeluruh (GARCH) telah digunakan dalam kajian ini kerana pembolehubah cuaca mempunyai volatiliti yang tinggi dan model DCC dapat merakam volatiliti dalam model. Namun, disebabkan kekalan yang tinggi dalam proses volatiliti, model DCC sahaja tidak mampu merakam perubahan struktur dalam proses volatiliti. Untuk memperbaiki model, model gabungan bersama dengan model Markov tersembunyi (HMM) dicadangkan, di mana kaedah HMM akan mengambil kira perubahan struktur dalam proses volatiliti yang mengalami volatiliti yang tinggi, sederhana dan rendah. Dapatan kajian menunjukkan bahawa, disebabkan oleh perubahan struktur yang tidak berubah dalam volatiliti, siri masa multivariat VAR dengan hibrid model DCC tidak dapat merakam volatiliti data cuaca. Walau bagaimanapun, model gabungan yang dicadangkan menggunakan HMM untuk mempertimbangkan perubahan struktur dalam proses volatiliti itu dapat merakam tahap kekekalan dalam data cuaca. Ketepatan ramalan luar sampel adalah kurang daripada sepuluh peratus ralat peratusan mutlak (MAPE) bagi model gabungan yang dicadangkan. Kajian simulasi membuktikan bahawa model yang dicadang, VAR-HMM-DCC menghasilkan keputusan yang lebih baik berbanding dengan hibrid model konvensional VAR-DCC. Model gabungan VAR-HMM-DCC baharu merupakan sumbangan yang menyediakan strategi untuk ramalan data cuaca pada masa hadapan.

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LIST OF ABBREVIATIONS

ADF	-	Augmented Dickey Fuller
ALS	-	Adaptive least square
ANFIS	-	Adaptive neuro-fuzzy inference system
ANN	-	Artificial neural network
AOGCM	-	Atmosphere-ocean global climate model
ARCH	-	Autoregressive conditional heteroscedasticity
ARFIMA	-	Autoregressive fractional integrated moving average
ARIMA	-	Autoregressive integrated moving average
ARMA	-	Autoregressive moving average
BEKK	-	Baba, Engle, Kraft, and Kroner
CCC	-	Constant conditional correlation
DCC	-	Dynamic conditional correlation
DFA	-	Detrended fluctuation analysis
DLNM	-	Distributed lag non-linear
ED	-	Emergency department
ESP	-	Ensemble streamflow prediction
GARCH	-	Generalised autoregressive conditional heteroscedasticity
GCM	-	Global climate model
GFM	-	Generalised fuzzy model
GLM	-	Generalised linear model
GLS	-	Generalised least square
HFMD	-	Hand foot mouth disease

HMM	-	Hidden Markov model
HMM-DA	-	Hidden Markov model-based drought analysis
LASSO	-	Least absolute shrinkage and selection operator
LM	-	Lagrange multiplier
LS-SVR	-	Least square-support vector regression
MGARCH	-	Multivariate generalised autoregressive conditional heteroscedasticity
MLE	-	Maximum likelihood estimation
MSDI	-	Multivariate standardised drought index
MTS	-	Multivariate time series
OLS	-	Ordinary least square
OLS-CUSUM	-	Ordinary least square-cumulative sum
PAEP	-	Pacific-Andean region of Ecuador and Peru
PV	-	Photovoltaic
SARIMA	-	Seasonal autoregressive integrated moving average
SVM	-	Support vector machine
TSA	-	Time series analysis
VAR	-	Vector autoregressive
VARMA	-	Vector autoregressive moving average
VECM	-	Vector error correction model
WT	-	Wavelet transform

LIST OF SYMBOLS

X_t	-	Time series
μ	-	Mean
σ^2	-	Variance
h	-	Distance in time
ΔX_t	-	Difference series
z_t	-	Exogeneous regressor
ε_t	-	Error term
p	-	Autoregressive parameter
d	-	Degree of integration
q	-	Moving average parameter
$\phi(\mathrm{B})$	-	Polynomial of order p
$\theta(\mathrm{B})$	-	Polynomial of order q
P	-	Seasonal autoregressive parameter
Q	-	Seasonal moving average parameter
$\Phi_{\mathrm{P}}\left(\mathrm{B}^{\mathrm{S}}\right)$	-	Polynomial of order P
$\Theta_{\mathrm{Q}}\left(\mathrm{B}^{\mathrm{S}}\right)$	-	Polynomial of order Q
L	-	Log likelihood
k	-	Number of variables
u_t	-	Independent white noise
η_t	-	Standardised residuals

