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Forecasting Daily Ridership for KTMB Services in Malaysia By Using Time Series Analysis

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Abstract

Proper prediction of the ridership in public transport is critical in operational planning, capacity management as well as optimisation of service. Daily ridership change, which is affected by weekends and weekdays and seasonal and special events, is one of the issues that demand prediction becomes a daunting task to rail operators. Poor forecasts can cause resource wastage, excess capacity or under-utilization of the services. Thus, this study compare, evaluate and analyse the time series forecasting models used to predict daily KTM Komuter ridership in Malaysia. The objectives of this study are to analyse the time series forecasting models Naïve, SARIMA, and Prophet using daily KTMB ridership data, to evaluate and compare the performance of these models using accuracy metrics such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE), and to forecast future daily ridership using the best-performing model. Three forecasting approaches were considered: the Naïve method, Seasonal Autoregressive Integrated Moving Average (SARIMA) and Facebook Prophet. First, the exploratory data analysis was performed to define the main attributes of the time series that is trend, variability, and the weekly seasonality. In the case of the SARIMA model, non-seasonal and seasonal differencing was used to obtain stationarity and suitable model structures were found based on ACF and PACF plots and then diagnostic checking was done. Facebook Prophet model was used to extract the trend and seasonal variations whereas Naïve method was used as a control baseline. The findings show that the SARIMA $(1,1,0)(0,1,1)_7$ model had the smallest errors in the test phase, proving it to be more precise and consistent than the Naïve and Facebook Prophet models. During the testing stage, the SARIMA model obtained the minimum percentage error in MAPE of 8.94%, which was lower than Facebook Prophet with a significantly high percentage error at 93.99%. Even though Facebook Prophet handled trends and seasonality well, it struggled with predictions beyond the training data. Ultimately, the results suggest SARIMA is the top pick for predicting daily ridership, delivering dependable forecasts to aid in operations and strategy.

1. Introduction

Effective planning and management of rail services require accurate understanding of passenger demand patterns. Ridership forecasting enables transport operators to anticipate demand, optimise service frequency, and allocate resources efficiently. Accurate ridership estimates also reflect actual travel behaviour and support real-time operational decision-making [1]. However, despite investments in rail infrastructure, public transport systems in many cities continue to experience low ridership and limited modal share. Kuala Lumpur faces similar challenges, where the shift from private vehicles to public transport remains limited [2].

To address these challenges, time series forecasting models have been widely applied in public transport demand analysis. This study evaluates the performance of Naïve, Seasonal Autoregressive Integrated Moving Average (SARIMA), and Facebook Prophet models in forecasting daily KTMB ridership. The Naïve model serves as a baseline approach, SARIMA captures trend and seasonal structures through differencing [3], while Facebook Prophet offers flexible modelling of trend and seasonality using an additive framework with automated parameter tuning [4]. Facebook Prophet was integrated with SARIMA because it can automatically model various seasonalities and changes of trend, which would be suitable in the case of intricate daily ridership patterns.

Accurate ridership forecasting is essential for public transport operators in planning service schedules, managing resources, and supporting long-term investment decisions. Despite its importance, KTMB continues to face operational challenges related to inconsistent service frequency and rolling stock shortages, which have resulted in increased train headways and reduced service reliability [5]. These operational issues may negatively affect passenger confidence and ridership levels.

Although forecasting models such as Naïve, SARIMA, and Facebook Prophet have been widely used in public transport studies, most existing research has focused on different transport systems or international contexts. Additionally, examined intercity land public transport mode preferences and competition between bus and train services in Malaysia [6]. [7] focused on evaluating the service quality of public transport services in the Lembah Bujang area of Kedah, Malaysia. Therefore, a research gap exists in systematically evaluating and comparing time series forecasting models for daily KTMB ridership using recent Malaysian data.

Considering such difficulties of operation and the absence of localised forecasting studies of daily KTMB ridership, the study is important to give empirical evidence to help in planning and decision-making. The objectives in this study are to analyse time series forecasting models Naïve, SARIMA, and Prophet using daily KTMB ridership data, to evaluate and compare the performance of the forecasting models using accuracy metrics such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) and to forecast daily ridership for future periods using the best performing model.

