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Rainfall Forecasting with Time Series Model in Senai, Johor

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Abstract
Waterlogging is the most common cause of natural disasters such as floods and droughts. Furthermore, weather forecasts play a critical role in pilots' and passengers' safety, as heavy downpours can cause affect the pilot's assessment of runway distance and location. The use of weather forecasts is helpful to any organization in making decisions in the event of disaster or incident prevention. Rainfall forecast is a part of the weather forecast. A variety of methods and techniques had been proposed for predicting rainfall, including physical, statistical, and hybrid methods. The aim of this research is to forecast the rainfall amount by using the most appropriate forecasting model and hence, determine which model performed the best. Senai was chosen as the research area and the monthly rainfall data, with the range from January 2009 to December 2019, were obtained from Malaysia Meteorological Department (METMalaysia). It was revealed that the rainfall pattern in Senai has a trend and annual seasonality. In this research, Holt-Winters method, Box-Jenkins method, and a hybrid method were proposed to forecast the rainfall data. The performance of the models had been evaluated based on performance indicators, which are Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Mean Absolute Error (MAE). It was revealed that the Holt-Winters model produces a more accurate result, and it can be used to forecast rainfall for the future.

Keywords: Rainfall; Box-Jenkins; Holt-Winters; SARIMA; Hybrid model; Time Series Forecasting; Exponential Smoothing

1. Introduction

Malaysia is located between 2º North and 7º North of the equator in Southeast Asia, along the Strait of Malacca and the South China Sea. It has a tropical climate with warm weather all year round. According to the report by Malaysian Metrological Department (Met Malysia), the annual average rainfall for Peninsular Malaysia is 2420 mm [1], and during monsoon seasons, Malaysia will receive rainfall which ranges from 2000 to 4000 mm with 150 – 200 rainy days [2]. Malaysia has never been subject to major natural disasters but is at risk for natural hazards such as floods, forest fires [3] as well as man-made disaster.

In the past several years, Malaysia had experienced several extreme flood events, with the most recent flood happened in January 2021 in Peninsular Malaysia. This was the most destructive flood event in 50 years, resulting in at least 6 deaths and around 50, 000 displaced residents [4]. Hence, rainfall forecasts are crucial for catchment management applications, especially flood warning systems [5]. Furthermore, in aviation industry, heavy rains can cause distorted visual perceptions that affect the pilot's evaluation of the runway's distance and location. Statistical analysis of all accidents of all American airline companies from 1962 to 1984 revealed that rainfall made up 40% of all weather factors controlling flight safety [6]. Thus, A reliable weather forecast is imperative for the safety and security of pilots and passengers, as well as for the economic health of the aviation industry.

Forecasting is a process of examining past events to predict, setting assumptions of future, using historical data as indicators, and generating predictions that are reliable to be used in the future[7].

A time series analysis is a specific method used in forecasting to analyze sequences of data points collected over an extended period of time.
This research aims to (1) identify the pattern or trend of the rainfall amount using the most appropriate model, (2) to forecast the rainfall amount by using forecasting model such as Holt-Winters model, SARIMA model and a hybrid model and (3) to evaluate the performance of forecasting models based on the performance indicator, which are Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE) and Root Mean Square Error (RMSE).

2. Literature Review

2.1. Exponential Smoothing Method

Exponential Smoothing is one of the traditional and most widely used forecasting methods time series data [8]. The formulation of exponential smoothing was proposed in the late 1950s by Brown [9] and Holt [10], with the purpose to create an inventory control system's forecasting model. In basic terms, this method uses the weighted averages from past observations to make future forecasts [11].

There are three main types of Exponential Smoothing methods, which are Simple Exponential Smoothing (SES), Double Exponential Smoothing and Triple Exponential Smoothing. Simple Exponential Smoothing is used for univariate data that has no trend and no seasonality [12]. The observations that having trends but no seasonal component should implement Double Exponential Smoothing method [8], which is also known as Holt's Method. Triple Exponential Smoothing method or Holt–Winters Method is suitable for the data which have trends coupled with seasonality [12].

Sinay and Kembauw [13] discovered that Holt- Winters multiplicative model was best to describe rainfall with seasonality. Dhamodharavadhani and Rathipriya [8] also proved that Holt-Winter's Exponential Smoothing shows the better accuracy for rainfall prediction. Karmaker et al. [14] had discovered Holt-Winters additive model gives the highest performance predict jute yard demand in Bangladesh.

