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TIME SERIES MODEL FOR TRAIN PASSENGER FORECASTING

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ABSTRACT

Trains as a means of public transportation have an important role in connecting various regions of Jabodetabek. Therefore, it is necessary to have a deep understanding of the trend of train passenger movements and predict the number of train passengers in the next period in order to optimize the management and service of train passengers properly. In this study, we examine two methods that can be used as forecasting methods for train passenger data sourced from the Central Statistics Agency (BPS), namely ARIMA and Prophet. This study demonstrates that the optimal ARIMA model is ARIMA (0,2,1), achieving a Mean Absolute Percentage Error (MAPE) of 4.91% and a Root Mean Square Error (RMSE) of 1754.970. In addition, the Prophet model, which is an additive regression model designed by Facebook for time series forecasting was also obtained with a MAPE of 0.04% and an RMSE of 1170.59. Considering the MAPE and RMSE values of the two models, the Prophet model emerges as the most suitable for forecasting the number of train passengers in the Jabodetabek region.

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1. INTRODUCTION

Forecasting is a method of analysis carried out using qualitative and quantitative approaches to predict future events based on past data references. Forecasting can be a reference for short, medium, or long-term design [1]. Forecasting can be done with various methods, including using Autoregressive Integrated Moving Average (ARIMA) and Prophet.

ARIMA is a forecasting model introduced by Box and Jenkins in 1970 that has evolved considerably. Originally concentrating on improved model identification and order selection, it now includes non-linear models and can integrate external variables to boost forecasting accuracy [1]. In producing short-term forecasts, the ARIMA model has proven to be very efficient and able to surpass the performance of more complex structural models [2]. The ARIMA model is a combination of AR (auto regressive), differencing (integration), and MA (moving average) models. The general notation used in the ARIMA model is (p,d,q), with p and q being the order of the AR and MA models respectively while d is the degree of differencing [3].

In addition to the ARIMA model, Prophet is also popularly used in forecasting studies. The Prophet model was first invented by the Facebook team on 2017. Since becoming open-source in 2018, Prophet has continuously improved in terms of accuracy, flexibility, and the scope of its applications. Prophet is tailored for time series forecasting using a straightforward methodology. The Prophet model consists of three fundamental elements: seasonality, trend, and holidays [4]. The Prophet model has easy-to-understand parameters and does not require a lot of time series data to perform forecasting. In addition, the Prophet model can also handle missing data, trend variation, and outlier detection well [5]. Both models have been widely used in forecasting research, one of which is in the field of forecasting train passenger data [6][7][8]. Some of the differences between this research and previous research lie in the use of research forecasting methods. J. Chang and X. Song [6] compared Long Short-Term Memory with ARIMA and Prophet, Chuwang and W. Chen [7] focused on comparing ARMA with Prophet, and Queenty [8] who only used ARIMA to predict the number of train passengers in Binjai city, North Sumatra.

As we know, transportation mobility is crucial in the economic development of a country. In Indonesia, trains as a means of public transportation have an important role in connecting various regions, especially in the Jabodetabek area. Therefore, it is necessary to have a deep understanding of the trend of train passenger movements and predict well the number of train passengers in the next period. This is done with the aim of optimizing the management and service of train passengers properly. Efficient management of the train system, which offers a good solution to the transportation problems in big cities that are getting more congested every day, is essential for operational efficiency and passenger service satisfaction [9].

In this article, we aim to contribute to the field of train passenger forecasting by comparing the performance of ARIMA and Prophet specifically in the context of Indonesian train passenger data. We will employ MAPE (mean absolute percentage error) and RMSE (Root Mean Square Error) to evaluate the accuracy of both models.

2. RESEARCH METHODS

2.1 Data Description

The dataset consists of the number of train passengers in the Jabodetabek region, measured in thousands, sourced from the Central Statistics Agency (BPS) website [10]. Covid-19 affects the time series data pattern where the intervention period starts in March 2020 and ends in March 2022.

2.2 Data Analysis Stages

Time series model analysis in this research uses Python. The steps in data analysis are as follows:

1. Analyze the data descriptively to understand the data through plots. Data exploration is carried out with the aim of examining the patterns or characteristics of the data. After data exploration, it was continued with data stationarity analysis in terms of variance and mean value.
2. Divide the data into train data and test data.
3. Building ARIMA and Prophet models. The ARIMA modeling steps are as follows:

a. Examining Stationarity in Mean and Variance.

