Forecasting Indonesia's Non-Oil and Gas Exports Using Facebook Prophet: A Seasonal and Trend Analysis

Erfiani[1*] and Ferdian Bangkit Wijaya[2]
[1]The Statistics and Data Science Study Program, IPB University, Bogor, Indonesia
[2]Department of Statistics, Universitas Sultan Ageng Tirtayasa, Serang, Indonesia
*erfiani@apps.ipb.ac.id

Received: 10 May 2025
Revised: 08 November 2025
Accepted: 10 November 2025

ABSTRACT – This study aims to analyze and predict the trend of Indonesia's non-oil and gas exports using the Facebook Prophet model, focusing on identifying seasonal patterns, trends, and volatility present in the export data. Monthly export data from 2015 to 2025, sourced from the Statistics Indonesia (BPS), were used as the basis for analysis. The dataset revealed notable seasonal patterns and substantial volatility, particularly in the period following 2020. To model these dynamics, three Prophet model configurations were tested: one considering only annual seasonality, combining both annual and monthly seasonality, and another incorporating only monthly seasonality. The evaluation of these models showed with an initial Mean Absolute Percentage Error (MAPE) of 8.70%. This model was then optimized through hyperparameter tuning. The optimal parameter configuration (changepoint_prior_scale = 0.5, seasonality_prior_scale = 0.01, fourier_order = 3) resulted in a significant improvement, reducing the MAPE to 4.73%. This optimized model demonstrated its capacity to more precisely capture the complex patterns. Furthermore, the study projected Indonesia's non-oil and gas exports for the period from April 2025 to December 2026. The projections indicate a relatively stable export trend within the range of 20,000 to 22,000 million USD per month, with consistent seasonal patterns.
Keywords – facebook prophet, forecasting, hyperparameter tuning, non-oil and gas exports, time series

I. INTRODUCTION

Indonesia's non-oil and gas exports are one of the key pillars supporting national economic growth. Non-oil and gas exports have proven to have a positive and significant impact on Indonesia's economic growth, both in the short and long term [1]. The diversification of exports to non-traditional markets and the increase in non-oil and gas exports can reduce dependence on the oil and gas sector and strengthen the national economic resilience [2]. According to data from the Statistics Indonesia, the contribution of non-oil and gas exports to Indonesia's total exports reached 94.5% in the first quarter of 2025, with a value of US$62.98 billion [3]. Major commodities driving non-oil and gas exports include agricultural products, plantations, manufacturing, and mining, with key destination countries such as China, the United States, and India. However, the trend of Indonesia's non-oil and gas exports over the past decade shows high volatility, both annually and seasonally. For example, in January 2025, there was a 6.96% decrease in exports compared to December 2024, while November 2024 recorded a 9.54% increase compared to the previous month [4]. These fluctuations indicate the existence of complex dynamics that require more adaptive and precise trend analysis.

The main issue in the analysis of non-oil and gas export trends lies in the inability of conventional predictive models to capture seasonal patterns, volatility, and structural changes (changepoints) that often occur due to external factors such as trade policies, global demand changes, and extraordinary events such as the COVID-19 pandemic [5]. In recent years, machine learning models have shown promise in handling such non-linear data. Methods such as Support Vector Machines (SVM) [6], [7] and deep learning models like Long Short-Term Memory (LSTM) [8], [9] have been applied to various economic forecasting challenges, including crude oil prices, which are often correlated with trade [10], [11]. Several previous studies have used classical time series methods such as ARIMA, ARMA-GARCH, and Exponential Smoothing to forecast non-oil and gas exports. Alongside these, the Facebook Prophet model has emerged as a robust alternative, particularly for business forecasting, demonstrating strong performance against traditional models like ARIMA [12], [13] and finding applications in related fields such as tourism demand [14], [15], [16]. Additionally, the use of Fuzzy Time Series has also been employed in previous research. The ARIMA method was used to predict Indonesia's non-oil and gas exports in 2023. The ARIMA (5,1,3) model resulted in the lowest MAPE value of 8.142% [17]. The ARMA(2,1)-GARCH(1,1) model was also effective for non-oil and gas export data, yielding a MAPE of 6.92% and was able to predict up to 12 months ahead with significant results [18]. The double and triple exponential smoothing (Holt-Winters) methods were used for data with trends and seasonality. The triple exponential smoothing additive model provided a MAPE <10%, with the best results for predicting non-oil and gas exports [19]. Fuzzy Time Series and its variants (e.g., Singh FTS, Stevenson-Porter FTS) were used to handle volatile and uncertain non-oil and gas export data. The Singh FTS yielded a very low MAPE of 1.31%, indicating highly accurate predictions for the next three months [20], , while the Stevenson-Porter FTS had a higher MAPE of 36.17% [21]. The use of Box-Cox transformation on Fuzzy Time Series significantly reduced prediction errors (MAPE decreased from 74.89% to 19.56%) [22].