Q_t	-	Dynamic conditional correlation matrix
$(\alpha + \beta)$	-	Volatility persistence measure
π	-	Initial state probabilities
a_{ij}	-	Transition state probability distribution
b_j^k	-	Emission probability

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Chapter 1

INTRODUCTION

1.1 Introduction

Climate is characterised as the state of the environment at a particular area over a long period of time. Climate is the long-term summation of the atmospheric components and it is measured by assessing the pattern of variation in solar radiation, temperature, humidity, rainfall, wind and atmospheric pressure. The perplexing nature of climate phenomena has been acknowledged for decades. According to Seneviratne et al. (2012), the natural decadal or multi-decadal in the climate set the environment for anthropogenic climate change. Notably, natural climate variability in the forms of tropical cyclones, monsoon, haze, thunderstorm, and El Niño or La Niña causes the weather and climate extremes. These climate phenomena have encouraged us to extract more information from the available meteorological data.

Therefore, modelling the multivariate meteorological data specifically in Peninsular Malaysia could be an important contribution since it explores the characteristics of Peninsular Malaysia's meteorological data series. According to Kennett and Marwan (2015), future cannot be predicted by people. They can however constrain possible outcomes based on the historical information and life experience. The exact outcome is unpredictable due to the variability, where variability exist based on direct observations or learning. Thus, the motivation behind this research is to develop a model that is able to forecast meteorological data. The researcher attempted to execute a model that has the capability to capture the future pattern of data series.

1.2 Background of the Study

Basically, climate is defined as the average weather in a particular area. It covers the patterns of humidity, temperature, wind, precipitation, and seasons. Climate patterns have a significant influence on natural ecosystems, cultures, and economies. Kreienkamp et al. (2011) explained that the magnitude and characteristics of climate change was traditionally assessed using a tool, namely a coarse resolution numerical model that enabled the current climate to be extended and the future climate to be projected. However, the climate nowadays has evolved and hence, the past information may not be a reliable predictor for the future pattern.

Climate change has occurred in a rapid pace and has led to many catastrophes. A lot of systems are affected by climate; therefore, climate change may disrupt aspects such as availability and usage of water, health risks, and food production in the lives of people, animals, and plants. For instance, shifts in the normal timing of rain or the temperature can affect when insects hatch, when plants bloom and produce fruit, or when stream levels are at their fullest. This can affect the usual pattern of crop pollination, fish spawning, food for migrating birds, water supplies for drinking and irrigation, and many more.

Few short-term climate variations are a normal occurrence but the present long-term trends signal severe climate change. Malaysia is reported to be the 26th largest greenhouse gas emitter in the world with a population of 27 million people. Due to the growth rate of gas emissions throughout the country, the temperature is projected to rise by 0.3 to 4.5 degree of Celsius (Alam et al., 2012). “Climate change" encompasses a broad range of changes to the environment. As an example, global warming which refers to the rising global temperatures causes the climates to change.

As a global issue, climate change has been recognised as an imperative factor in water resources. Evaluating weather parameters such as temperature, relative humidity, wind speed, and precipitation may provide practical solutions in risk management, and water resource management, apart from assisting the decision-making process regarding climate change. For example, the characteristics of precipitation during its occurrence depend greatly on temperature and the weather situation. Hence, changes in any of these aspects alter precipitation. Undeniably, these four variables affect agriculture, environment, and the hydrological cycle.

The complexity of natural systems presents a challenge to model the physical processes deterministically, therefore, the stochastic models are applied. These models commonly have a relatively simple structure and incorporates the element of uncertainty in the result. This element signifies the part of the process which may not be explained deterministically. In addition, the stochastic models use the existing knowledge of the physical processes to duplicate the prominent patterns or behaviour in the data sets.

