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Prophet with Google Trends for Forecasting Train Passengers in Java

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Abstract

As a popular transportation method for long-distance travel, trains were also a preferred choice during the homecoming period before Eid Al-Fitr, one of the major religious holidays in Indonesia. During this period, known locally as ‘mudik,’ millions of people travel from the urban cities back to their hometowns to celebrate with their families, creating a significant surge in transportation demand. However, since the holiday follows the Islamic calendar, which changes slightly every year, forecasting train passengers becomes tricky, thus requiring a different approach to achieve accurate predictions. This study utilizes the Prophet method to forecast train passengers in Java (excluding the Jabodetabek area) using the data from 2006 to 2024. We also incorporated the COVID-19 period as a fixed external regressor, along with external regressors from Google Trends data using the keywords ‘kereta api’, ‘mudik’, and ‘lebaran’, which are commonly searched by the public in relation to train travel and the Eid homecoming period. The results on the test set, 2024 data, showed that the word ‘mudik’ was the most effective in improving forecast accuracy, with a MAPE of 9.12 and RMSE of 797.76, a decrease of 11.57% and 9.34% compared to the updated baseline. This indicates that public search behavior around the term ‘mudik’ closely aligns with actual travel demand patterns. The findings of this study suggest that Prophet with external regressors are capable of forecasting train passengers and Google Trends can be a valuable addition for capturing data patterns related to specific phenomenon.

Keywords : *External Regressor, Forecast, Google Trends, Prophet, Train Passengers.*

1. INTRODUCTION

Train is one of the popular public transportation options, often used by people traveling between cities and provinces in Java. It is also a popular option for ‘mudik’ or homecoming, when people return to their hometowns during Eid Al-Fitr, one of the major Islamic holidays celebrated in Indonesia [1]. As a country with a large Muslim population, this homecoming activity has become a yearly occurrence. However, since the holiday follows the Islamic calendar, the seasonality is trickier to predict, as it shifts forward by about ten days each year in the Gregorian calendar. In time series analysis, this is often described as the calendar variation effect.

Various forecasting methods have been used to address this irregular seasonal patterns arising from calendar variation, such as the Autoregressive Integrated Moving Average (ARIMA) with a calendar variation effect and additional outlier detection for predicting train passengers in Semarang [2], Sumatra Island [3], and predicting ship passenges in Makassar Port to capture changes in pattern due to Eid Al-Fitr [4]. Studies in several areas in Indonesia also showed that, other than the calendar effect, the forecast was significantly affected by COVID-19 [5]. These findings highlight the importance of incorporating both calendar variation and external information on into forecasting models.

One of the forecasting methods often mentioned also includes Prophet, a model developed by Meta to handle prediction tasks. Not only handling transportation related problems, Prophet has performed well in various applications compared to other models, such as forecasting supermarket sales [6], coronavirus disease cases in Indonesia [7], air temperature [8], air pollution [9], and energy consumption [10]. On the side of transportation studies, it has also been utilized for forecasting traffic flow [11] and predicting passenger flow in China [12]. Prophet also performed fairly well in predicting passenger flow in Beijing [13] and Lima [14], even when compared to other methods such as ARIMA Random Forest or other machine learning methods.

Regarding its performance in forecasting train passenger data in Indonesia, Prophet has also shown promising results. A previous study on train passenger data in Java in 2021 found that Prophet produced better results compared to the Feed Forward Neural Network [15]. The method also demonstrated better predictive capability compared to ARIMA for forecasting train passengers in the Jabodetabek (Jakarta–Bogor–Depok–Tangerang–Bekasi) area [16].

In recent years, online search data have emerged as an alternative source of external information for forecasting. Google Trends provides search intensity data that reflect public interest over time. During the pandemic, it revealed possible effects of the crisis on mental health based on search intensity [17] and showed the public's attempts to seek information [18]. Google Trends, as a predictor, has been shown to improve predictions of changes in exchange rates for several currency pairs, outperforming random walk models [19], used to help predict market demand during the pandemic [20] and showing its potential to play a greater role and gain popularity in health-related research in infodemiology studies [21].