Data stationarity, both in mean value and variance, is important to analyze in order to find out an accurate model in forecasting [11][12]. Data stationarity can be assessed by examining patterns in the data plot. Differentiation is performed if the data is not stationary in terms of the mean. Plot is used to examine stationarity in variance, while ADF test is used to examine stationarity in mean [13].

b. Model Specification.

The autocorrelation function (ACF) and partial autocorrelation function (PACF) plots are useful for identifying the appropriate ARIMA model and detecting any seasonal patterns in the data after achieving stationarity in the time series [14].

c. Parameter Estimation, estimated Arima model parameters obtained from the Model Specification process.

d. Model Diagnostic.

Checking the residuals from the ARIMA model obtained. Perform a diagnostic analysis of the model to determine if the residuals display properties of white noise. The independence and normality of the residuals are assessed through diagnostic tests. The Ljung-Box test statistic is used to assess the independence of the residuals. The hypotheses are as follows:

H_0 : the time series data has no serial autocorrelation, and

H_1 : the time series data exhibits serial autocorrelation.

The Kolmogorov-Smirnov test is employed to evaluate normality. The hypotheses are as follows:

H_0 : the data conforms to a normal distribution, and

H_1 : the data deviates from a normal distribution.

The model meets these assumptions if the p-value exceeds α (5%) [15].

e. Overfitting.

Overfitting is mitigated by gradually increasing the orders of the ARIMA model. The selected overfitting model is defined by having all coefficient estimates that are statistically significant.

f. Forecasting

Data forecasting uses the best model obtained.

The Prophet modeling steps are as follows:

a. Modelling

Prophet modeling employs training data augmented with additional regressors representing the duration of Covid from April 2020 to February 2022.

b. Forecasting

Data forecasting employs the most optimal model obtained.

4. Comparing the two ARIMA and Prophet models.

The ARIMA and Prophet models will be compared using testing data. Both models will undergo testing using two datasets: one with 3 months of testing data and another with 6 months of testing data. Evaluation will be based on MAPE and RMSE metrics. The forecasting outcomes from both models will be assessed to determine which model better predicts train passenger data. MAPE is used to see model performance in percentages while RMSE is used to compare model predictions with original data values, namely train passengers in thousands. The value of MAPE and RMSE can be calculated using formulas [16]

$$MAPE = \frac{\sum_{t=1}^{n} \left| \frac{(A_t - F_t)}{A_t} \right|}{n} \quad (1)$$

$$RMSE = \sqrt{\frac{1}{n}\sum\nolimits_{t=1}^{n}(A_t - F_t)^2} \tag{2}$$

Where A represents the genuine value, F stands for the predicted value, and n denotes the total count of data points. The model that achieves the lowest MAPE and RMSE values is chosen as the optimal forecasting model [17].

3. RESULTS AND DISCUSSION

3.1 Data Exploration

Figure 1 illustrates the time series data plot of Jabodetabek domestic passenger counts.