Around the world, the stochastic models have been applied extensively to these meteorological variables. Nevertheless, a majority of the literature addressed single variable. For example, Gil-Alana (2012) analysed the precipitation in United Kingdom's monthly rainfall data from a long-term persistence perspective. The researcher considered the strong dependence and seasonality in the data, and applied various modelling approaches. Furthermore, Valdez–Cepeda et al. (2012) obtained long-term monthly precipitation series of data from 56 meteorological stations located within Zacatecas, Mexico, and analysed the data accordingly. Telesca et al. (2012) examined the time variant scaling behaviour of six monthly rainfall series from 1860 to 2006 in central Argentina. In addition, Lovallo et al. (2013) studied the time dynamics of monthly rainfall series which were recorded intermittently from 1939 to 2010 at seven climatic stations in north Lebanon.

Kane and Yusof (2013) accessed the risks of rainfall events in several locations in Peninsular Malaysia. Moreover, Smith (1993), Fraedrich and Blender (2003) and Cohn and Lins (2005) described natural temperature variability as a stochastic process with long memory. In terms of humidity, Shiri et al. (2011) investigated and forecasted the relative humidity variation using ARIMA model in Pars Abad e-Moghan, north-west of Iran. Other studies on the variability of relative humidity include Jamiyansharav et al. (2010) and Jäntschi (2011).

Apart from that, time series analysis has two common goals, namely perceiving or modelling random mechanism and prediction of future series based on the past data. Precipitation, temperature and relative humidity are three main effective parameters in drought study. The minimum fluctuations of these parameters would extremely damage the agriculture and the economy of a country (Shamsnia et al., 2011).

Notably, in a number of time series problems, two or more random variables evolve over a period of time. These variables are linked and dependent on one another. Even though most situations require modelling and forecasting of only one variable, Y. Li & Genton, (2009) stressed the need to treat all of these variables as a vector time series. For instance, recent modelling framework highlighted the fluctuating nature of precipitation which is caused by anthropogenic climate change (Wong et al., 2009; Zin et al., 2012). Despite the lingering uncertainties, it is generally agreed that a rise in temperature increases the intensity of heavy precipitation events. This include regions where precipitation is anticipated to drop (Meehl & Stocker, 2007).

These forecasts were partly based on the physical reasoning that the water holding the capacity of the atmosphere rises at an exponential rate due to the Clausius-Clapeyron (C-C) relationship (Jones et al., 2010). Trenberth et al. (2003) added that the moisture content of the atmosphere is measured at the same rate. Temperature and humidity are two of the most significant driving agents of precipitation which are empirically positively correlated (Hu, Wang, & Zeng, 2013). In general, when two or more variables have empirically dependent relationship, the multivariate models are the most appropriate approach to be considered.

The quantitative analysis of these stochastic meteorological variables and the understanding of their fluctuations on different scale or their general variability have fundamental importance in the literature on climate change. Although Malaysia is one of the countries that are affected by climate change (Baharuddin, 2007), the country however has not received adequate attention in such literature.

1.3 Problem Statement

Developing an analytical time series model to explain the relationships among correlated meteorological variables has been difficult due to the complexity of the system and the inadequate understanding of the physical mechanisms responsible for the interaction. In many situations, univariate time series analysis is sufficient. However, in other cases, univariate analysis may be restrictive. Univariate analysis only focus on one variable, but for some variables, they are interrelated and required to be included in the analysis as well. This research proposes a multivariate model for the effects of precipitation, temperature, humidity and wind speed on the climate in Malaysia. The model incorporates the joint analysis of the corresponding time series for both systems. Due to the multivariate nature of the problem under study, the vector autoregressive (VAR) methodology was adopted.

The VAR model is a mechanism that is used to link multiple stationary time series variables together. This linear VAR model is an effective tool for modelling and forecasting vector time series. Oftentimes, the present value in the vector time series is produced through non-stationary stochastic processes. The non-stationarity is the result of an in-time changing variance or an in-time changing mean value. Notably, the variance of the series variables over time is not constant. When these variables contain unit roots, a different mode of analysis named cointegration, is needed. Many meteorological time series exhibit the property of statistical autocorrelation of the time series including precipitation (Yusof & Kane, 2013), temperature (Yusof & Kane, 2012) and humidity (Chiawa et al., 2010). These characteristics can be better be analysed by incorporating non-linear effect in the VAR modelling strategy.