This study aims to analyze the trend of Indonesia's non-oil and gas exports with a focus on decomposing trends, seasonality, and volatility using the Facebook Prophet method. This research will map the export trend patterns of Indonesia's non-oil and gas exports from 2015 to 2024, test the accuracy of export projections for 2025 using Facebook Prophet, determine the best model from Facebook Prophet through hyperparameter simulation, and identify critical changepoints that impact national export performance. Therefore, the findings of this study are expected to contribute significantly to the development of a more accurate and adaptive non-oil and gas export forecasting method that aligns with global economic dynamics.

II. LITERATURE REVIEW

II.1 Facebook Prophet Model

In general, the Prophet model can be expressed as follows [23] :

$$y(t) = g(t) + s(t) + h(t) + \varepsilon(t) \tag{1}$$

Where, $y(t)$ the actual value at time t,
$g(t)$ is the trend component,
$s(t)$ is the seasonal component,
$h(t)$ is the holiday effect,
$\varepsilon(t)$ is the noise or error.

II.2 Trend/ Growth Component in Prophet

In the Prophet modeling, there are four options for tuning the trend/growth parameters, which are [24]:

(1) Non-linear Saturating Growth
The growth component aims to model how the population develops. Facebook designed the growth component to resemble natural ecosystems as closely as possible. Growth is typically modeled using a logistic growth model in its simplest form, which is:

$$g(t) = \frac{C}{1+\exp(-k(t-m))} \tag{2}$$

Where,
C : Carrying capacity
k : Growth rate
m : Offset parameter
Alternatively, a piecewise logistic growth model can be used, which is:

$$g(t) = \frac{C(t)}{1+\exp(-(k+a(t)^T\delta)(t-(m+a(t)^T\delta))} \tag{3}$$

Where,
$C(t)$: time~varying capacity
$k + a(t)^T\delta$: rate at time t
δ : vector of rate adjustment
$a(t)$: vector $\{0,1\}^s$

(2) Linear Trend with Changepoints
Changepoints are moments when the data changes direction. For forecasting that does not exhibit growth and has a piecewise constant rate of growth, the trend model becomes:

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

Where,
k : Growth rate
δ : Vector of rate adjustments
m : *Offset parameter*
γ : Define as $-s_j\delta_j$ to make the function continuous
Changepoint prior scale is used to control the flexibility of the trend. This aims to address the issue of overfitting and underfitting

(3) Automatic Changepoint Selection
This model is used when the timing of the trend change is known. This process is done automatically by filtering candidates and selecting based on equations 3 and 4.

(4) Trend Forecast Uncertainty
When the model is extrapolated to make forecasts, the trend will have a constant number. A generative forward model can be used to estimate the uncertainty in the forecast trend. Future changepoints are taken randomly so that the average frequency of the changepoint aligns with the historical data.