In transportation studies, Google Trends has been used as an external covariate for several methods, such as linear regression, ARIMA, and random forest, to predict passenger flow in Taiwan, successfully improving prediction accuracy [22], improve forecasting of inbound flight passengers in Thailand [23] and were used as an exogenous variable in SARIMAX to improve in forecasting tourists arrival, outperforming other methods [24]. It has also been utilized in aiding nowcasting train passengers in 2021, showing increasing forecasting accuracy with SARIMAX methods [25].

So far, limited studies have examined the integration of Google Trends data with Prophet for forecasting train passenger volumes in Indonesia. This study aims to investigate whether Google Trends keywords, especially terms related to homecoming activity as predictors, can assist Prophet in modeling train passenger data in Indonesia. As mudik or homecoming is an activity closely related to the volume of passengers traveling between provinces, the focus of this study is on Java, excluding data from the Jabodetabek area. There were many words associated with homecoming activity, which peaked periodically in the Google Trends search results. Therefore, this study aims to investigate whether homecoming related keywords in Google Trends, as predictors, can assist Prophet in modeling train passenger data in Indonesia and improve the forecasting results.

2. METHOD

This study utilized data from two main sources: BPS Indonesia and Google Trends. Detailed information regarding the specific terms for data collection is provided in Section 2.1. The key method in this study is Prophet model with external regressors, evaluated using Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE).

2.1. Data

The data period for this study covers monthly data from 2006 to 2024, a total of 228 months. Train passenger data were collected from the BPS Indonesia website, focusing on the number of passengers in Java (excluding the Jabodetabek area). The numbers are presented in thousands. The complete list of variables for this study is shown in Table 1.

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Table 1. Dataset

Source	Variable
BPS Indonesia	Y: number of train passengers in Java (Non Jabodetabek area)
Google Trends	X represents search volume for the words: X1 : 'kereta api' X2 : 'mudik' X3 : 'lebaran'

The Google Trends data for this study was collected from the Google Trends page using the search terms: 'kereta api' (train), 'mudik', and 'lebaran', with the region set in Indonesia, showing results of Web Search. The search term frequency refers to the number obtained when searching for each term individually, rather than from a combined search using multiple keywords. Each keyword frequency ranged between 0 to 100.

2.2. Prophet

Prophet is a method developed by Meta, based on an additive model to produce highly accurate forecasts. Equation (1) shows the basic Prophet model.

$$y(t) = g(t) + s(t) + h(t) + \varepsilon_t \quad (1)$$

where $y(t)$ is the additive regression model, and $g(t)$, $s(t)$, $h(t)$, and ε_t denote trend, seasonality, holidays, and noise in the data, respectively [26]. All these components can be adjusted to improve forecast performance. In this study, we used the component $g(t)$ for the train passengers' trend, $s(t)$ for the periodic yearly seasonality of the data, while we did not include $h(t)$ component in the model. External regressors are added as a linear addition to the equation .

We train the Prophet model with the default parameter settings: linear growth; 25 potential changepoints; 0.05 changepoint prior scale. We did not include the default country holiday parameter since it was covered by the external regressors in this study. The external regressors were fitted as additive seasonalities in the model.

2.3. Evaluation Metrics

The models were evaluated using MAPE and RMSE as the evaluation metrics. MAPE illustrates the model's performance in terms of percentage, while RMSE depicts the standard deviation of the prediction errors. The formulas for MAPE and RMSE are shown in Equations (2) and (3) [27],

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y_t - F_t)^2} \quad (2)$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{(Y_t - F_t)}{Y_t}\right| * 100 \quad (3)$$

where n is the number of observations, Y_t is the actual value and F_t is the forecast value at time t.

2.4. Steps of analysis

The research steps in this study are illustrated in Figure 1.

The number of train passengers was set as Y_t, and the COVID-19 dummy variable was set as an external regressor. The data is split into two, as training and testing set. The training part consisted of data points from 2006 to 2023, while the testing part is 12 months data points in 2024. An autocorrelation check is conducted on the residuals of the models. Since it was still observed in the residuals of the

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earlier model, an additional external regressor, the lag-1 of the number of train passengers, was added into the model. The final Prophet model was trained based on four scenarios: updated baseline, with 'kereta api',with 'mudik', and with 'lebaran'. We then checked for autocorrelation in the residuals again and proceeded to use the resulting models for forecasting the testing set. The evaluation metrics were calculated using MAPE and RMSE, and the results of the four scenarios were compared to find the best fit for the train passengers data.