2.2. Box-Jenkins Method

Autoregressive Moving Average (ARMA) model play a significant role in time series modelling Compared to autoregressive models (AR) and moving average models (MA), ARMA models provide the most efficient linear models of stationary time series, since they can model unknown processes with the fewest parameters [15].

Having a nonlinear pattern with large variations in intensity [16], rainfall prediction is complex and difficult to forecast. One of the efficacious methods is Autoregressive Integrated Moving Average (ARIMA) modelling [16]. The ARIMA model is a generalization of an autoregressive moving average (ARMA) model, developed by George Box and Gwilym Jenkins in the 1970s [17]. As it covers a variety of styles, including stability, lack of stability, and seasonal time series, the ARIMA model is claimed as a comprehensive statistical modeling methodology [18].

In research from Momani [19], ARIMA model had been used to predict rainfall data and it was claimed that the result of the forecast is good. Ponnamperuma and Rajapakse [20] also found that ARIMA was suitable to be used for short-term forecast of rainfall. Ediger and Akar [21] had concluded ARIMA forecasts of short-term primary energy demand of Turkey is more reliable, but both ARIMA and SARIMA methods was suggested to be used in forecasting future primary energy demand.

2.3. Hybrid Method

Hybrid model is a fusion of classical models and/or modern. Hybrid methods was proposed to combine the best aspects of statistics and machine learning for improving time series forecasting [22]. In time series analysis, Exponential Smoothing and ARIMA models are the most commonly used methods [23].

Hybrid models is suggested by Grigonytė and Butkevičiūtė [24] to increase the effectiveness of in wind speed forecasting. A hybrid model of ARIMA and SES was proposed in a case study by Kamisan et al. [25], and the hybrid model offers a promising result. Safi and Sanusi [26] had conducted research on hybrid time series models to predict COVID-19 across the globe. A hybrid model was developed including ARIMA, exponential smoothing, and Artificial Neural Networks (ANN) model. It was found that the hybrid model did a better job than the ANN model. Xie et al. [27] proposed a hybrid model of ARIMA and Holt-Winters to predict real-time Docker Container Resource Load. By comparison, the hybrid model had enhanced prediction accuracy.

The above research proved that the hybrid model of ARIMA and exponential smoothing is superior to most time series models in different fields. However, the hybrid model of SARIMA and Holt-Winters is not adequately supported by scientific papers to make rainfall predictions; therefore, hybrid model was discovered deeper in this research.

3. Research Methodology

3.1. Holt's Method

A Double Exponential Smoothing model, which is also called Holt's method, is an extension of Simple Exponential Smoothing. In addition to one single exponential smoothing model, a second one is added to capture trends. The equations used are as follows:

Level : $L_t = \alpha y_t + (1-\alpha)(L_{t-1} + b_{t-1})$ (1)

Trend : $b_t = \beta(L_t - L_{t-1}) + (1-\beta)b_{t-1}$ (2)

Forecast : $F_{t+m} = L_t + mb_t$ (3)

To find the initial values in Holt-Winters Additive method, the formula for the level L_1, the growth rate $b_1$and seasonal factors $S_1, S_{2,\dots,}$is as shown as follows:

$$L_1 = y_1 \quad (4)$$

$$b_1 = \frac{y_4 - y_1}{3} \quad (5)$$

where L_t and b_t is the smoothing for level and trend respectively; y_t is the observed value from the data; F_{t+m} is the forecast value at m period ahead. α:level and β:trend are the smoothing constants, and m is the forecast period.

3.2. Additive Holt-Winters Method

To account for seasonality, a third parameter is added, with an equation corresponding to it. This set of equations is called Holt-Winters equations. Generally, there are two types of Holt-Winters models, depending on the type of seasonality. In this research, additive Holt-Winters was used.