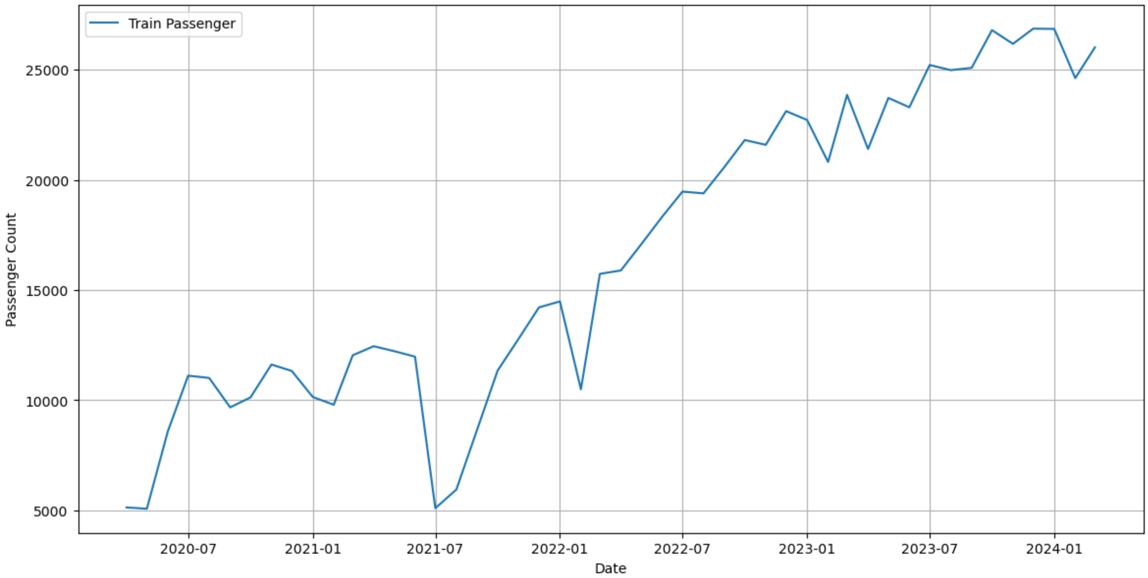


Figure 1. A Plot of Time Series Data for Jabodetabek Train Passenger

The number of passengers will start to increase rapidly from March 2022. The long-term trend indicates an overall increase in train passengers in the Jabodetabek area.

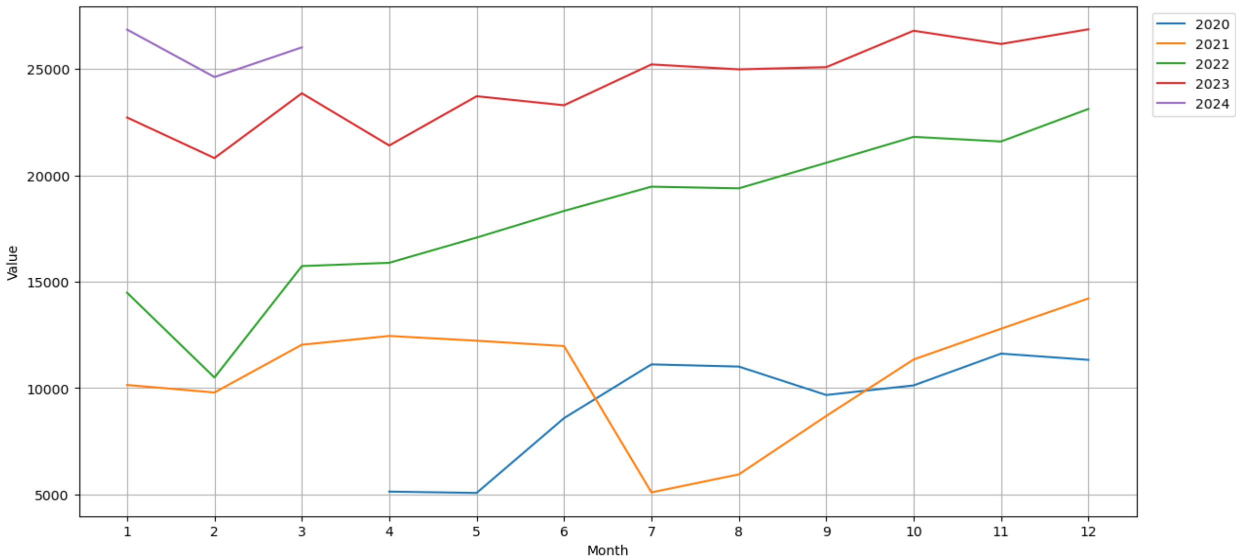


Figure 2. A Plot of Train Passenger Data by Month

In Figure 2, the plot line shows the absence of a seasonal pattern. This may have happened because during the Covid period there was a lockdown and PPKM policy due to COVID-19. After October 2022, seasonality will start to appear, which shows that the number of train passengers has started to stabilize and return to normal after COVID-19.

3.2 Splitting Data

For train and test data, we will try several variations, namely 42 months of train data (April 2020 – September 2023) with 6 months of test data (October 2023 - March 2024) and 45 months of train data with 3 months of test data (January 2024 – March 2024).