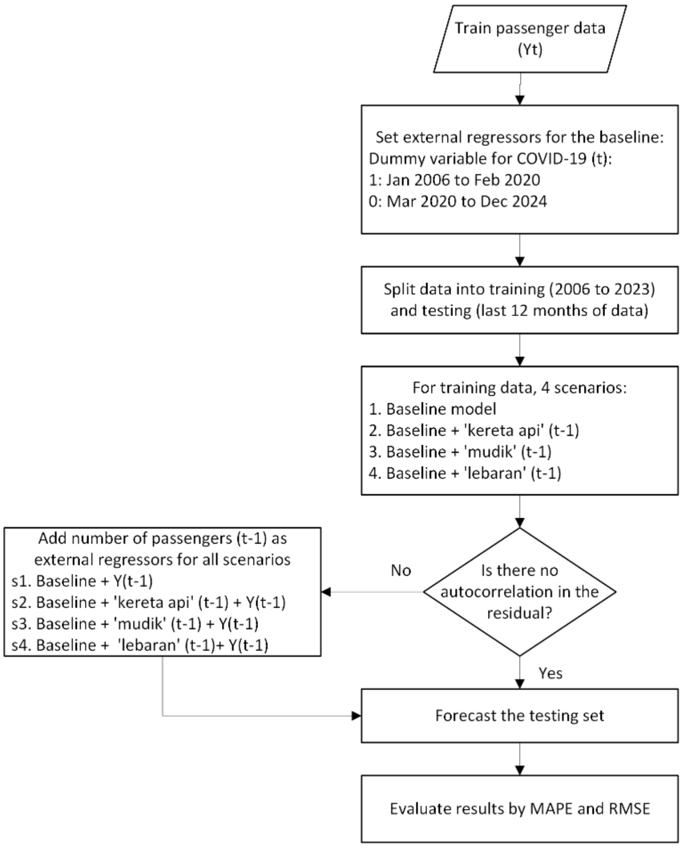

Figure 1. Flowchart of Research Steps

3. RESULT

This section describes the results of the analysis. We began by exploring the data, including both the number of train passengers and the Google Trends search frequency data. The patterns in the data were displayed in time series plots, which allowed us to observe changes over time from the beginning of the data period in January 2006 to the end of 2024. During this exploration, we identified general trends, seasonal fluctuations, and disruptions in the data, such as the decrease in train passengers during the COVID-19 pandemic. These visual observations were referred in selecting variables for the forecasting models.

We then proceeded to the forecasting steps using the train passenger data. To improve forecast accuracy, additional variables, such as the COVID-19 dummy variable and lagged values of train passengers, were incorporated into the model. We further examined the effect of including Google Trends search volumes for keywords related to train travel, such as 'kereta api', 'mudik', and 'lebaran', on the forecast results. The models were evaluated through diagnostic checks on the residuals to identify autocorrelation patterns, and the forecast was evaluated using MAPE and RMSE. This process allows for comparison of multiple scenarios to determine the best approach for forecasting the number of train passengers in Java.

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3.1. Data Exploration

The time series plot for train passengers in Java (excluding the Jabodetabek area) is shown in Figure 2. The train passenger data spans from January 2006 to December 2024, showing changes happening in the number of passengers for 228 months. The black line, representing data from 2006 to 2023, serves as the training set for the analysis, while the last 12 months are assigned as the test period to evaluate the forecast results, depicted as the blue line in the figure.