In the Additive Holt-Winters method, seasonal fluctuations are considered regardless of the level of the series, in which there is no pattern or indication that the seasonal pattern is dependent on data size. The equations used in the additive model are as follows:

Level : $L_t = \alpha(y_t - S_{t-s}) + (1-\alpha)(L_{t-1} + b_{t-1})$ (6)

Trend : $b_t = \beta(L_t - L_{t-1}) + (1-\beta)b_{t-1}$ (7)

Seasonal : $S_t = \gamma(y_t - L_t) + (1-\gamma)S_{t-s}$ (8)

Forecast : $F_{t+m} = L_t + mb_t + S_{t-L+m}$ (9)

To find the initial values in Holt-Winters Additive method, the formula for the level L_1, the growth rate $b_1$and seasonal factors $S_1, S_{2,\dots,}$is as shown as follows:

$$L_s = \frac{1}{s}(y_1 + y_2 + \cdots + y_s) \quad (10)$$

$$b_s = \frac{1}{s}\left(\frac{y_{s+1} - y_1}{s} + \frac{y_{s+2} - y_2}{s} + \cdots + \frac{y_{s+s} - y_s}{s}\right) \quad (11)$$

$$S_1 = y_1 - L_s, S_2 = y_2 - L_s, \dots, S_s = y_s - L_s \quad (12)$$

where S_t is the smoothing for seasonal and γ is the smoothing constants. s is the seasonal length.

3.3. Seasonal Autoregressive Integrated Moving Average (SARIMA)

A seasonal ARIMA model is formed by including additional seasonal terms. Basically, it is written as SARIMA $(p,d,q)(P,D,Q)_S$ which S is the seasonal period. The lowercase notation part stands for the non-seasonal part of the model while the uppercase notation part represents the seasonal part of the model. The seasonal component of the model includes similar terms as the non-seasonal component, but with a back shift during the season. The equation is as below:

$$\emptyset_p(B)\Phi_p(B^S)(1-B)^d(1-B^S)^D Y_t = \theta_q(B)\Theta_q(B^S)\varepsilon_t \tag{13}$$

with

$$\emptyset_p(B) = 1 - \emptyset_1 B - \cdots - \emptyset_p B^p$$
$$\Phi_p(B^S) = 1 - \Phi_p B^S - \cdots - \Phi_p B^{pS}$$
$$\theta_q(B) = 1 + \theta_1 B + \cdots + \theta_q B^q$$
$$\Theta_q(B^S) = 1 + \Theta_1 B^S + \cdots + \Theta_p B^{qS}$$

where Y_t is the actual data; $\emptyset_p$ and θ_q represents AR component coefficient and MA component coefficient respectively; c is the constant value; μ is the mean value of the series and ε_t is the random error, which also known as white noise. B represents the non-seasonal backshift operators and d is the non-seasonal differencing order. For seasonal part, Φ_p is the seasonal AR component coefficients while Θ_q is the seasonal MA component coefficients. B^S is the seasonal backshift operators and D representing the seasonal differencing order.

3.4. Hybrid Method

Zhang [28] had proposed a hybrid ARIMA and Artificial Neural Network (ANN) model, which composed of linear and nonlinear component as follows:

$$Z_t = L_t + N_t \tag{14}$$

where Z_t represent the original time series, L_t is the linear component and N_t is the non-linear component.

In this research, linear component will be from SARIMA and non-linear component will be from Holt's model. The proposed hybrid model is described as following steps:

STEP 1	:	Obtain the forecasted value, $\hat{L}_t$ by running a SARIMA analysis.
STEP 2	:	Calculate the residuals, e_t from the in-sample forecast.
STEP 3	:	Obtain the forecast for residuals, $\widehat{N}_t$ by using Holt's method.
STEP 4	:	Combine the out sample forecast from SARIMA model (STEP 1) and out-sample forecast from Holt's model (STEP 3).
STEP 5	:	New forecast for the hybrid model, $\hat{Z}_t$ was obtained.

3.5. Anderson-Darling Test

Anderson-Darling Test is a statistical test of whether or not a dataset or residuals follows a certain probability distribution, such as normal distribution. It was developed in 1952 by Theodore Anderson and Donald Darling.