II.3 Seasonality Component in Prophet

For determining seasonality or seasonal patterns, Fourier series are often used to provide a flexible model for periodic effects. The equation for arbitrary smooth seasonal effects is:

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

Where,
Parameter $\beta = [a_1, b_1, \ldots, a_n, b_n]^T$

$a_n = \frac{1}{P} \int_{-P}^{P} f(x) \cos\left(\frac{2\pi nt}{P}\right) dx$

$b_n = \frac{1}{P} \int_{-P}^{P} f(x) \sin\left(\frac{2\pi nt}{P}\right) dx$

III. METHODOLOGY

The forecasting model used in this study is Facebook Prophet, an additive regression method developed by Facebook. Prophet is designed to handle long-term trends as well as recurring seasonal patterns with a flexible approach [25]. In addition, the Prophet model is capable of handling outliers by considering change_points within its framework [26].

III.1 Data

This study uses secondary data in the form of monthly non-oil and gas export values of Indonesia from January 2015 to March 2025. The primary data source is obtained from the Statistics Indonesia (BPS) and has been downloaded in Microsoft Excel (.xlsx) format. The data consists of time variables (month and year) and non-oil and gas export values (in millions of USD). Prior to analysis, the data undergoes a data cleansing process to ensure consistency in format and alignment with the modeling requirements. This process includes standardizing month names into English, merging the year and month columns into a single date variable, and converting the data type into datetime format. Subsequently, the data is filtered to cover only the period from 2015 to Q1 2025, in accordance with the scope of the study. The final data is then adjusted to the input format required by the Facebook Prophet model, consisting of two columns: ds (date) and y (non-oil and gas export value).

III.2 Data Analysis

The data analysis in this study uses a prediction method based on Facebook Prophet, which is designed to handle time series data with seasonal trends and high volatility. The steps taken in the data analysis are as follows:

(1) Data Exploration and Visualization

The initial stage of the analysis involves visualizing the historical export trends to identify seasonal patterns, long-term trends, and potential volatility. Visualization is performed using a time series plot, with time (year) on the X-axis and export values on the Y-axis.

(2) Modeling and Model Evaluation

Time series modeling is conducted using the Facebook Prophet algorithm. Three main model configurations are developed to evaluate the influence of annual and monthly seasonal components, which are:
Model 1: Only annual seasonality.
Model 2: Combination of annual and monthly seasonality.
Model 3: Only monthly seasonality.
In Model 2 and Model 3, the monthly seasonal component is explicitly added with a period of 30.5 days and a Fourier order of 5. All models use the additive mode (additive seasonality), consistent with the base model of Facebook Prophet. Model performance is evaluated by calculating the Mean Absolute Percentage Error (MAPE) between the actual data and the predicted results. The model with the lowest MAPE value is selected as the candidate for the best model.

(3) Model Parameter Hyper tuning

To improve prediction accuracy, an optimal parameter combination search (hyper tuning) is performed on the Prophet model. The parameters optimized include the following simulations:

- changepoint_prior_scale (0.001, 0.01, 0.1, 0.5),
- seasonality_prior_scale (0.01, 0.1, 1.0, 10.0),
- fourier_order for monthly seasonality (3, 5, 7).

Each parameter combination is evaluated using the MAPE value. The MAPE for each combination is recorded, and the parameters with the lowest MAPE are selected as the optimal parameters.

(4) Model Validation and Cross-Validation

The best model from the hyper tuning results is then revalidated using cross-validation techniques with various combinations of horizon (15, 20, 30 days), period (10, 15, 20 days), and initial (730, 1095, 1460 days). The goal of this stage is to ensure that the model performs consistently and accurately across different prediction scenarios.

