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Prophet Hyperparameter Optimization with Grid Search and Time Series Cross-Validation for ANTM Stock Prediction

Ardiyatul Putri & Yenni Kurniawati
Universitas Negeri Padang, Indonesia
ardiyatulputri@gmail.com

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Abstract

Stock prices are difficult to forecast, and systematic evaluations of Prophet hyperparameter tuning for Indonesian equities remain limited. This study optimized Prophet to forecast the daily closing price of PT Aneka Tambang Tbk (ANTM). The dataset comprised 712 daily closing prices from January 2, 2023, through December 30, 2025, partitioned chronologically into 569 training observations (80%) and 143 test observations (20%). A grid search evaluated 250 combinations of four hyperparameters using time series cross-validation on the training set, with a 365-day initial training window, a 90-day interval between forecast origins, and a 90-day forecast horizon. The configuration with the lowest mean absolute percentage error (MAPE) in cross-validation (12.59%) used a changepoint prior scale of 0.1, a seasonality prior scale of 0.1, a holidays prior scale of 20, and multiplicative seasonality. On the held-out test set, the tuned model reduced MAPE from 12.37% with the default configuration to 6.75%, a decrease of 5.62 percentage points (approximately 45%). The results show that systematic tuning with time series cross-validation improved Prophet's forecast accuracy for ANTM over the test period. The evaluation procedure provides a reproducible basis for comparing forecasting models and hyperparameter search methods and for evaluating performance on other stocks.

Keywords: Grid Search; Hyperparameter Optimization; Prophet; Stock Price Forecasting; Time Series Cross-Validation

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INTRODUCTION

The capital market plays a strategic role in a country's economy because it mobilizes long-term funds and serves as an indicator of economic performance (Darmawan & Haq, 2022). In Indonesia, the capital market is organized through the Indonesia Stock Exchange (IDX), where various financial instruments, including stocks, are traded. Stock price movements are closely watched by investors when making investment decisions. One company whose shares are actively traded on the IDX is PT Aneka Tambang Tbk (ANTM), a mining company whose main commodities are gold and nickel (Anwar & Rassiyanti, 2025). Because of its active trading, the price of ANTM shares is an interesting object for stock price forecasting research, and stock prices in the energy and mining sectors have received similar attention elsewhere (Sakinah et al., 2024).

The price of ANTM shares changes under the influence of internal factors, such as company performance and condition, and external factors, such as global commodity prices, government policy, the rupiah exchange rate, and macroeconomic conditions (Darmawan & Haq, 2022). Market sentiment can also affect investor decisions and thereby prices (Anwar & Rassiyanti, 2025). These factors cause sharp changes in trend and volatility, so the price movement is difficult to predict. This study therefore uses ANTM daily closing prices from January 2023 to December 2025, a period that follows the early phase of the COVID-19 pandemic and provides more recent historical data for forecasting.

Time series forecasting is a quantitative approach that uses historical data ordered in time, such as trends and seasonality, to estimate future values (Hyndman & Athanasopoulos, 2018). In this article, the term "prediction" refers to such time series forecasts of the ANTM closing price. One method for time series forecasting is Prophet, a decomposable additive model that represents a series as the sum of trend, seasonality, holiday effects, and an error term (Taylor & Letham, 2018). Prophet can capture changes in trend and seasonal patterns, can include holiday effects, and is relatively tolerant of incomplete data and outliers (Jange, 2021; Taylor & Letham, 2018). It has been applied to many kinds of data, including tourist arrivals (Alandra et al., 2025; Auliya et al., 2023), COVID-19 cases (Satrio et al., 2021), air quality (Oktavia & Witanti, 2024), energy consumption (Arslan, 2022), inventory (Gunawan & Ramadani, 2023), and stock prices (Ghosh & Jana, 2024; Jange, 2021).

The performance of Prophet, however, depends on its hyperparameters. The changepoint prior scale controls how flexibly the trend follows changes in direction, the

seasonality prior scale controls the strength of the seasonal component, the holidays prior scale controls the influence of holiday effects, and the seasonality mode determines whether seasonal effects are additive or multiplicative (Taylor & Letham, 2018). A high changepoint prior scale makes the model more flexible but raises the risk of overfitting, whereas a value that is too low makes the model too rigid and risks underfitting (Atamimi et al., 2025; Taylor & Letham, 2018).