Hypothesis: H_0 : The data follows the normal distribution
H_1 : The data do not follow the normal distribution

Test Statistics:

$$A^2 = -n - S$$

The modified statistic was as:

$$A^{*2} = A^2\left(1 + \frac{0.75}{n} + \frac{2.25}{n^2}\right) \tag{15}$$

3.6. Performance Indicator

3.6.1. Mean Absolute Error (MAE)

The absolute error is the absolute value of the difference between the forecasted value and the actual value. The formula to calculate MAE is as follow:

$$MAE = \frac{1}{n}\sum_{t=1}^{n} |y_t - F_t| \tag{16}$$

3.6.2. Mean Absolute Percentage Error (MAPE)

MAPE is determined as the average absolute percent error for each time period minus actual values divided by actual values to calculate this accuracy as a percentage. The formula is as follow:

$$MAPE = \frac{100}{n}\sum_{t=1}^{n} \left|\frac{y_t - F_t}{y_t}\right| \tag{17}$$

3.6.3. Root Mean Square Error (RMSE)

RMSE indicates the absolute fit of the model to the data–how close the observed data points are to the model's predicted values. The formula to calculate it is as follow:

$$RMSE = \sqrt{\sum_{t=1}^{n} \frac{(y_t - F_t)^2}{n}} \tag{18}$$

where F_t is the forecast value at time t.

4. Results and discussion

4.1. Time Series of Rainfall Data in Senai, Johor

Senai is a town and mukim in Kulai District, Johor, Malaysia. Senai is a transit town and positioned 25 kilometres northwest of Johor Bahru, with longitudes 1.6020º N and latitudes 103.644º E. Senai international Airport was located within this area.

In this research, the monthly rainfall data of Senai were extracted from Malaysia Meteorological Department (METMalaysia). This data collection period lasted from January 2009 to December 2019. In this research, the data is divided into two parts. The in-sample data, which is from January 2009 till December 2018 is to find the most appropriate combinations of forecasting model, while the out-sample data, which is from January 2019 to December 2019 is used to make evaluation to select the best forecasting models based on the performance indicator.

According to time series plot in Figure 4.1, there is a slightly upward movement of data over the specified period of time and thus, trend exist in the data. Moreover, the data does reveal a consistent pattern of up and down variations within a year. Therefore, it was concluded that the data is having annual seasonality. Anderson Darling (AD) Test was carried out to test the normality of the dataset. The p-value of the AD-Test shows 0.303, which is more than 0.05. Hence, it can be concluded that the data followed the normal distribution and it is suitable to be used as a time series data.

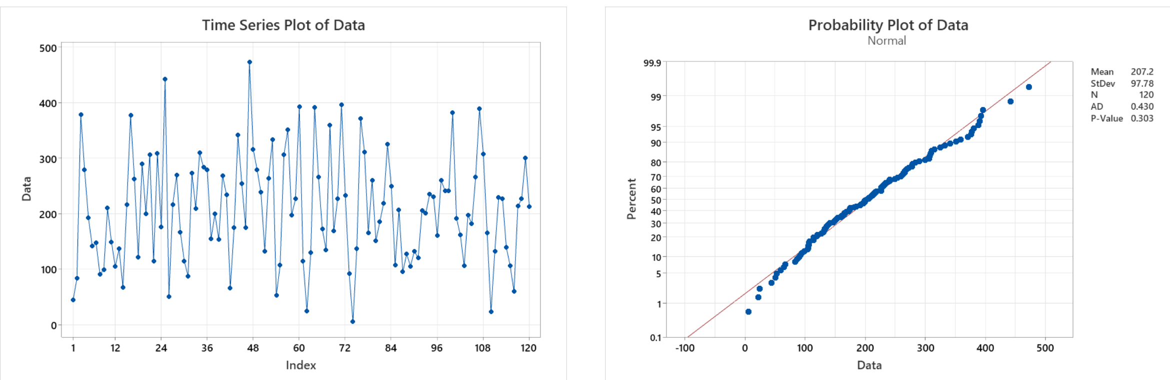

Figure 1 Time Series Plot and Probability Plot of Data

4.2. Holt-Winters Method

Holt-Winters method with three parameter is suitable to be used as this model will account for the trend or seasonality in the data. In the time series plot shown in Figure 4.4, there are several fluctuations from time to time but it looked to be the same magnitude over time. Hence, Additive Holt-Winters method is selected to be used. The best set of parameters was calculated by using the solver function in Microsoft Excel is $\alpha = 0.0308, \beta = 0.1793$ and $\gamma = 0.3758$, with minimum sum square error, SSE= 1094622.2762.