2. Methodology

The section explains all the information that necessary to get the study results. This study applied three different forecasting methods, including Naïve, SARIMA and Facebook Prophet. The selection of these forecasting models is grounded upon their proven accuracy in time series analysis, especially for short-term forecasting that incorporates trend and seasonal components. All models experienced training and evaluation with the identical dataset to maintain consistency in comparison.

2.1 Data Description

The dataset utilized in this study consisted of daily ridership numbers for Keretapi Tanah Melayu Berhad (KTMB) services in Malaysia and was obtained from the Department of Statistics Malaysia (DOSM) [8] via https://data.gov.my/data-catalogue/ridership_ktmb_daily?visual=ridership. This study seeks to forecast the ridership trends and demand for KTM Komuter services operated by KTMB. This dataset consists of daily ridership data from January 2020 through March 2025. The analytical instruments utilized for this study are Microsoft Excel, Minitab, and Python.

2.2 Naïve

Naïve method is a forecasting method that only uses last year's actual value data as a forecast for this year, and so on. Naive Bayes algorithm is a set of algorithms that are applied in the classification technique [9]. The next year's forecast is only $(t + 1)$ will be the same as this year's data. The assumption that demand in the future period will be the same as the demand in the last period. The formula of the Naïve Method is shown in Equation (1):

$$F_t = Y_{t-1} \tag{1}$$

Where:
F_t is the new forecast
Y_{t-1} denotes as the actual observed ridership value at the previous time.

2.3 Seasonal Auto-Regressive Integrated Moving Average (SARIMA)

SARIMA is a time series method that combines additional seasonal terms (seasonal), autoregressive (AR), average moving (MA), and integration [10]. The seasonal ARIMA process noted as SARIMA (p, d, q) $(P, D, Q)_s$ is given by:

p, d, q = The nonseasonal part
$(P, D, Q)_s$= The seasonal part of the model
s = Number of periods per season

The general formula of SARIMA (p, d, q) $(P, D, Q)_s$ is as follows in Equation (2):

$$\Phi(B^s)\phi(B)(1-B)^d(1-B^S)^D y_t \ = \ \Theta(B^s)\theta(B)\varepsilon_t \tag{2}$$

Where:
y_t denotes as observed value at time t
ε_t denotes as white noise error term
B denotes as Backshift (lag) operator
$\phi(B)$ denotes as non-seasonal AR polynomial of order p
$\theta(B)$ denotes as non-seasonal MA polynomial of order q
$\Phi(B_s)$ denotes as seasonal AR polynomial of order P
$\Theta(B_s)$ denotes as seasonal MA polynomial of order Q

2.4 Facebook Prophet

Facebook Prophet is an additive regression model suitable for time series with multiple seasonality and changepoints [10]. While having many automation features, Prophet simply uses a decomposable time series model such as the generalized additive model (GAM). Specifically, Prophet uses a generative model with three main components which are trend, seasonality, and holidays or events [11].

Facebook Prophet is constructed so that it provides opportunities to the adjustment of parameters. With this, it has tailored seasonality components that are essential in enhancing the predictions and the users are able to come up with immensely accurate predictions [12]. The equation model is expressed in Equation (3):

$$y(t) \ = \ g(t) + s(t) + h(t) + \varepsilon_t \tag{3}$$

Where:
$g(t)$ denotes as trend component
$s(t)$ denotes as seasonality modelled via Fourier series
$h(t)$ denotes as effects of holidays or special events
e_t denotes as error terms

The trend component $g(t)$ is expressed in Equation (4):

$$g(t) = \ (k + a(t)^T\delta)t + (m + a(t)^T\gamma) \tag{4}$$

Where:
k denotes as growth rate
δ denotes as rate adjustments
m denotes as offset parameters

The seasonal effects $s(t)$ is expressed in Equation (5):

$$s(t) = \sum_{n=1}^{N}\left(a_n\cos\left(\frac{2\pi nt}{P}\right) + b_n\sin\left(\frac{2\pi nt}{P}\right)\right) \tag{5}$$

Where:
P denotes as period (7 for weekly, 365 for yearly)
N denotes as number of terms used (Fourier order)
a_n, b_n denotes as coefficients learned from the data

The holiday effects $h(t)$ is expressed in Equation (6):

$$h(t) = Z(t)k \tag{6}$$

Where:
$Z(t)$ denotes as indicator function for holiday at time
k denotes as holiday effect coefficients

Facebook Prophet was applied to the trend and weekly seasonality components in this study, and the effects of the holidays were added depending on the major Malaysian public holidays.