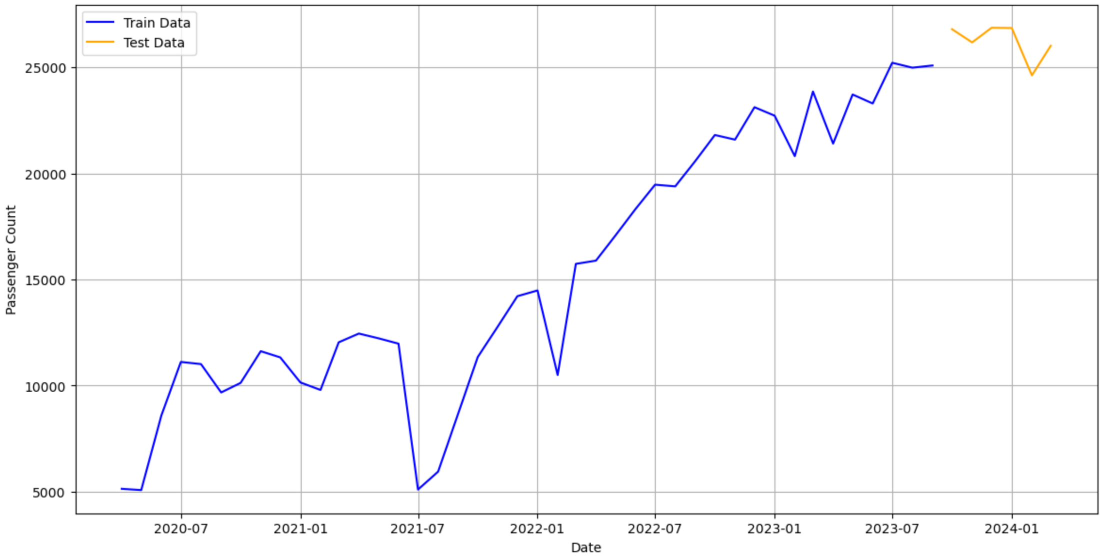


Figure 3. A Plot of Time Series Split Data

3.3. ARIMA Modelling

In 1970, Box and Jenkins pioneered the ARIMA model, a statistical framework widely known as the Box-Jenkins methodology. This approach encompasses a comprehensive set of procedures for identifying, estimating, and diagnosing ARIMA models in the context of time series data [2]. In the ARIMA model, the future value of a variable is represented as a linear combination of its previous values and past errors, formulated in the following manner:

$$Y_t = \phi_0 + \phi_1 Y_{t-1} + \cdots + \phi_p Y_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots - \theta_q \varepsilon_{t-q} \tag{3}$$

where Y_t is the actual value and ε_t is the random error at t, ϕ_i and ϕ_j are the components, the integers p and q are commonly referred to as autoregressive and moving average terms, respectively.

3.3.1 Checking Stationarity

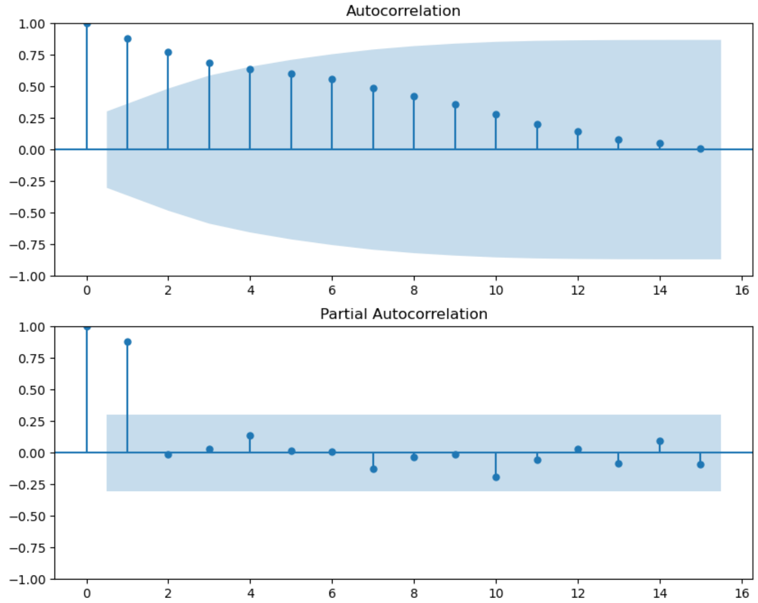


Figure 4. ACF and PACF Plot of Data

The data was not stationary, as seen by the progressive decline in the ACF plot (**Figure 4**). The ADF test yielded a p-value of 0.754, which exceeds the significance level of 0.05. This indicates that the data can be interpreted as non-stationary and that the null hypothesis cannot be disproved.