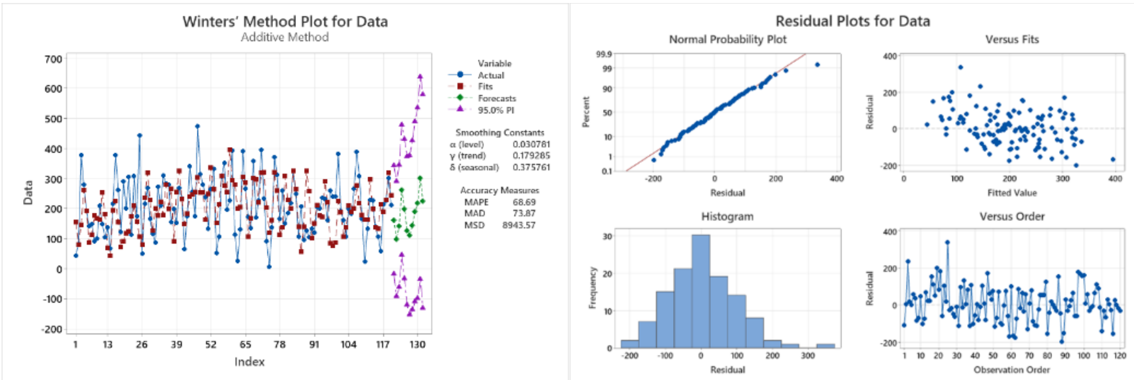

Figure 2 Time Series Plot with Forecasted Value and Residual Plot of Data for Holt-Winters Model

From time series plot in Figure 2, it was noticed that the original data (blue colour in line) fits into and follow the trend of the predicted data (red colour in line). It can be said that the forecast model is fitted to the original dataset. For the residual plot, all these 4 plots are supporting that the variance is constant and the mean of residuals is zero. Hence, the residuals data is following a normal distribution and it can be concluded that this Holt-Winters model is appropriate model to be used.

4.3. SARIMA model

In order to perform a Box-Jenkins analysis, the process is divided it into five steps, which are testing for stationarity of data, model identification, coefficients and parameters estimation, model diagnostics, and model forecasting. The process is carried out with the aid of Minitab.

Taking a look at the ACF plot and PACF plot for original data in Figure 3, it was noticed that there is a strong correlation at the first season lag (lag 12), and it decreases over several seasons. Hence, , the data should be differenced using a lag of 12, which is equal to the seasonal length. After applying seasonal differencing, the dataset is in stationary state and the plots, which indicated in Figure 4 do not clearly demonstrate the tail off pattern. The significant spike at lag 12 in the PACF suggests a seasonal AR(1) component and the significant spike at lag 12 in the PACF suggests a seasonal MA(1) component. For the non-seasonal AR or MA part, AR(1) and MA(1) is considered as these are basic estimation of model for stationary time series data.