Default hyperparameters do not necessarily give optimal forecasts for every dataset. For ANTM, Anwar and Rassiyanti (2025) reported that Prophet with default hyperparameters produced a mean absolute percentage error (MAPE) of 15.59% on monthly closing prices, higher than the 7.88% of ARIMA. Conversely, Atamimi et al. (2025) showed that hyperparameter tuning reduced the MAPE of Prophet from 9.50% to 6.80% on retail data. These findings suggest that the prediction error of Prophet can be lowered through hyperparameter optimization. A systematic way to find good hyperparameters is grid search, which evaluates every combination in a predefined set (Bergstra & Bengio, 2012). Because time series observations are temporally dependent, conventional cross-validation that shuffles the data can cause data leakage, in which information from the future is used to train the model; time series cross-validation, which preserves the chronological order of the data, is therefore needed (Bergmeir et al., 2018).

Prediction error is the difference between the actual stock price and the value produced by the model, and a large error can make forecasts less informative for investment decisions (Anwar & Rassiyanti, 2025). It can arise from changes in the data pattern, short-term random fluctuation (noise), changes in trend, and model settings that do not match the characteristics of the data (Taylor & Letham, 2018). In Prophet, a setting that is too flexible raises the risk of overfitting, while one that is too rigid raises the risk of underfitting, so predictions can deviate from actual values (Atamimi et al., 2025). Hyperparameter optimization is therefore needed to obtain a Prophet model with lower prediction error.

The combination of grid search and time series cross-validation for optimizing Prophet on ANTM stock prices has received limited attention. Previous studies on ANTM compared ARIMA and Prophet using default Prophet settings and did not examine whether systematic tuning lowers the error (Anwar & Rassiyanti, 2025), while the benefit of grid search with cross-validation for Prophet has so far been shown mainly for other kinds of data, such as retail (Atamimi et al., 2025). This gap motivates the present study. Its novelty

lies in the application of this tuning procedure, with a chronologically independent test period, to the daily closing price of a single Indonesian mining stock.

This study aims to apply grid search with time series cross-validation to optimize the hyperparameters of Prophet for the closing price of ANTM from January 2023 to December 2025, to determine the optimal hyperparameter values, and to compare the prediction error of the Prophet model before and after optimization on the testing data. The error is measured with MAPE, among other metrics, and the study is grounded in the decomposable time series model of Prophet (Taylor & Letham, 2018). The results are expected to inform the application of hyperparameter optimization for stock price prediction in the Indonesian capital market and to serve as a reference for further research.

METHODS

1. Type and Design of Research

This study is applied research with a quantitative approach, using numerical stock price data analyzed with time series modeling. The design compares two configurations of Prophet: a model with default hyperparameters and a model whose hyperparameters were optimized by grid search with time series cross-validation. Both were evaluated on the same chronologically separated testing data, so that the effect of optimization on prediction error could be assessed. The scope of the study is limited to the closing price of ANTM, to the four hyperparameters described below, and to grid search evaluated with time series cross-validation on the training data.

2. Data and Variables

The data are secondary data in the form of daily closing prices of ANTM shares obtained from Investing.com. They comprise 712 observations from January 2, 2023 to December 30, 2025. The analyzed variable is the closing price as a univariate time series. Following the input format of Prophet, the date is denoted ds and the closing price is denoted y (Prophet, 2024).

3. Preprocessing and Data Splitting

Dates were converted to datetime format, the data were sorted from oldest to newest, and prices were converted to numeric values. A check for missing values found none. Outliers were examined with the interquartile range (IQR) method, which flagged 33

observations (Figure 2); these were not removed because they were regarded as part of natural stock price fluctuation. The data were then split chronologically into 569 training observations (80%) and 143 testing observations (20%), the latter starting on June 4, 2025. The testing data were not used in the optimization.