(5) Visualization of Results and Predictions

The final optimized model is used to predict Indonesia's non-oil and gas export values for the next 21 months (April 2025–December 2026). The prediction results are visualized alongside confidence intervals to illustrate the uncertainty in the forecast. The flowchart of this study is shown in Figure 1

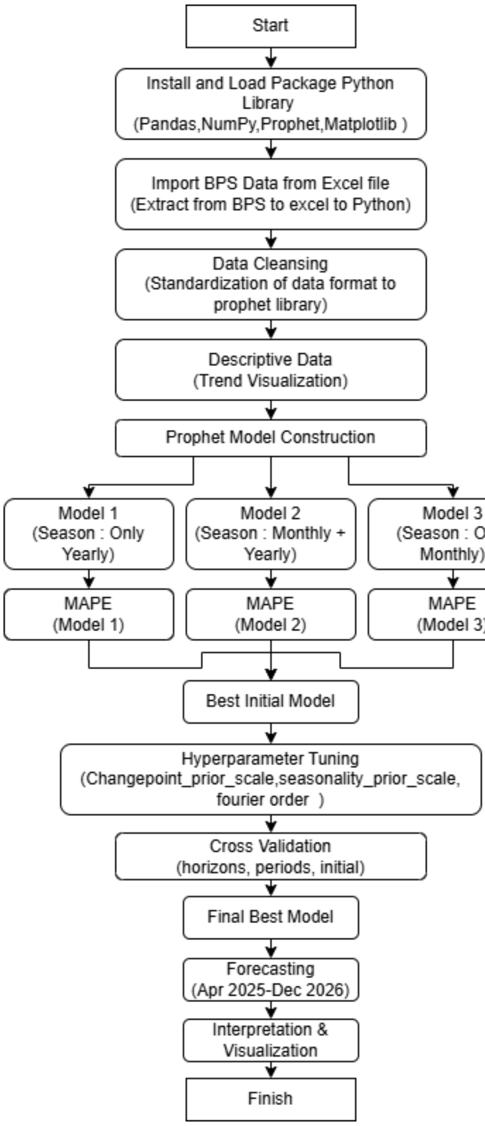

Figure 1 Facebook Prophet Research Flowchart

IV. RESULTS AND DISCUSSIONS

Based on Figure 2, the trend of Indonesia's non-oil and gas exports from January 2015 to early 2025 shows a dynamic pattern with a general upward tendency. In the early period (2015–2019), the non-oil and gas export values remained relatively stable, ranging from 10,000 to 15,000 million USD, with seasonal fluctuations evident each year. This period of consolidation, while flat in its long-term trend, was not without significant short-term volatility, including a notable dip in mid-2016 before the trend recovered. Entering 2020, a significant surge in non-oil and gas export values is observed, which then peaked in 2022 with the highest value exceeding 25,000 million USD. This sharp upward trajectory represents a clear structural break from the previous five-year baseline, likely reflecting shifts in post-pandemic global demand and commodity prices. After this peak period, there was a sharp decline; however, the export values remained at a higher level compared to the period before 2020. This establishment of a new, higher baseline suggests a persistent and fundamental shift in Indonesia's export capacity.

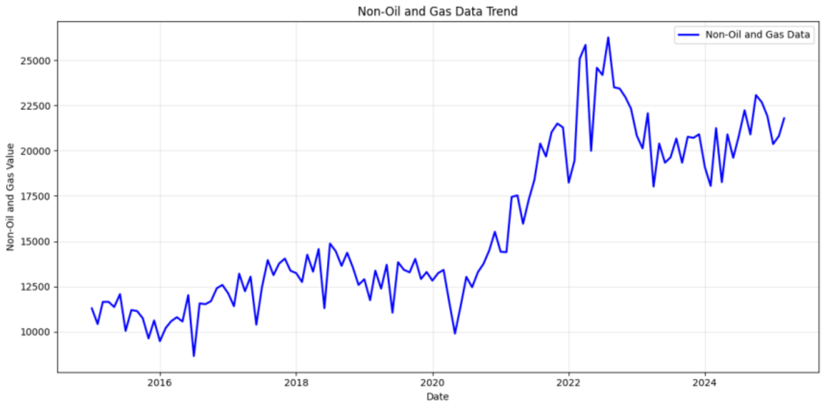

Figure 2 Trend of Indonesia's Non-Oil and Gas Exports from January 2015 – March 2025

Next, from 2023 to early 2025, the trend of non-oil and gas exports still shows fluctuations but tends to stabilize in the range of 20,000 to 23,000 million USD. Seasonal patterns and volatility are still evident, indicating the influence of external factors and annual cycles on Indonesia's non-oil and gas export values. Overall, this chart indicates a positive long-term growth in Indonesia's non-oil and gas exports, albeit accompanied by relatively high volatility, particularly after 2021.