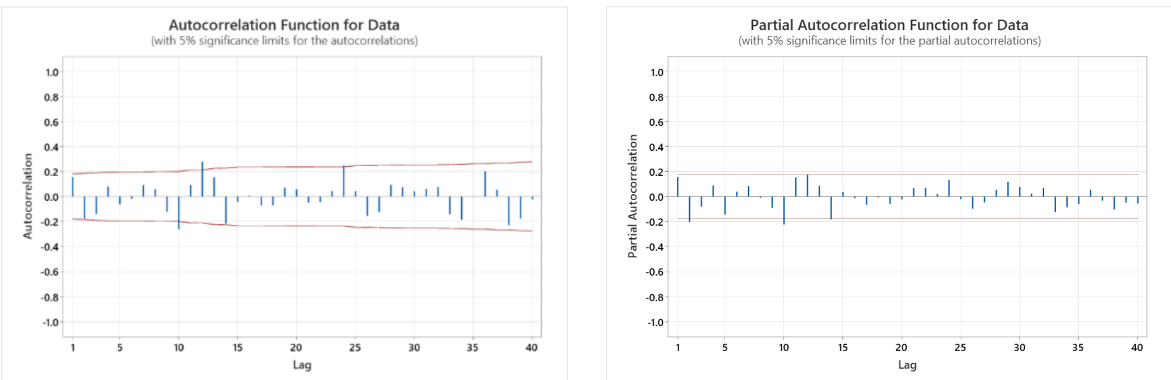

Figure 3 ACF and PACF Plot for Original Data

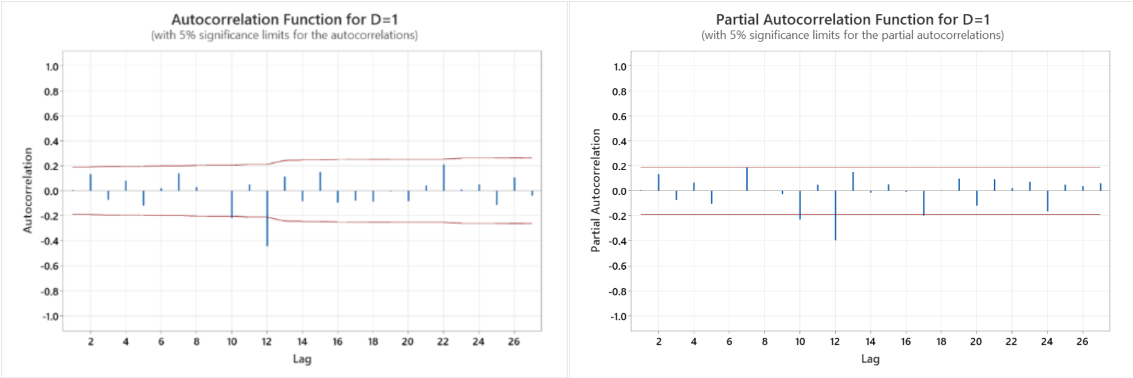

Figure 4 ACF and PACF Plot for Data After Seasonal Differencing (D=1)

Based on the results from the model identification charts, a few models were proposed and the value for AIC and BIC was calculated to penalize the models in order to avoid over-fitting.

Table 1 Overfitting Models of SARIMA $(p, d, q)(P, D, Q)_{12}$

Model	Significant	r	AIC	BIC
SARIMA $(0,0,0)(1,1,1)_{12}$	No	4	3.8769	4.4048
SARIMA $(0,0,0)(1,1,0)_{12}$	Yes	3	4.0410	4.4625
SARIMA $(0,0,0)(0,1,1)_{12}$	Yes	3	3.8685	4.2900
SARIMA $(1,0,1)(1,1,1)_{12}$	No	6	3.9238	4.5909
SARIMA $(1,0,0)(1,1,1)_{12}$	No	5	3.9039	4.5103
SARIMA $(1,0,0)(1,1,0)_{12}$	No	4	4.0546	4.5826

Among these models, SARIMA $(0,0,0)(0,1,1)_{12}$ model was chosen as it has the lowest value of AIC and BIC when compared to other models.