4. Prophet Model and Hyperparameters

Prophet models a time series as the sum of trend, seasonal, holiday, and error components (Taylor & Letham, 2018), as given in Equation (1):

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

where $y(t)$ is the observed value at time t, $g(t)$ is the trend component, $s(t)$ is the seasonal component, $h(t)$ is the holiday effect, and ε_t is the error term. Parameters are estimated by maximum a posteriori (MAP) estimation using the default optimizer of Prophet, and Indonesian national holidays were included in the model. Four hyperparameters were optimized: the changepoint prior scale, the seasonality prior scale, the holidays prior scale, and the seasonality mode. Table 1 lists their default values and the candidate values searched.

Table 1. Default Values and Candidate Values of the Prophet Hyperparameters

Hyperparameter	Default	Candidate values	Number of candidates
Changepoint prior scale	0.05	0.001; 0.01; 0.05; 0.1; 0.5	5
Seasonality prior scale	10	0.01; 0.1; 1; 10; 20	5
Holidays prior scale	10	0.01; 0.1; 1; 10; 20	5
Seasonality mode	additive	additive; multiplicative	2

Table 1 defines the search space of the grid search. Each row is one hyperparameter, the Default column gives the value Prophet uses when nothing is specified, and the Candidate values column lists the values that were tried. The last column shows how many values each hyperparameter contributes to the search; their product determines the total number of models to be trained.

5. Grid Search and Time Series Cross-Validation

If there are k hyperparameters and the i-th hyperparameter has n_i candidate values, the number of combinations evaluated by grid search is given by Equation (2):

$$N = n_1 \times n_2 \times \ldots \times n_k \quad (2)$$

Based on Table 1, there are $5 \times 5 \times 5 \times 2 = 250$ combinations. Each combination was trained on the training data and evaluated with time series cross-validation using an expanding window, implemented with the cross_validation function of Prophet with an initial window of 365 days, a period of 90 days, and a horizon of 90 days. This setting produces five folds with cutoffs between March 10, 2024 and March 5, 2025. The cross-validation score is the average error over all folds, as given in Equation (3):

$$CV(\lambda) = \frac{1}{K}\sum_{i=1}^{K} E_i(\lambda) \quad (3)$$

where K is the number of folds and $E_i(\lambda)$ is the error in the i-th fold for combination λ. The combination with the smallest cross-validation MAPE was selected as the optimal configuration, and the model was then retrained on the entire training set. The default and optimized models were finally compared on the testing data.

6. Model Evaluation

Prediction error was measured with the mean absolute percentage error (MAPE) (Hyndman & Athanasopoulos, 2018), where n is the number of testing observations, y_i is the actual value, and $\hat{y}_i$ is the predicted value (Equations (4)):

$$MAPE = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \quad (4)$$

The optimal configuration was selected on the basis of MAPE. The accuracy level was interpreted following Lewis (1982), as shown in Table 2. All processing was carried out in Python using the Prophet library in Google Colab.

Table 2. MAPE Assessment Criteria (Lewis, 1982)

MAPE value	Accuracy level
< 10%	Highly accurate
10% – 20%	Good
20% – 50%	Reasonable
> 50%	Inaccurate

Table 2 is read from the top: the smaller the MAPE, the higher the accuracy. A MAPE below 10% is classified as highly accurate, and a MAPE between 10% and 20% as good. These bands are used later to describe the default model (12.37%) and the optimized model (6.75%).

RESULTS

1. Data Description

Figure 1 shows the daily closing price of ANTM over the observation period, from the first observation on January 2, 2023 (1,980) to the last on December 30, 2025 (3,150). In the figure, the horizontal axis is the date and the vertical axis is the closing price in rupiah. The lowest closing price was 1,210 (June 14, 2024) and the highest was 3,670 (September 23, 2025).