2.5 Forecast Evaluation Metrics

Forecast performance evaluation was used to determine the accuracy of the forecasting results that have been made on the actual data. The evaluations include Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE).

The use of single error measure is prone to biased conclusion in estimating performance appraisal. A multi-criteria assessment method which concurrently considers several accuracy indices, including RMSE, MAE and MAPE offers a more solid and holistic view of the model's performance [13]. The measure of each forecast error has its advantages and disadvantages, and no single metric is adequate to comprehensively assess forecasting performance [14].

The units of the estimation variable are preserved by the first criterion, RMSE. This method is more sensitive and can reduce the number of significant errors. Nevertheless, the ability to compare a variety of time series is limited by the application of this measure. The equation of the RMSE is expressed in Equation (7):

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_t - \hat{y}_t)^2}{n}} \tag{7}$$

MAE determines the degree to which forecasts correspond to actual results. This metric does not take into consideration the direction of the forecasts. Furthermore, these criteria determine the precisions of continuous variables. The equation of the MAE is expressed in Equation (8):

$$MAE = \frac{\sum_{i=1}^{n}|y_t - \hat{y}_t|}{n} \tag{8}$$

The subsequent measure, MAPE, enables the comparison of a variety of time-series data without requiring the relationship or percentage error to be specified. MAPE was chosen as a major indicator as it is a percentage measure of forecast errors, which can be easily compared across models, but it is affected by low ridership values. The equation of the MAE is expressed in Equation (9):

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_t - \hat{y}_t}{y_t}\right| \tag{9}$$

Where:
yt denotes as the actual value at time, t
$\hat{y}t$ denotes as the forecast value at time, t
n denotes as the sample size

3. Results and Discussions

Fig. 1 shows the time series plot of KTM Komuter daily ridership. The dataset contains daily observations of $n =$ 530, with ridership values ranging from approximately 4,000 to more than 90,000 passengers. High variability is seen in the dataset as depicted by the wide difference between the maximum and the minimum ridership. There is no apparent upward or downward trend in the data over the long term. The ridership is quite irregular in the long-run but there are short-term fluctuations. This implies that the series is non-stationary and level, then it needs differencing first then SARIMA models are used.

The extreme spikes and sharp drops observed in the time series are likely associated with public holidays, festive seasons, and post-pandemic mobility changes, which introduce irregular demand patterns into the ridership data.

The original ridership series' ACF plot shows large autocorrelations that gradually disappear, especially at decreasing delays. The series is not stationary and likely has a trend or strong persistence. A few spikes above the significance criteria, indicating that the series is autocorrelated and needs differencing.

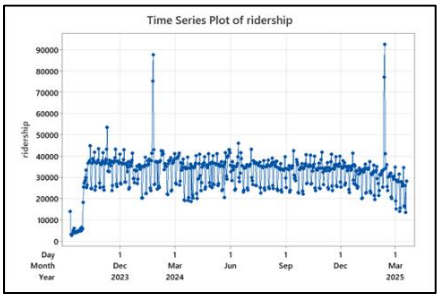
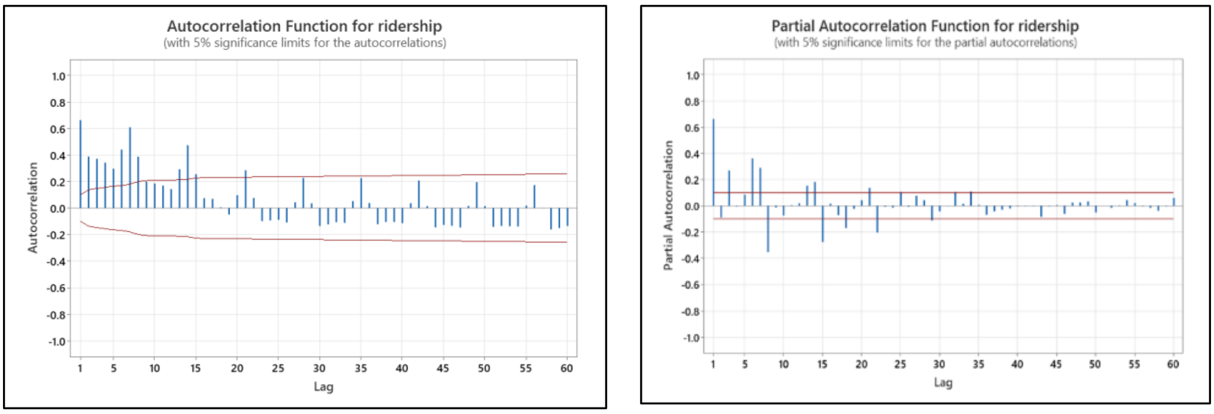