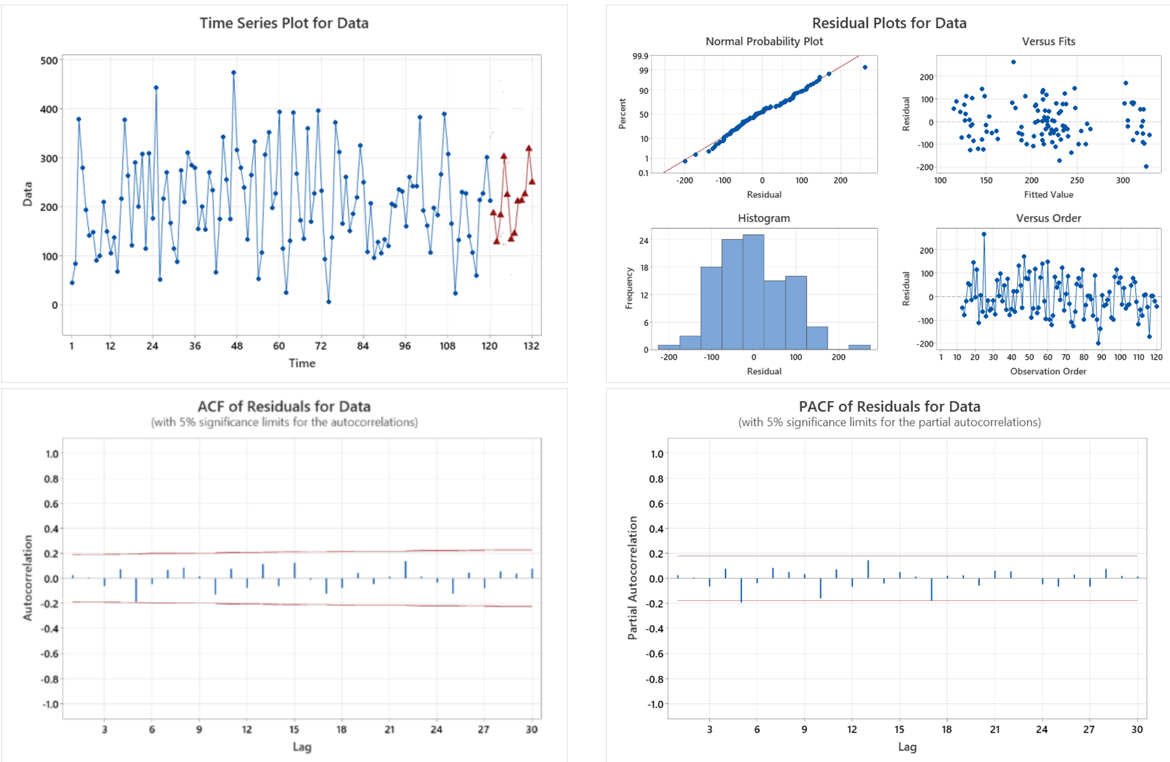

Figure 5 Time Series Plot with Forecasted Value, Residual Plot of Data, ACF and PACF Plot of Residuals for SARIMA $(0,0,0)(0,1,1)_{12}$ Model

Based on the ACF plot and PACF plot of residuals in Figure 5, the spikes are within the bounds, which indicates that none is significant and thus not autocorrelated. For the residual plot, all these 4 plots are supporting that the variance is constant and the mean of residuals is zero. Hence, the residuals data is nearly following a normal distribution. Thus, it can be concluded that this model is appropriate model to be used, and the forecasted value is illustrated in the middle red line of the time series plot .

4.4. Hybrid Model

Table 1 shows that SARIMA $(0,0,0)(0,1,1)_{12}$ model is selected to construct the hybrid model as it has the lowest AIC and BIC value. Based on the proposed method in 3.4., the hybrid model is applied to predict the rainfall data.

4.5. Model Evaluation

Table 2 The Comparison of The Performance of Prediction Models

	Holt-Winters' Model	SARIMA $(0,0,0)(0,1,1)_{12}$ Model	Hybrid Model
RMSE	91.9225	97.6503	104.0852
MAPE	66.6460	83.1423	62.7401
MAE	80.7741	80.8743	87.9996

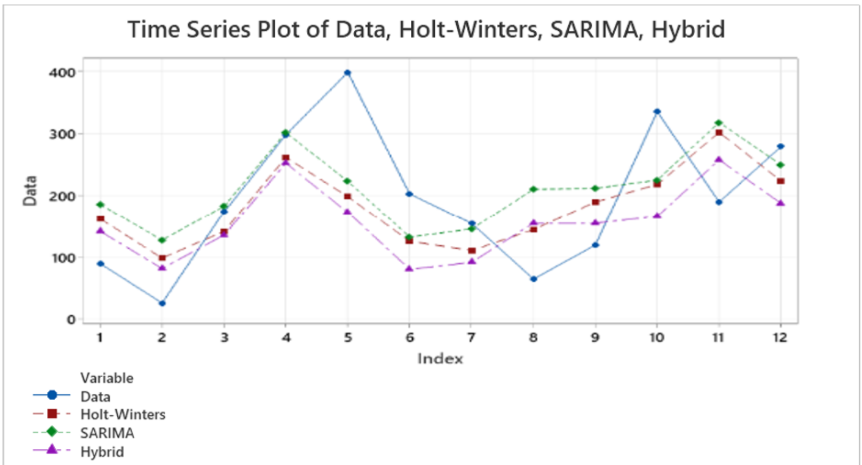

Figure 6 Comparison of Forecasted Out-Sample Results for All Models

The lower the values of MAE, MAPE, and RMSE, the more accurate the prediction model is. In terms of performance, Holt-Winters model performed the best when compared with other two models since it has two lowest readings for the metrics, followed by the hybrid model and the SARIMA model.

5. Conclusion

In this research, Holt-Winters, SARIMA and a hybrid model was proposed and use to forecast the rainfall data. The performance of each model had been evaluated based on the Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Root Mean Square Error (RMSE). After analysing the data, the Holt-Winters model has the smallest values of RMSE and MAE, indicating that the Holt-Winters model has a better accuracy than other models proposed. As a result of the analysis, actual data looks different from forecasting data. For future research, another forecasting method is needed so that the obtained results are able to reflect the actual rainfall data.

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