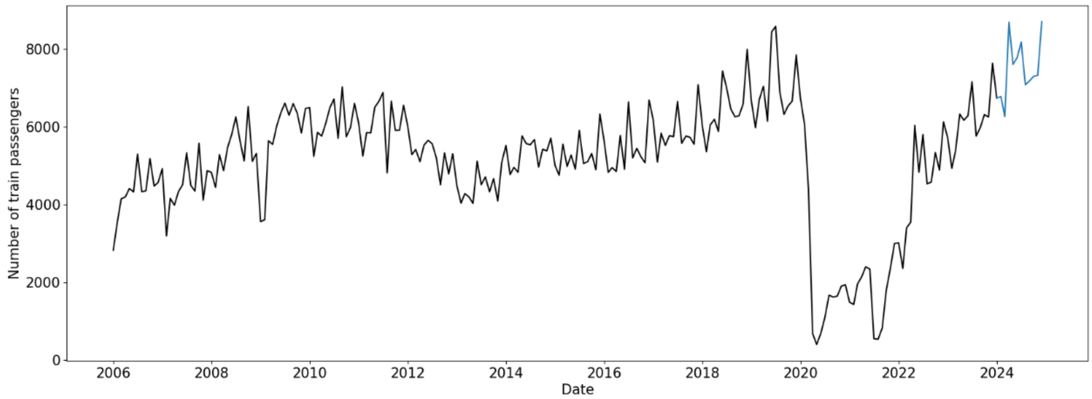

Figure 2. Time Series Plot of Train Passengers in Java (Non Jabodetabek area)

The plot in Figure 2 shows a general increasing trend from 2006 to 2019, with a slight decrease from 2012 to 2014, followed by a climb back up until a sharp drop in 2020 due to COVID-19. The trend began to recover in 2022 and continued to rise until the latest data period in 2024. The time series plot of train passenger data suggests that there was a clear disruption in passenger numbers caused by COVID-19, resulting in a sharp decline.

Other than the data obtained from BPS Indonesia, we also collected Google Trends data for the keywords ‘kereta api’, ‘mudik’, and ‘lebaran’, which are Indonesian terms closely related to trains and passenger habits. These three keywords were obtained independently, one at a time, with a score of 100 representing the peak search volume during the data collection period. Figure 3 shows the time series plots for these keywords.

Figure 3(a) displays the search frequency for ‘kereta api’. The figure shows a seasonal pattern, with peaks every few months that coincide with Eid Al-Fitr months. After an overall stable trend, a decline in frequency is observed after 2022, and the search frequency for the word ‘kereta api’ remained relatively low compared to previous months until the end of the data period in 2024. Slightly different from the previous figure, the seasonal pattern is especially apparent in Figures 3(b) and 3(c). While the search frequency is higher in the early period of 2006 to 2011 compared to the rest of the data, the seasonal pattern remains very clear: a peak followed by a much smaller search frequency for the remaining months. A closer look at the figures shows that the peak search volumes for these keywords shifted to earlier months in 2024 compared to earlier years starting in 2006, which was not so apparent in Figure 3(a) due to changes also happening in other months, not only in months close to Eid Al-Fitr.

These variables were then independently assigned as external regressors for the model forecast with a time lag of 1, meaning that the search volume at time t-1 was used to aid the forecast of train passengers at time t. This approach allowed the model to incorporate the effect of search frequency from the previous month into the prediction of the current month. We considered four models involving all the Google Trends search frequencies in this study, as described in the research methodology section. Model 1 used no keyword data, Model 2 added ‘kereta api’, Model 3 added ‘mudik’, and Model 4 added ‘lebaran’, each obtained and evaluated separately to compare the influence of these words on forecast accuracy.

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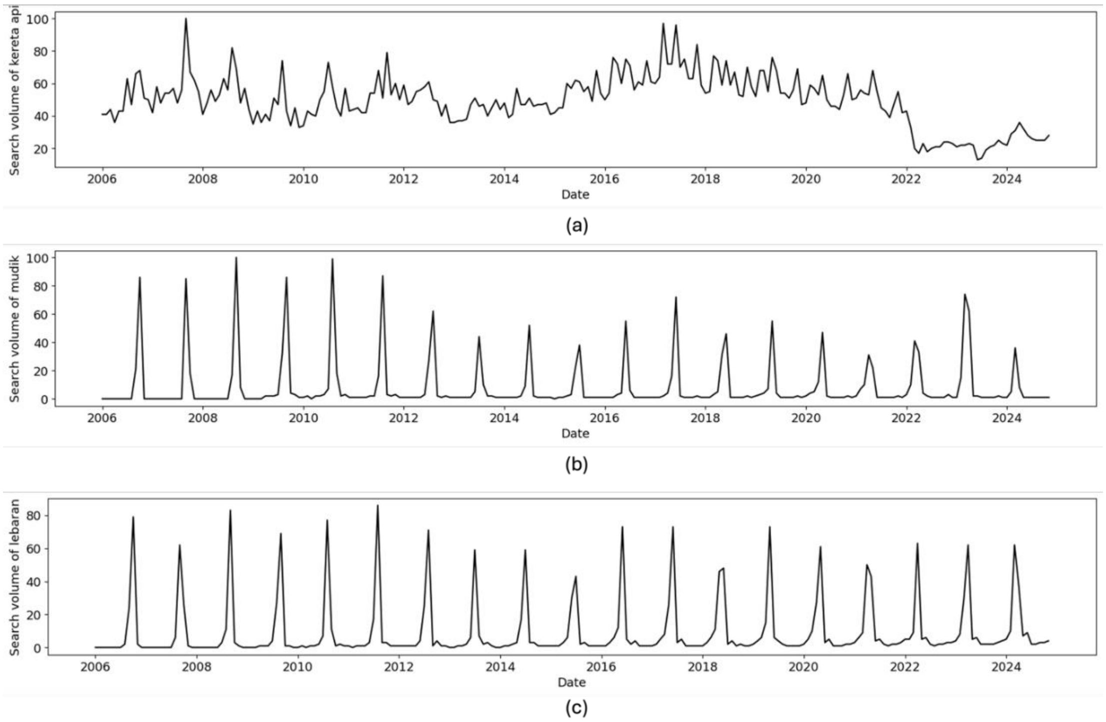