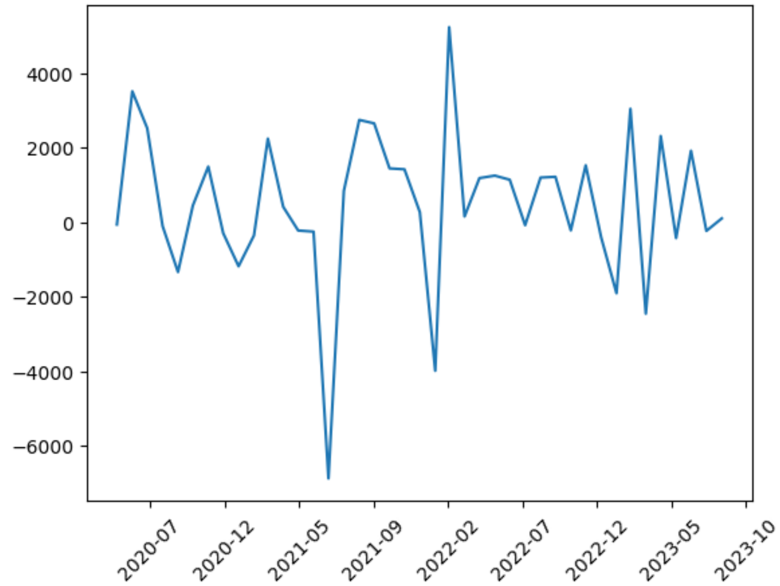


Figure 5. A Plot of Differenced Time Series Data

After performing first-order differencing, as depicted in **Figure 5,** the data appears to exhibit stationarity. This observation is further corroborated by the ADF test result, which yielded a p-value below 0.05, indicating statistical significance. This indicates that the data can be interpreted as stationary and that the null hypothesis is rejected.

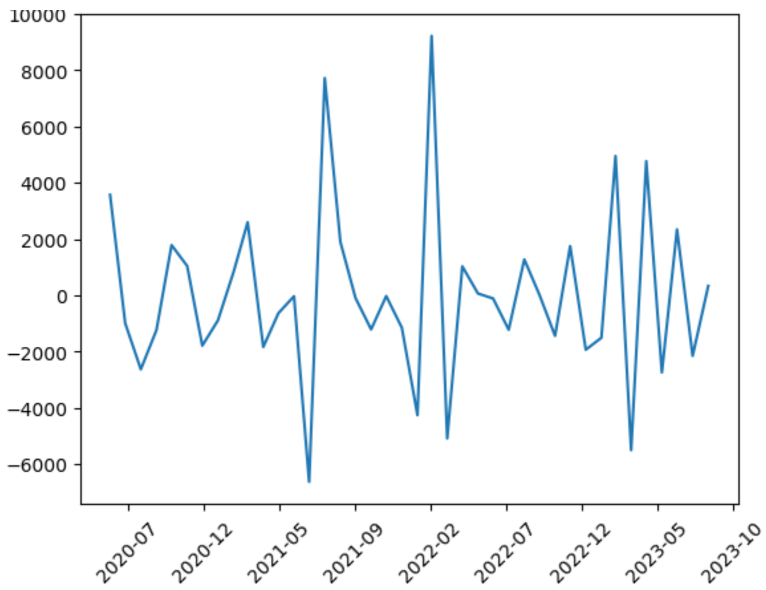


Figure 6. Data After Second Order Differencing

We also check the second order differentiation for further analysis as in **Figure 6**. From the figure we can conclude that the data appears to exhibit stationarity after performing first-order differencing.

3.3.2 Model Specification

The goal of this step is to select appropriate values for p, d, and q for the data being analyzed. This process is done by looking at the ACF and ACF plots as below.