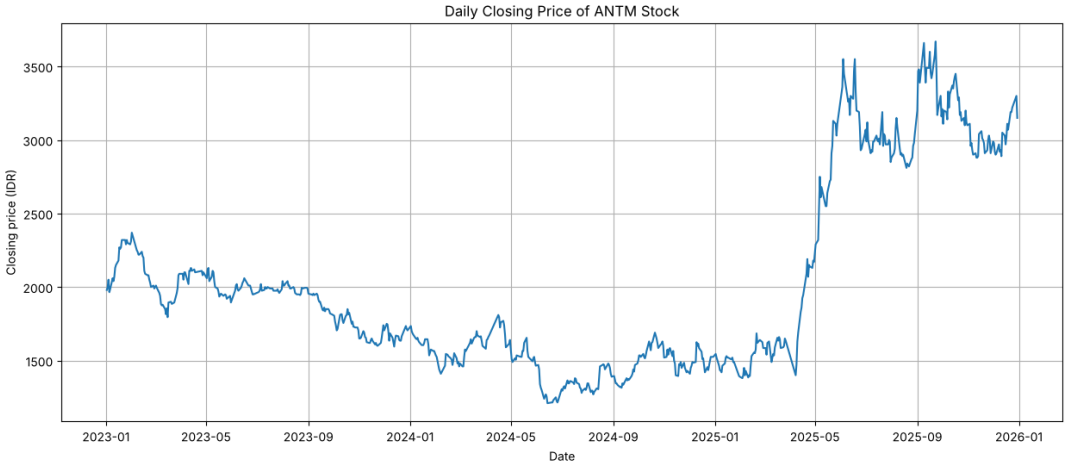

Figure 1. Daily Closing Price of ANTM Stock, January 2, 2023 to December 30, 2025

Figure 1 shows that the price tended to decline with short-term fluctuations from early 2023 to mid-2024, falling from roughly 2,300 to a low of roughly 1,200, and then moved relatively sideways. Around April to May 2025 the price rose sharply and stayed at a much higher level, mostly between about 2,800 and 3,700, until the end of the period. Because the data were split chronologically, the whole testing period (June to December 2025) lies in this high-price regime, that is, after the sharp change in trend.

The outlier check is summarized in Figure 2, a boxplot of the closing price. The box spans the first quartile (1,534) to the third quartile (2,240), the orange line is the median (1,810), and the whiskers extend to the most extreme values within 1.5 times the IQR. The circles above the upper whisker are the 33 observations flagged as outliers, with prices from 3,300 to 3,670; all lie above the upper fence (about 3,299) and none lie below the lower fence, which is consistent with the high prices after the 2025 surge in Figure 1.

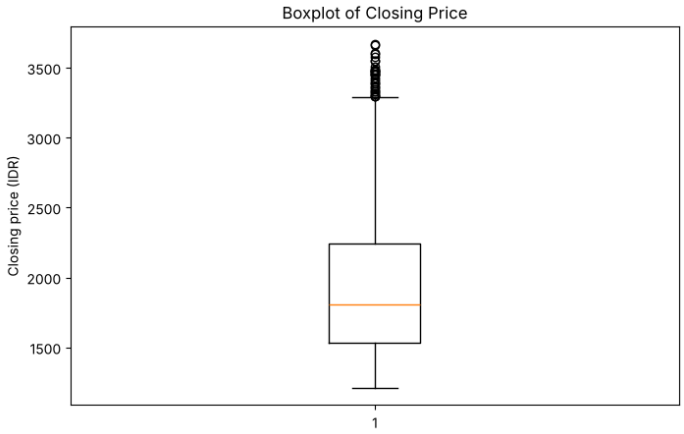

Figure 2. Boxplot of the ANTM Closing Price Used for Outlier Detection

The data were split into 569 training observations (80%) and 143 testing observations (20%), with the testing data beginning on June 4, 2025.

2. Hyperparameter Optimization Results

Grid search with time series cross-validation over the 250 combinations produced an optimal configuration with a cross-validation MAPE of 12.59%. Table 3 summarizes the best-performing groups of combinations. The five best combinations all had a changepoint prior scale of 0.1 and identical metric values, while the next five had a changepoint prior scale of 0.5 and a MAPE of 13.31%. The combination ranked first was selected as the optimal configuration.

Table 3. Cross-Validation Performance of the Ten Best Hyperparameter Combinations

Rank	Changepoint prior scale	CV MAPE (%)
1–5	0.1	12.59
6–10	0.5	13.31

Table 3 reads as follows. Each row groups combinations that share exactly the same cross-validation scores. Moving from the first group to the second group, in which the trend is more flexible (0.5 instead of 0.1), all three error measures increase: MAPE by 0.72 percentage points. A changepoint prior scale of 0.1 is therefore preferred over 0.5 in this search. The comparison between the default hyperparameters and the optimized ones is given in Table 4.