Figure 3. Time series plot for the Google Trends data (a) 'kereta api' (b) 'mudik' (c) 'lebaran'

3.2. Prophet Model Training

The first step in training the Prophet model was using the number of train passengers data only as Y_t. The results are shown in Figure 4(a), where it is clearly observed that the forecast was unable to capture the disruption caused by COVID-19, and the forecast interval became very large in an attempt to capture the data range. The overall forecast stayed within the same range even when a significant drop occurred in 2020. This indicates that using the train passenger data only without any additional variables was not enough to reflect the trend in the data.

To address this drop, we trained the model again with the addition of COVID-19 as an external regressor variable, assigned a value of 1 during the pandemic and 0 afterward. The result of this addition is displayed in Figure 4(b), showing that the forecast now follows the data pattern more closely. The forecast interval became narrower, with the model now able to better capture the changes, particularly the sudden drop in the number of train passengers at the onset of COVID-19 in 2020 and the subsequent recovery. This model, using the number of train passengers and the COVID-19 variable, was defined as the baseline model for further analysis in this study.

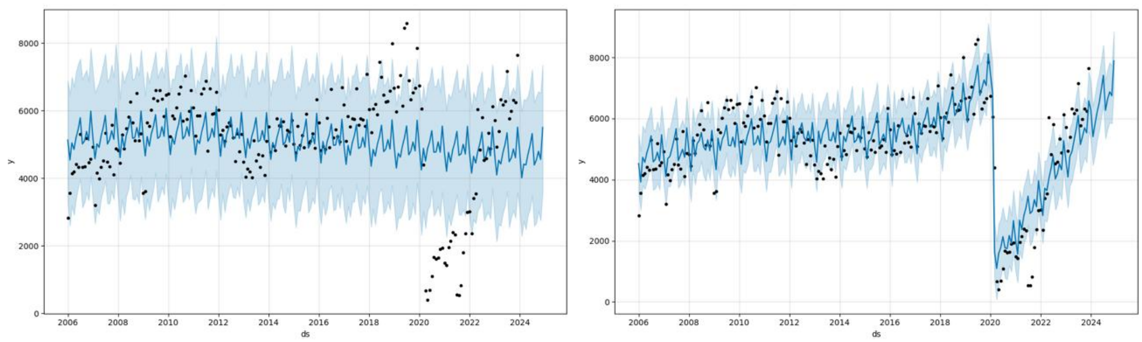

Figure 4. Prophet model fitting results for (a) baseline model (b) with the addition of COVID-19 variable

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Since the model was able to capture the patterns and disruption caused by COVID-19 in 2020, we then continued by assigning the extra regressors from the Google Trends search queries into the model, as described in the previous section. Each keyword: 'kereta api', 'mudik', and 'lebaran', was added separately to evaluate its individual effect on the forecast results. The summary of the results for the training and testing sets is presented in Table 2, showing the forecast performance of each model in terms of MAPE and RMSE for both datasets.