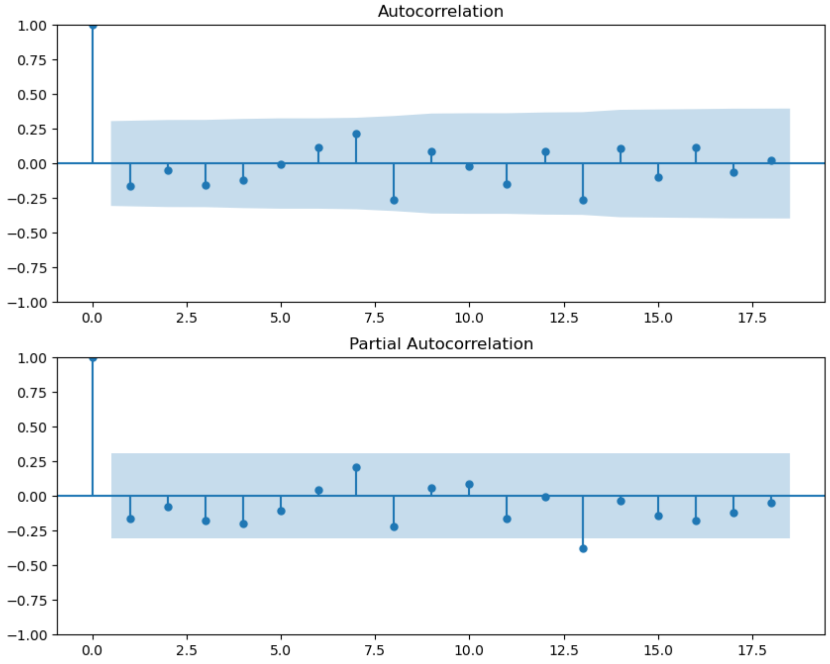


Figure 7. ACF and PACF of Data First Order Differencing Data

Figure 7 displays the autocorrelation function (ACF) and partial autocorrelation function (PACF) plots of the differenced data. These two plots support Figure 2 and it can be concluded that there is no seasonality in the Jabodetabek train passenger data. Meanwhile, the p and q orders can be seen from the ACF and PACF plots. The ACF plot shows no significant lag and the PACF plot shows no significant lag.

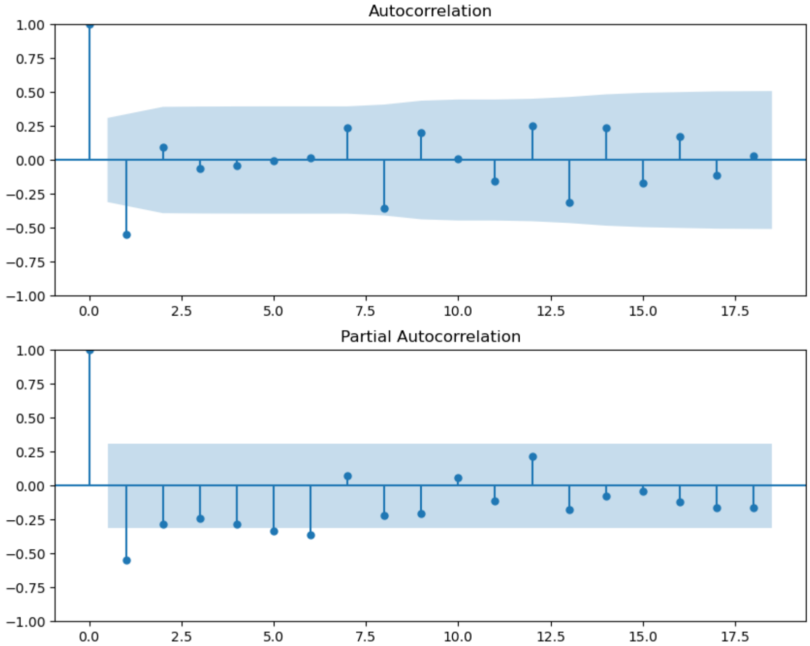


Figure 8. ACF and PACF of Second Order Differencing Data

Because of that we carried out second order differentiation to find significant lags with the results in **Figure 8**. Thus, the obtained model is ARIMA(0,2,1).

3.3.3 Parameter Estimation

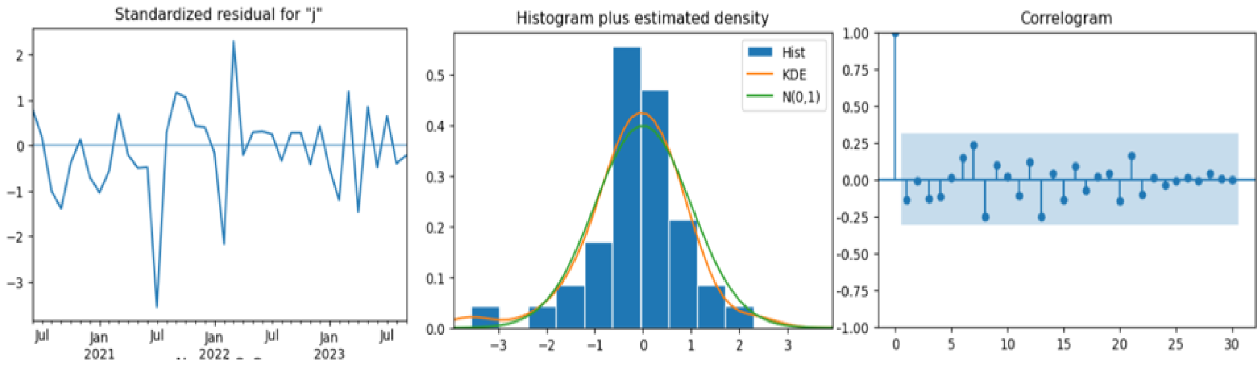
After deriving the model, the subsequent step involves estimating the model parameters. The outcomes of the parameter estimation can be observed in **Table 1**. The p-values for all the parameters in both models are below the threshold of α (0.05), suggesting that every parameter estimate is statistically significant.