Fig. 1 Time series plot of KTM Komuter daily ridership

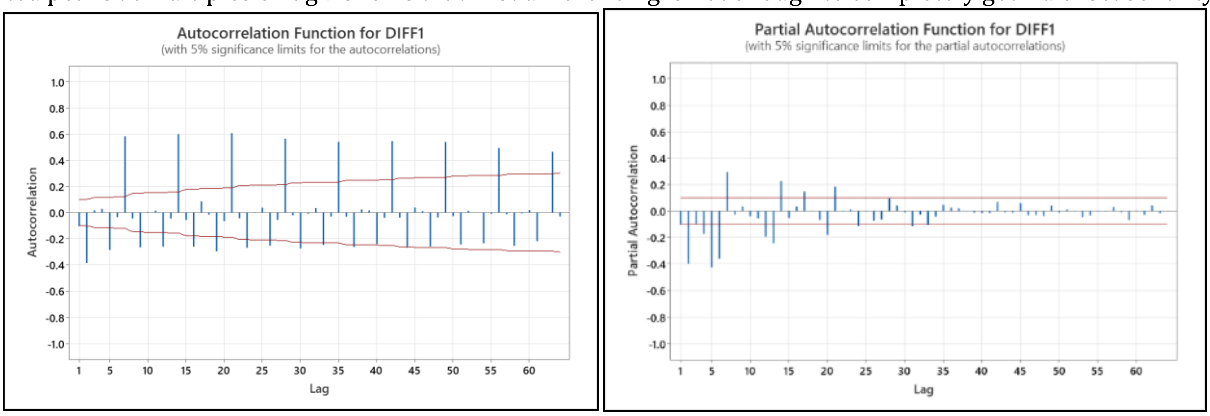
The PACF in Fig. 2 shows early big rises at certain lags. This suggests strong weekly and short-term seasonal tendencies. The progressive decline pattern in the ACF and PACF supports the assumption that the original series is not stationary and needs to be differenced before SARIMA modelling.



(a) (b)

Fig. 2 Plot of the ridership before differencing (a) ACF, (b) PACF

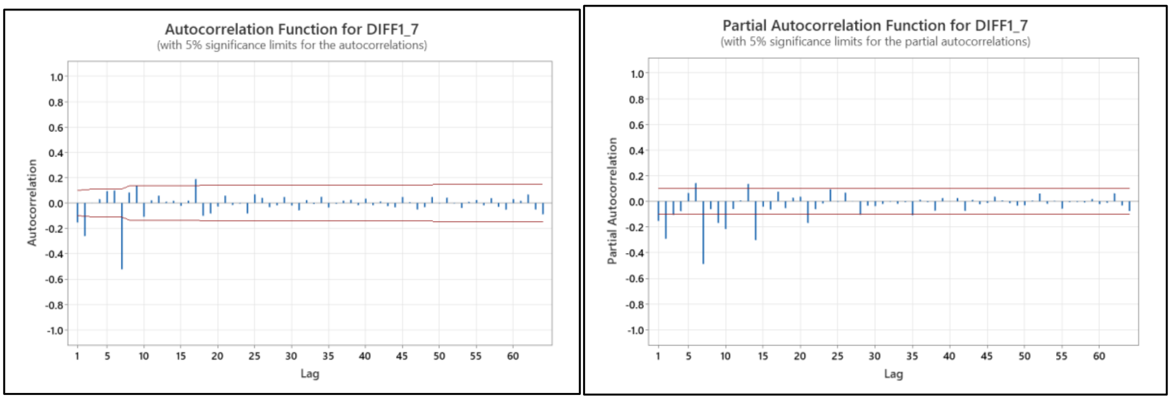
After performing first differencing in Fig. 3, the ACF shows a clear repeating pattern every 7 lags, which means that the ridership data has weekly seasonality. The overall autocorrelation is lower than it was in the original data, but the ACF still shows a number of large spikes after lag 7, which suggests that seasonal structure is still present. There are fewer significant jumps on the PACF plot for DIFF1 than on the ACF plot, but the fact that there are repeated peaks at multiples of lag 7 shows that first differencing is not enough to completely get rid of seasonality.