Based on this summary, the addition of Google Trends search volume in Models 3 and 4 was able to improve the forecast results in both the training and testing sets. Model 3, which included the word 'mudik', showed a reduction in MAPE and RMSE compared to the baseline, while Model 4 with the word 'lebaran', achieved the best results overall in both training and testing, with a result of MAPE 10.92 and RMSE 1,001.70 in testing set. In contrast, the addition of 'kereta api' in Model 2 did not improve the forecast accuracy, and its performance was worse compared to the baseline, Model 1 with MAPE of 20.69 and RMSE of 1,656.15.

Table 2. Forecast Evaluation for Model 1 to 4

Model	MAPE (train)	RMSE (train)	MAPE (test)	RMSE (test)
1	19.95	752.57	12.01	1,063.89
2	21.29	806.80	20.69	1,656.15
3	19.35	746.55	11.19	1,017.46
4	19.22	739.84	10.92	1,001.70

After training the Prophet model in Models 1 to 4, we also did a diagnostic check in the residual of the model. We discovered that the residuals were still highly autocorrelated in all models, as shown in Figure 5(a), which shows the autocorrelation plot for residual from Model 1. Model 2 to 4 also shows the same decaying pattern. The slow decaying trend in the autocorrelation plot showed that there were still autocorrelation in the residuals, suggesting that there were patterns in the train passenger data which were still not captured by the model.

To address this problem in the residuals, we added the number of train passengers with a time lag of 1 as an additional external regressor in our model, which became the updated baseline for the training. This updated baseline was then used to re-run Models 1 to 4, now called scenarios 1 to 4 with the additional lagged variable included. After adding this variable, the autocorrelation in the residuals was reduced, as shown in Figure 5(b), where the autocorrelation values became much smaller for the residual of the updated baseline model in scenario 1, with the similar results observed in other scenarios. This addition was deemed sufficient in handling the autoregressive components in the residual, hence we stopped the addition of lag variable in $\boldsymbol{Y_{t-1}}$.

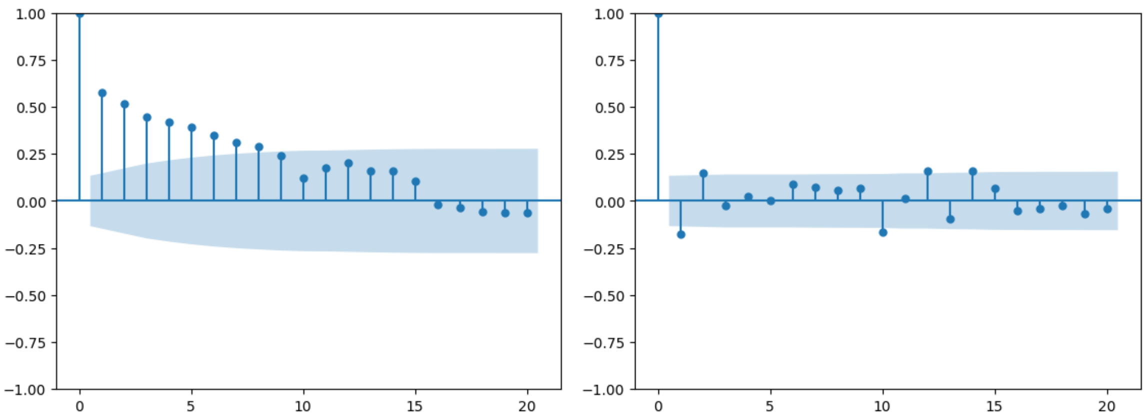

Figure 5. Autocorrelation plot for residual (a) Model 1 (b) Scenario 1 (s1)

After the addition of a new external regressor, the number of train passengers with a time lag of 1, $\boldsymbol{Y_{t-1}}$, we trained the model with four scenarios: the updated baseline and the other scenarios with Google Trends search volume added, models s1 to s4, as explained in the research methodology. Each variable was trained separately to evaluate the effect of the variables in the forecast results. We also did another check for the residuals where the slow decay was no longer observed in Figure 5(b), indicating independent residuals. This training process was then assigned as the final training scenario, with the forecast results presented in the following section. In both the initial and final training, we used the default parameter settings in the Prophet model as described in the method section.