Table 1. Model Parameter Estimation

Model	Parameter	Estimation	p-value	Significance	AIC	MAPE	RMSE
ARIMA(0,2,1)	MA(2)	-0.9999	< 0.05	yes	744.975	4.91%	1754.970
	σ^2	4.26E+06	< 0.05	yes			

3.3.4 Model Diagnostic

Based on the diagnostic tests depicted in **Figure 9** below, there is no observable autocorrelation present in the residuals of the model. The residuals' in correlogram plot remaining within the bounds of significance provide supporting evidence. Moreover, the residual plot suggests that the residuals in the model are dispersed around the mean value. The histogram plot indicates that the residuals follow a normal distribution. The assumption test for homogeneity of residual variance, residual independence, and Shapiro test shows a p-value greater than 0.05, so the assumption is met. These findings suggest that the residuals of the model, ARIMA(0,1,0) satisfy the white noise assumption.



(a) **(b)** **(c)**

Figure 9. **Plot Model Diagnostic ARIMA(0,2,1) (a) Residuals Plot, (b) Histogram Plot, and (c) Correlogram Plot**

3.3.5 Overfitting

After getting an ARIMA model that fits the data, the next stage is overfitting. Overfitting is the process of trying another ARIMA model with the aim of confirming that the model we got previously is appropriate. This process is done by adding the order p or q one by one. **Table 2** presents the outcomes of overfitting analysis, indicating that not all models have statistically significant parameter estimates at the 5% level. So for our training data ARIMA(0,2,1) is the optimal model.

Table 2. **Model Overfitting Estimation**

Model	Parameter	Estimation	p-value	Significance	AIC	MAPE	RMSE
ARIMA(1,2,1)	AR(1)	-0.1207	> 0.05	no	732.358	4.97%	1780.766
	MA(1)	-0.9999	< 0.05	yes			
	σ^2	4.17E+06	< 0.05	yes			
ARIMA(0,2,2)	MA(1)	-1.125	< 0.05	no	732.352	4.99%	1787.432
	MA(2)	0.1251	> 0.05	yes			
	σ^2	4.17E+06	< 0.05	yes			

The ARIMA(1,2,1) model includes one autoregressive and one moving average term. The AR term is not significant, indicating it might not be contributing much to the model, but the MA term is highly significant, which could mean the model's predictions rely more on the moving average component. The ARIMA(0,2,2) model relies solely on the moving average terms. While the first MA term is significant, the second is not, suggesting that the second term may not be necessary. Both model has a slightly better AIC than ARIMA(0,2,1) but worse predictive performance compared to the ARIMA(0,2,1) model. So ARIMA(0,2,1) will be used for forecasting.

3.3.6 Forecasting

Once the optimal model is identified, the subsequent step involves forecasting data for both the three-month and six-month test datasets **[18]**. The forecasting results of the ARIMA model are summarized in **Figure 10**.

3.4 Prophet Modelling

Prophet is a model that used for time series forecasting. It was designed primarily to address three key components: trend, seasonality, and holidays **[4]**, while also meeting the need for high-quality forecasting. The model can be expressed as shown in **Equation (4)**

$$y(t) = g(t) + s(t) + h(t) + \epsilon_t \tag{4}$$

In this model, the parameters $g(t)$, $s(t)$, $h(t)$, and ϵ_t serve distinct purposes. Specifically, $g(t)$ represents a piecewise linear curve used to capture non-periodic changes in the time series, while $s(t)$

accounts for periodic variations. The parameter $h(t)$ models the effects of holidays with irregular schedules, and ϵ_t represents the error term, capturing any unexpected fluctuations that the model does not explicitly account for. To incorporate seasonality effects into the proposed model and generate forecasts, a Fourier series is utilized. This approach offers a flexible representation of seasonal patterns. The seasonal effects, denoted as $s(t)$, can be mathematically expressed as shown in **Equation (5)**.

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

Here, P denotes the regular period of the seasonal pattern, ensuring that the Fourier series effectively captures recurring fluctuations over time **[19]**.

3.4.1 Modelling

Modeling using training data with a regressor in the form of binary 1 for the Covid period and 0 for outside the Covid period. The model used is the default model without hyperparameter tuning because there is too little data to carry out cross-validation.

3.4.2 Forecasting

After the model is obtained, the next process is data forecasting for both three months test data and six months test data. The Prophet model forecasting results are summarized in **Figure 10**.