(a) (b)

Fig. 3 Plots of the ridership after first differencing series (a) ACF, (b) PACF

The ACF plot in Fig. 4(a) demonstrates that most autocorrelations fall inside the significant thresholds. Only a few minor spikes remain, indicating that most of the trend and seasonality has been eliminated. The PACF plot in Fig. 4(b) likewise reveals no significant spikes beyond lag 1 and lag 7, indicating that the modified series is now stationary and appropriate for SARIMA modeling.



(a) (b)

Fig. 4 Plot of the ridership after seasonal differenced series (a) ACF, (b) PACF

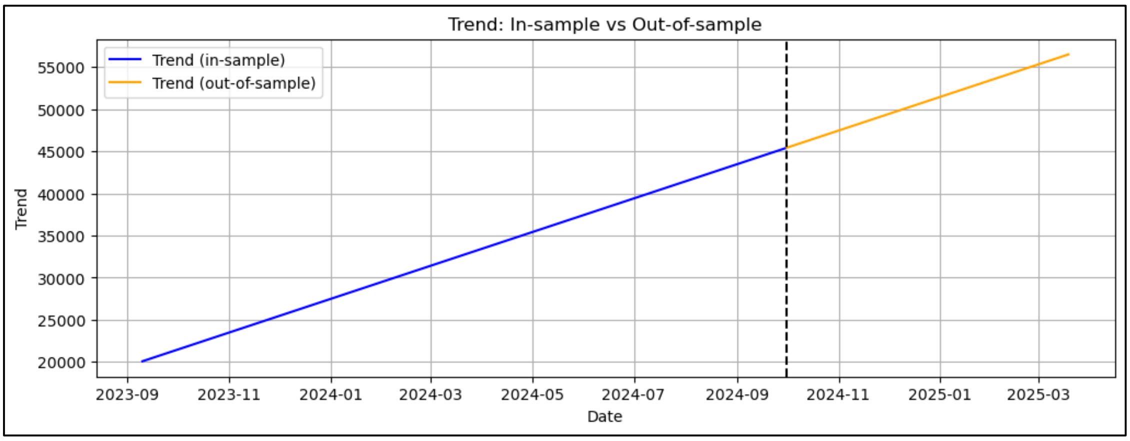


Fig. 5 Trend of Ridership In-Sample and Out-of-Sample

A comparison of long-term ridership trends in Fig. 5 estimated during training and testing. The smooth and steady ascending curve of the in-sample trend shows a continual increase in daily ridership during training. Passing the forecast boundary increases the out-of-sample trend. Facebook Prophet expects latent riding demand to rise after training data. The smooth linear trend suggests Facebook Prophet could not identify any dramatic structural shifts in demand, even though the data represents actual values with festive spikes.