3.3. Forecast Results

The forecast results on the test data are displayed in Figure 6. The actual data, shown as a blue line, represents the number of passengers in the last 12 months. The figure shows that the majority of the forecasts underestimated the actual passenger numbers during this period, resulting in a lower predicted values compared to the actual data. The first few months of the forecast shows a slightly different pattern compared to the actual data, where the high and low are predicted differently compared to the actual values. However, after May 2024, the forecast pattern started to align closely with the actual data until the end of the forecast. It is also apparent from the figure that scenarios 3 and 4 (s3: red; s4: purple) produced the best forecasts, with predicted number of passengers closest to the actual data. Overall, the forecasts were able to follow the general pattern of the passengers data during the forecast period, demonstrating the forecasting capability of the Prophet model.

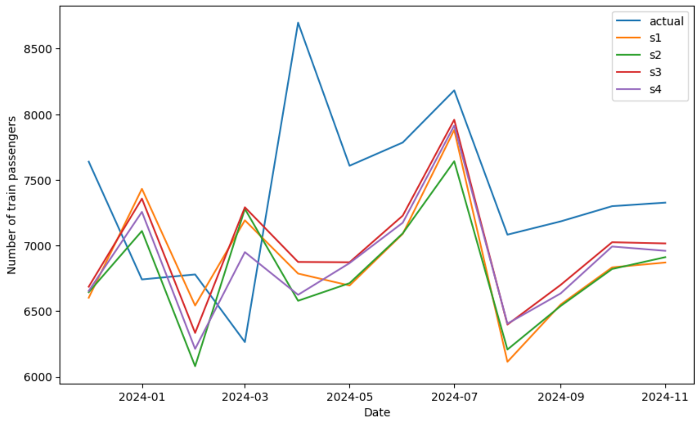

Figure 6. Forecast Results for Test Data

Compared to results shown in Table 2, the accuracy of the Prophet models improved after the addition of the lag 1 of train passengers. The overall MAPE and RMSE scores in both the training and testing sets are much lower, indicating a better fit to the data. This improvement is also supported by the autocorrelation plot in Figure 5(b), which shows that the residuals of the models are now independent. However, the results from the scenarios in the training show that s2 with the word 'kereta api', performed only slightly worse compared to the other scenarios. This contrasts with the results of test set of Model 2 in Table 2, which had a much larger difference compared to the rest of the models.

The detailed evaluation measures for the test data across all scenarios are shown in Table 3. The results for the training data are mostly consistent with those of the test set, with improvements observed in scenarios 3 and 4 compared to the baseline scenario, which used only train passenger data and COVID-19 as predictors. While the keyword 'kereta api' showed improvement in the training set compared to the updated baseline, it did not perform well on the test set, as indicated by higher MAPE and RMSE values compared to the other scenarios. The keyword 'mudik' achieved the lowest MAPE for both training and testing, while 'lebaran' had a slightly lower RMSE for the training set. Overall, 'mudik' produced the best results on the test set among all scenarios, with a MAPE of 9.12 and an RMSE of 797.76. Scenarios 3 and 4 showed a decrease in both MAPE and RMSE values compared to scenarios 1 and 2, indicating improved forecast accuracy when using the keywords as external regressors.

Table 3. Forecast Evaluation for Scenarios 1 to 4

Scenario	MAPE (train)	RMSE (train)	MAPE (test)	RMSE (test)
s1	13.14	603.75	10.32	879.92
s2	12.86	599.19	10.84	925.69
s3	12.66	590.87	9.12	797.76
s4	12.68	585.69	9.25	831.98

4. DISCUSSIONS

The train passenger data shows a general increasing trend, as shown in Figure 2. However, this upward pattern was disrupted during COVID-19. While this disruption might have been caused by government measures [28], it may also have been influenced by people's reluctance to use public transportation due to the risk of virus transmission [29]. The disruption began in March 2020 when COVID-19 first became a concern in Indonesia, with passenger numbers declining in the following months; in April 2020 and reaching the lowest point in May 2020. These observations align with studies on people's mobility in the early stages of COVID-19, which showed reduced long-distance travel based on mobility data [30]. During this period, continuing into late 2020 and early 2021, the government imposed restrictions to curb the spread of COVID-19, which further affected people's mobility [26]. According to a survey, government policies significantly influenced people's decisions to avoid homecoming activities that year [31].