Table 4. Default Hyperparameters and Optimization Results

Hyperparameter	Default	Optimized
Changepoint prior scale	0.05	0.1
Seasonality prior scale	10	0.1
Holidays prior scale	10	20
Seasonality mode	additive	multiplicative

Table 4 shows that all four hyperparameters changed from their default values. A larger changepoint prior scale lets the trend follow changes in direction more flexibly, the multiplicative mode makes the seasonal amplitude change in proportion to the price level, a smaller seasonality prior scale restricts the influence of the seasonal component, and a larger holidays prior scale gives holiday effects more room.

3. Evaluation on the Testing Data

The performance of the default and optimized models on the 143 testing observations is presented in Table 5.

Table 5. Prediction Errors on the Testing Data

Metric	Default Prophet	Optimized Prophet	Difference	Reduction (%)
MAPE (%)	12.37	6.75	5.62	45.44

Table 5 shows that the optimized model has a smaller error on every metric. MAPE falls from 12.37% to 6.75%, a decrease of 5.62 percentage points or about 45%. According to Table 2, a MAPE of 12.37% is in the good category, whereas 6.75% is in the highly accurate category.

4. Actual Versus Predicted Prices

Figure 3 compares the actual closing price with the predictions of the default and optimized Prophet models over the whole period. In the figure, the blue line is the actual price, the orange line is the predicted price of the default Prophet model, and the green line is the predicted price of the optimized Prophet model. The train–test boundary (June 4, 2025) is not marked in the figure.

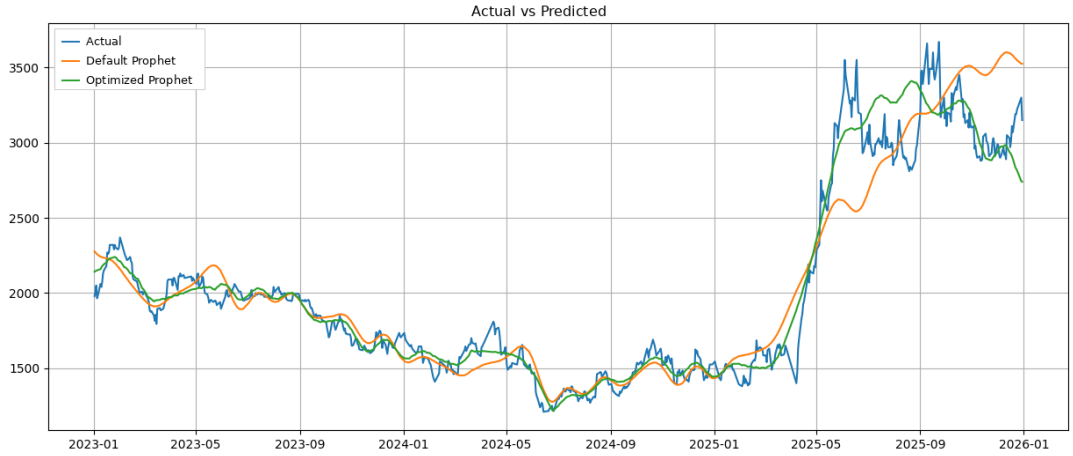

Figure 3. Actual Closing Prices Compared with Predictions of the Default and Optimized Prophet Models

In the training period both models follow the price pattern fairly closely. At the beginning of the testing period, after the sharp price increase, the default curve lags well behind the actual price, whereas the optimized curve rises faster and stays closer to the actual price. Toward the end of the testing period the optimized model tends to fall below the actual price, ending at roughly 2,700 against an actual price of about 3,150, while the default model tends to lie above it, ending at roughly 3,500.

5. Divergent Patterns

Two findings do not follow the general pattern. First, the five best combinations in Table 3 have identical cross-validation scores, so the grid search could not distinguish between them, and the first-ranked one was chosen. Second, the optimized model is not better at every date: in Figure 3 it underestimates the actual price near the end of the testing period, where the default model is closer than the optimized model is at some dates. In addition, the cross-validation MAPE of the optimized model (12.59%) is higher than its testing MAPE (6.75%).