Volatility measures risks and hence, it is an important knowledge. In any model, the future forecast is extremely sensitive to the chosen volatility modelling. Over time, volatility tends to vary and to cluster in periods. In addition, small changes are succeeded by small changes, while large changes are followed by large changes as well. In this situation, the standard deviation varies over time. The fluctuation in variance is called heteroscedasticity. Furthermore, the autocorrelation of the volatility means the present volatility is dependent on the past volatility. Particularly, the non-linear generalised autoregressive conditional heteroscedasticity (GARCH) family model, including multivariate GARCH has been very successful in capturing the heteroscedasticity effect in the volatility.

The volatility persistence is measured by calculating the total amount of the two parameters in multivariate GARCH model. When the sum of these two parameters is close to one, the persistence is deemed to be too high. If structural change is suspected to interfere with the volatility process, the multivariate GARCH model is not sufficient to capture the persistency in volatility (Lamoureux and Lastrapes, 1990) and the results may be misleading (Zhuang and Chan, 2004). In order to solve the multivariate GARCH model's problem in modelling the volatility persistence, this study established an advanced multivariate GARCH model from linear VAR model that incorporates volatility persistence in the modelling process.

In summary, not much meteorological literature that focus on solving both problems, heteroscedasticity and persistence in volatility. Hence, in this study, these two problems will be tackle using meteorological data series.

1.4 Research Objectives

This work aims to develop a new class of VAR model for the study of meteorological variables, specifically to:

1. Model the volatility of heteroscedastic residual time series using multivariate GARCH, called Dynamic Correlation Coefficient (DCC) model.

2. Propose a hidden Markov model (HMM)-based-VAR model to identify the hidden state in reducing the volatility persistence in the residual.

3. To test the forecasting ability of the developed model in (2).

4. To assess the performance of the developed model in (3) via simulation.

1.5 Significance of the Study

Selecting the best model is important in forecasting the multivariable meteorological data as it will help the authorities in making decision on weather forecast or future planning. Furthermore, meteorological forecasting from the optimal fitted model gives an accurate insight towards the future pattern. Accordingly, the estimated calculation can be made for usage in the future. Thus, this thesis contributes to the literature on meteorology studies in several ways as explained below.

Firstly, this research formulates a hybrid model of VAR and dynamic conditional correlation (DCC) model, that is, VAR-DCC model, to the seasonal differencing of monthly meteorological data series. This model is also able to capture the heteroscedasticity effect. Although the multivariable meteorological data can perform better with the application of the linear model, the presence of heteroscedasticity must be checked to reconfirm the adequacy of the model constructed. The existence of this effect indicates that the linear model is not appropriate to fit the data behaviour. Plus, the heteroscedasticity effect is a major concern in regression analysis as its presence can invalidate the statistical test of significance. Therefore, this research highlights the handling of heteroscedasticity effect.

Secondly, this study introduces the HMM model using expectation-maximisation (EM) algorithm to the base of VAR model by separating the volatility into three levels. This VAR-HMM-DCC approach offers a valuable way of modelling the relationship between the conditional mean and variance of a process that exhibits strong persistence in its level, while considering the time varying volatility.

Finally, the study provides a forecasting formulation to compare the meteorological data series by focusing on both in-sample and out-sample model performance. The out-sample data were forecasted using proposed 12-step-ahead formulation. Simulation analysis was done in order to determine the ability of the model to simulate meteorological data based on the proposed hybrid model. This simulation-based method was vital to ensure that the model was successful in modelling the meteorological data series by comparing the model performance.

1.6 Scope and Limitations

The scope of this study covers (i) explanatory analysis of the meteorological data series in classifying the pattern and characteristics of each variables, (ii) modelling the temporal linear behaviour of meteorological data including the stationarity process and structural analysis, (iii) incorporating the family of GARCH model to the linear model in order to model the persistence in meteorological data series, (iv) proposing a probabilistic approach with hidden states model to reduce the persistence of volatility, (v) forecasting the new proposed hybrid model and making comparison with the observed training data, and (vi) simulation analysis.

1.7 Organisation of the Thesis

The structure of this thesis starts with Chapter 1 which presents an introduction to the research. Consecutively, Chapter 2 outline a review of the relevant literature and Chapter 3 discusses the development of the conceptual methodology used in the research. Chapter 4 explores the analysis and findings of the research works. It compromises the study area, the data sources, the basic characteristics of meteorological variables, the mean and variance model, the proposed model that captures the limitations of the previous model, and the

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