3.5 Comparison of the Two Model

A summary of the forecasting of the two models for both data is in **Figure 10** and **Table 3**. It can be seen that the Prophet model has better results and can even capture data patterns well for both three months and six months testing data.

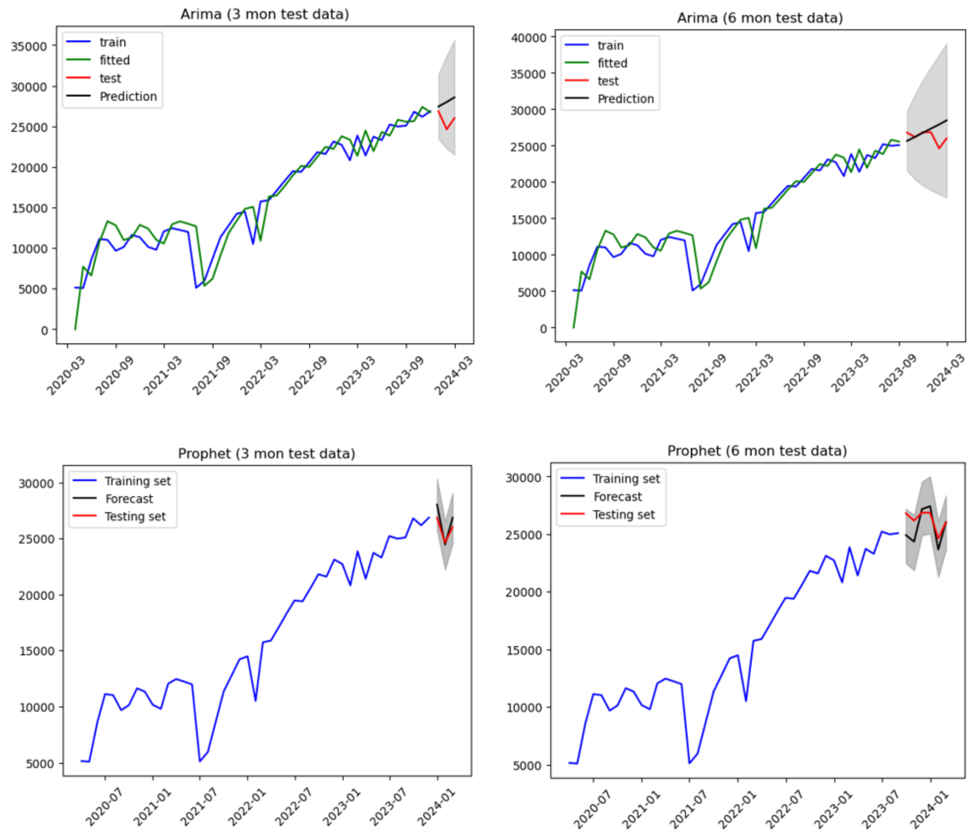


Figure 10. **Model Forecasting**

Meanwhile, ARIMA has a flat prediction value and does not capture the test data pattern for both data. This is further evidenced by the lower MAPE and RMSE values of the Prophet model compared to ARIMA (0,2,1).

Table 3 Model Forecasting Evaluation

Data	Model	MAPE	RMSE
3 months testing	ARIMA(0,2,1)	8.56%	2465.883
	Prophet	0.03%	836.32
6 months testing	ARIMA(0,2,1)	4.91%	1754.970
	Prophet	0.04%	1170.59

Table 3 shows that Prophet's performance is better for the analyzed JABODETABEK train passenger data. This is in contrast to research **[18]** who found that SARIMA intervention has better performance than Prophet. While Chuwang and W. Chen **[7]** they discovered that for the daily time series, the Facebook Prophet model outperforms the SARIMA model, and for the weekly time series, the ARIMA model outperforms the Facebook Prophet model.

4. CONCLUSIONS

The forecasting results show that for Jabodetabek train passenger data with a data range from April 2020 to March 2024, the Prophet model is better at forecasting data. This indicates that, based on the test dataset employed for model evaluation, encompassing three observations over a three-month testing period, the Prophet model demonstrates superior predictive performance in comparison to ARIMA. Furthermore, the findings of this research suggest that PT KAI could leverage the Prophet model as a forecasting tool for predicting future train passenger volumes. This would enable PT KAI to strategically plan and optimize its services in response to fluctuations in passenger demand, including adjustments to the number of carriages, train fleet deployment, and service schedules.

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