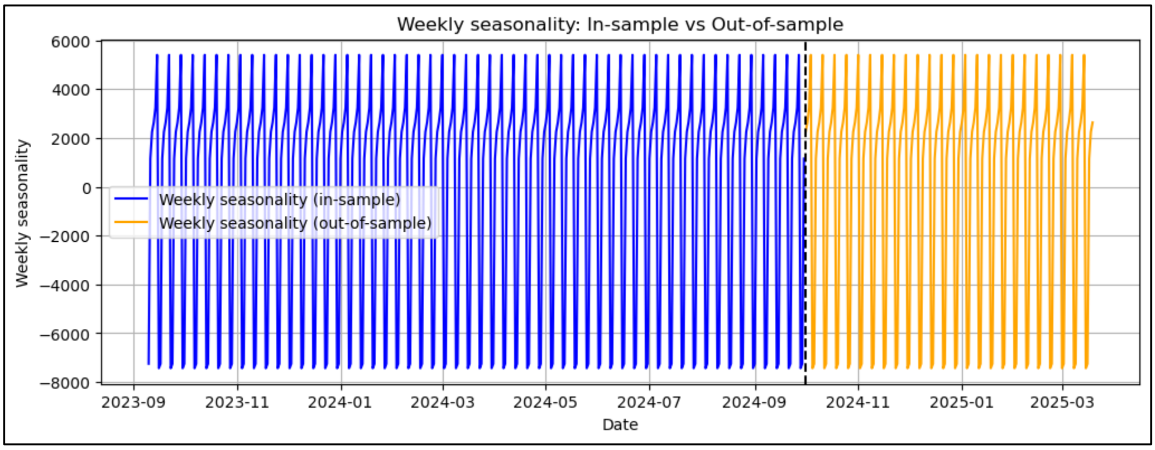


Fig. 6 Weekly Seasonality of Ridership In-Sample and Out-of-Sample

Ridership changes by weekday are shown in Fig. 6. The in-sample weekly trend shows that Fridays had the most ridership and Saturday and Sunday the least. Average weekday ridership rising slowly until Friday. The out-of-sample weekly trend matches the in-sample trend since weekly seasonality is predicted the same way. Prophet changes trend and uncertainty but not season structure between training and testing.

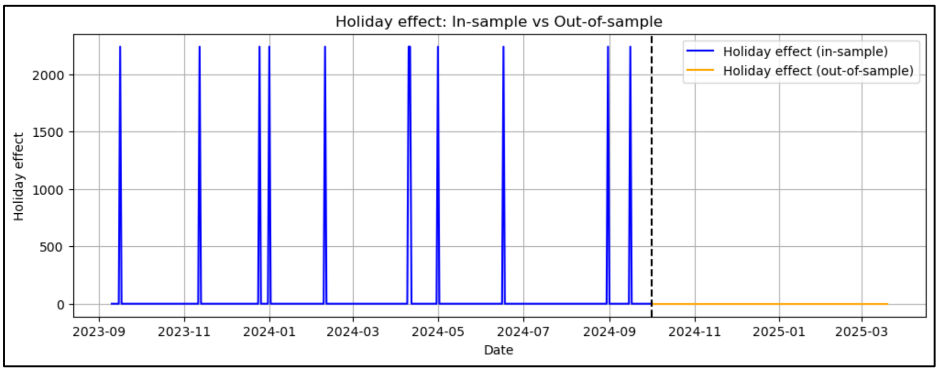


Fig. 7 Holiday Effect of Ridership In-Sample and Out-of-Sample

According to Fig. 7, the in-sample holiday effect exhibits prominent positive spikes on key holidays included in the holiday dataset, such as Deepavali, New Year, Christmas, and Thaipusam. This is due to the fact that these surges indicate a significant rise in ridership during these dates. The holiday effect within the forecast period remains largely unchanged, as the model is not provided with any holiday dates beyond September 2024 or the specified holidays are not encompassed within the testing range.

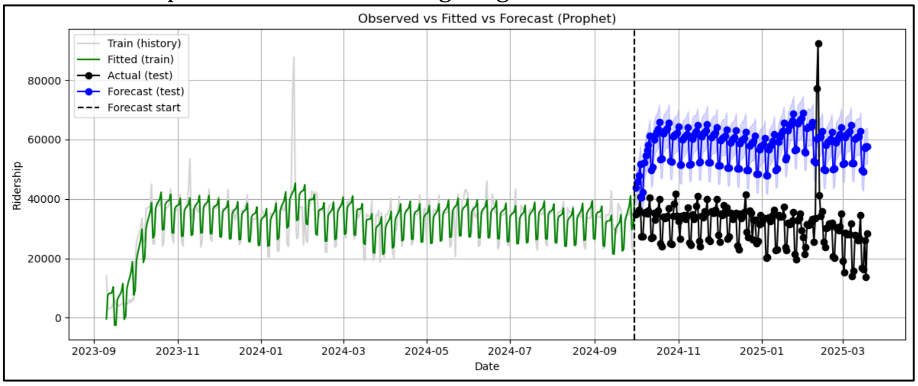


Fig. 8 Observed, Fitted and Forecast Plot using Facebook Prophet

Fig. 8 indicates that the fitted curve closely aligns with the trends of the historical data in-sample. Facebook Prophet effectively captures daily, weekly, and annual trends. The blue forecast curve signifies a higher anticipated ridership relative to the actual figures. This mismatch arises from the presence of significant declines in the testing data that are absent in the training data. It presumes that the trend will continue to rise, despite actual ridership declining after January 2025.