DISCUSSION

The results answer the objectives of the study. First, grid search combined with time series cross-validation can be applied systematically to Prophet without shuffling the data, so the testing data stay separate from hyperparameter selection. Second, the optimal configuration differs from the default on all four hyperparameters (Table 4). The larger changepoint prior scale agrees with the character of the data, which contain a sharp rise in 2025 (Figure 1); the fact that all five best combinations use 0.1 while those using 0.5 give a

higher cross-validation error (Table 3) suggests that a trend that is too rigid and one that is too flexible are both less suitable for this series. Third, the drop in MAPE from 12.37% to 6.75% (Table 5) shows that adjusting hyperparameters can improve the performance of Prophet on ANTM data and raises the accuracy category from good to highly accurate (Table 2).

The result should be interpreted with care. Because five combinations tie in cross-validation, the values chosen for the seasonality prior scale, holidays prior scale, and seasonality mode are not uniquely supported by the search, and other tied combinations would have scored the same in validation. The cross-validation MAPE is also higher than the testing MAPE. A possible reason is that the last cross-validation fold has a cutoff on March 5, 2025, so its 90-day horizon extends to early June 2025 and contains the sharp April–May 2025 rise, which is hard to forecast; this explanation was not tested in this study.

The direction of the finding is consistent with Atamimi et al. (2025), who reported a lower MAPE after hyperparameter tuning of Prophet on retail data (9.50% to 6.80%), and with Anwar and Rassiyanti (2025), whose default Prophet model left room for improvement on ANTM data (MAPE of 15.59%). The relative reduction found here, about 45%, is larger than the roughly 28% reduction in the retail study, although the datasets, frequencies, and test periods differ, so the magnitudes cannot be compared directly. The default MAPE in this study (12.37%) also differs from that of Anwar and Rassiyanti (2025), but the two are not directly comparable because they used monthly closing prices. Using time series cross-validation, rather than a shuffled scheme, follows the recommendation of Bergmeir et al. (2018) and avoids data leakage into the training of each candidate model.

Methodologically, the study offers a reproducible tuning procedure for Prophet: a defined search space (Table 1), an expanding-window cross-validation scheme, and an independent testing period. Practically, analysts can use the optimized Prophet as a more accurate descriptive tool for ANTM price movements, but a MAPE of about 7% still leaves uncertainty, and the predictions should support, not replace, other information in investment decisions.

This study is limited to one stock, one chronological split whose testing period lies entirely in the high-price regime after the 2025 surge, and a univariate model without external variables. Only Prophet was examined and no other forecasting model was used for comparison, and no statistical test was applied to the difference in errors. In addition, the

initial cross-validation window (365 days) is slightly shorter than the yearly seasonal period of 365.25 days, which Prophet flagged with a warning in every run, and for all 50 combinations with a changepoint prior scale of 0.001 the default optimizer terminated abnormally and Prophet fell back to the Newton optimizer (none of these combinations was selected). Future studies are encouraged to compare the optimized Prophet with models such as ARIMA, to try other search methods such as random search or Bayesian optimization, to use several data splits or other stocks, and to add explanatory variables such as commodity prices and exchange rates.

CONCLUSION

Optimizing the hyperparameters of Prophet with grid search over 250 combinations, each evaluated with time series cross-validation on the training data, gave an optimal configuration of changepoint prior scale 0.1, seasonality prior scale 0.1, holidays prior scale 20, and multiplicative seasonality. On the testing data, default Prophet produced a MAPE of 12.37% and the optimized model a MAPE of 6.75%, a reduction of 5.62 percentage points or about 45%, which raised the accuracy category from good to highly accurate.

The study shows, for the daily closing price of ANTM, that systematic hyperparameter tuning with a time-aware validation scheme can substantially reduce the prediction error of Prophet, and it provides a reproducible procedure and baseline results for later work.

Future research is recommended to compare the optimized Prophet with other models such as ARIMA, to try random search or Bayesian optimization, to use more than one testing period or other stocks, and to add explanatory variables such as commodity prices and exchange rates.

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