After that period, the number of train passengers started picking up again, showing an increasing trend for a few months before dropping to a low point again in July and August 2021, shortly after vaccination began in Indonesia. This decrease may have been caused by government regulations requiring vaccination proof to enter public facilities, travel, and access government services [32]. The number then continued to rise in the latter half of 2022 and eventually reached current levels in 2024. These changes illustrate how COVID-19 affected train passenger numbers, which was accounted for by including the COVID-19 period as an external regressor in the Prophet model.

The results of the initial model training with and without the COVID-19 variable show its importance in modeling the train passengers data in Indonesia. Without the COVID-19 variable, the model was unable to capture the pattern and trend of the data, producing a wide interval of stagnant forecasts. However, after including the COVID-19 variable, the forecasts were more accurate, able to follow the general pattern even after the disruption. The residual check shows the need to add an additional regressor to the data because of the decay pattern observed in the autocorrelation plot. After updating the baseline, now including COVID-19 and the lag 1 of train passengers, we proceeded to the four scenarios in the final training model.

The four scenarios represent the differences we aimed to investigate in this study. The first scenario (s1) served as the updated baseline, using only the number of train passengers along with COVID-19 and its lag 1 as external regressors. The second scenario considered the search volume for the word 'kereta api,' the Indonesian term for train. The third used the word 'mudik' for homecoming, a tradition where people working away from their hometown return home to celebrate the Islamic holiday with family. The fourth scenario involved the word 'lebaran,' which refers to the day of the holiday itself. While the two words represent events occurring around the same time and show similar frequency patterns, as seen in Figure 3, they have distinct differences. The term 'mudik' refers to a longer period of activity before and after 'lebaran,' while 'lebaran' itself focuses on the day of the event.

Based on the forecast result in the testing set in Table 3, the term 'mudik' had the lowest MAPE and RMSE with 9.12 and 797.76, the best among all scenarios in this study. The term 'lebaran' followed closely, while the term 'kereta api' performed worse compared to the original data. Both 'mudik' and 'lebaran', as shown in Figure 2 (b) and 2 (c), had a shifting seasonal holiday pattern following the Islamic calendar, shifting about ten days earlier each year. This phenomenon is usually tackled by introducing a variable in time series analysis called the calendar variation effect, similar to the method reported in a study forecasting ticket sales at East Lombok [33]. The use of Google Trends data here substituted the use of dummy variables for calendar variation effect. The improvement obtained from some of the keywords suggested that some relevant words for a certain phenomenon, which is homecoming activity in the period of Eid Al-Fitr, can aid forecasting as an external regressors obtained from digital data.

The result shown by scenario 2, with the word 'kereta api', illustrates that adding external regressors might not help improve the forecast in the test set. In this case, it actually performed worse, suggesting that the Google Trends data for 'kereta api' did not contribute to model improvement and not an optimal choice for the model. Other word choices related to train might be more suitable for the analysis. Based on the comparison with other keywords and the time series plot shown in Figure 3, words with a more apparent seasonality pattern following the calendar variation effect might prove to be more useful for forecasting train passengers in Java. There were other possible factors affecting homecoming, such as other holidays close to Eid Al-Fitr or sudden disruption in activities, such as disasters. Inclusion of other homecoming-related keywords can be a possible direction of future studies.

5. CONCLUSION

The COVID-19 pandemic posed significant challenges in forecasting the number of train passengers in Java. This problem was addressed by adding the period of the COVID-19 pandemic as a variable, serving as one of the default external regressors in this study. The other regressors, Google Trends data, used words with patterns relevant to train travel and holiday periods, which can improve the model as additional external regressors. The analysis of train passenger numbers in Java shows that adding search volume data from Google Trends using the words 'mudik' and 'lebaran' improved the forecasting capability of the Prophet model, achieving smaller MAPE and RMSE compared to the default method that relied on historical train passenger data only. These results show that adding suitable words related to the event analyzed can be an effective alternative to improve forecast results, reinforcing the practice of adding digital data-based external regressors in forecasting. For future analysis, considering the variation of words related to the causes of changes in train passenger numbers, such as other holidays, special events, or even natural disasters, are also interesting to explore. Incorporating more diverse and event-specific keywords could further enhance the model's performance and adaptability to various forecasting scenarios.

CONFLICT OF INTEREST

The authors declares that there is no conflict of interest between the authors or with research object in this paper.

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