Table 1 Comparison of forecast accuracy for different models

Method	**Training**			**Testing**		
	MAE	**MAPE**	**RMSE**	**MAE**	**MAPE**	**RMSE**
Naïve	4867.65 (3)	17.22% (3)	7690.34 (3)	5127.64 (2)	17.68% (2)	8455.35 (2)
SARIMA	2677.33 (1)	10.34% (1)	4620.81 (1)	2780.03 (1)	8.94% (1)	5891.77 (1)
Facebook Prophet	2925.95 (2)	14.56% (2)	4765.65 (2)	27256.04 (3)	93.99% (3)	27773.21 (3)

Based on training and testing datasets, Table 1 summarizes the forecasting accuracy of Naïve, SARIMA, and Facebook Prophet models. The Naïve technique has the greatest error rates in training and testing, with MAE of 4867.65, MAPE of 17.22%, and RMSE of 7690.34. The Naïve technique has been found to miss patterns like trends, seasonality, and unexpected changes. Thus, the approach is stable but has poor predictive power and is mostly used for comparison.

Facebook Prophet performs moderately throughout training but poorly during testing. A training MAE of 2925.95, MAPE of 14.56%, and RMSE of 4765.65 suggest that the model can capture trend and seasonality in the training data. Its testing performance rapidly declines, with an extremely high MAE of 27,256.04, MAPE of 93.99%, and RMSE of 27,773.21. The huge inaccuracies show Facebook Prophet cannot generalize to the testing timeframe.

The reason behind the massive rise in the testing MAPE of Facebook Prophet is that it assumes the trend to keep growing after the training process, which did not reflect the abrupt drop in ridership at the testing stage. Consequently, the effect of forecast errors was enhanced especially when the actual ridership values dropped drastically.

The SARIMA model performs far better, with high accuracy and generalization. SARIMA fits historical data well during training with an MAE of 2677.33, MAPE of 10.34%, and RMSE of 4620.81. Importantly, SARIMA performs well in testing with an MAE of 2780.03, MAPE of 8.94%, and RMSE of 5891.77. These figures are the lowest testing errors of all three approaches, proving that SARIMA models ridership data autocorrelation and weekly seasonal patterns well.

4. Conclusion

This study compared the accuracy of three forecasting methods Naïve, SARIMA, and Facebook Prophet in projecting daily ridership for KTMB services in Malaysia. RMSE, MAE, and MAPE were utilized to evaluate model performance using daily ridership data from September 2023 to March 2025. The Naïve method had the greatest error values in most accuracy tests, showing poor forecasting potential due to difficulties capturing trend and seasonal patterns. Facebook Prophet performed moderately throughout training, but its forecasting accuracy declined drastically in testing, as shown by greater MAE, MAPE, and RMSE values. Overfitting and weaker generalization to unseen data are possible. In contrast, the SARIMA model had the lowest MAE, MAPE, and RMSE values in training and testing datasets. These data show that SARIMA forecasts most accurately and reliably of the three models. SARIMA's ability to explicitly model seasonal and non-seasonal components in daily KTMB ridership data explains its improved performance. In conclusion, SARIMA was identified as the most effective forecasting model in this study, highlighting the significance of seasonality in predicting public transportation ridership. Precise ridership forecasts can assist KTMB in enhancing operational planning, service scheduling, and resource distribution. Future research could enhance predictive accuracy by incorporating external variables such as public holidays, weather conditions, and special events, as well as by utilizing advanced or hybrid forecasting models.

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Conflict of Interest

Authors declare that there is no conflict of interests regarding the publication of the paper.

Author Contribution

The authors confirm contribution to the paper as follows: ***study conception and design:*** *Nuraqilah Layanah A.Lotfi, Kamil Khalid;* ***data collection:*** *Nuraqilah Layanah A.Lotfi;* ***analysis and interpretation of results:*** *Nuraqilah Layanah A.Lotfi, Kamil Khalid;* ***draft manuscript preparation:*** *Nuraqilah Layanah A.Lotfi, Kamil Khalid. All authors reviewed the results and approved the final version of the manuscript.*

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