The next stage after descriptive data analysis is the development and evaluation of an initial model using the FB Prophet algorithm. Three model configurations are constructed to identify the impact of seasonal components on the accuracy of Indonesia's non-oil and gas export predictions, which are: Model 1 (annual seasonality), Model 2 (annual and monthly seasonality), and Model 3 (monthly seasonality). The performance of these three models is evaluated by calculating the Mean Absolute Percentage Error (MAPE) against actual data. The evaluation results are presented in Table 1 below:

Table 1 MAPE of Best Initial Model

Model	Seasonal	MAPE
Model 1	Yearly	9.92%
Model 2	Yearly + Monthly	8.70%
Model 3	Monthly	9.09%

Based on the results, Model 2, which combines both annual and monthly seasonal components, yielded the lowest MAPE value of 8.70%. This indicates that the model with a combination of annual and monthly seasonality is better at capturing fluctuations and seasonal cycles in Indonesia's non-oil and gas export data more accurately than a model with only one type of seasonality. Therefore, Model 2 is selected as the best initial model for the next stage, which involves parameter optimization (hyper tuning) and a more in-depth model validation.

Table 2 Best Hyperparameter Combinations and Prophet Model Accuracy

#Simulation	fourier_order	changepoint_prior_scale	seasonality_prior_scale	MAPE (%)
36	3	0.5	0.01	8.58279
38	7	0.5	0.01	8.616418
37	5	0.5	0.01	8.680053
39	3	0.5	0.1	9.47463
40	5	0.5	0.1	9.518452
41	7	0.5	0.1	9.542618
26	7	0.1	0.01	9.753916
25	5	0.1	0.01	9.953345
24	3	0.1	0.01	9.978451
28	5	0.1	0.1	9.990326
29	7	0.1	0.1	10.08223
27	3	0.1	0.1	10.27744
14	7	0.01	0.01	10.30019
2	7	0.001	0.01	10.32978
0	3	0.001	0.01	10.35829
13	5	0.01	0.01	10.39702
1	5	0.001	0.01	10.4211

12	3	0.01	0.01	10.55129
3	3	0.001	0.1	10.93946
17	7	0.01	0.1	11.22315
16	5	0.01	0.1	11.24533
4	5	0.001	0.1	11.36932
5	7	0.001	0.1	11.65248
15	3	0.01	0.1	11.68604
30	3	0.1	1	12.26048
43	5	0.5	1	12.71225
42	3	0.5	1	14.02669
31	5	0.1	1	14.39136
32	7	0.1	1	14.89164
7	5	0.001	1	15.63708
44	7	0.5	1	15.76687
6	3	0.001	1	15.80261
18	3	0.01	1	16.02835
8	7	0.001	1	16.91584
19	5	0.01	1	17.11856
20	7	0.01	1	17.71999
21	3	0.01	10	18.75704
33	3	0.1	10	20.42406
46	5	0.5	10	21.99652
10	5	0.001	10	23.88952
22	5	0.01	10	26.70582
34	5	0.1	10	28.94592
9	3	0.001	10	29.10589
45	3	0.5	10	29.2723
47	7	0.5	10	29.47692
11	7	0.001	10	31.50712
35	7	0.1	10	39.32569
23	7	0.01	10	43.01374

After obtaining the best initial model, parameter optimization (hyperparameter tuning) was performed to improve the prediction accuracy of the Prophet model. This optimization is crucial for identifying the parameter combination most suitable for the characteristics of Indonesia's non-oil and gas export data. The three main parameters that were optimized are:

- changepoint_prior_scale: This parameter controls the flexibility of the base trend in capturing structural changes (0.001, 0.01, 0.1, 0.5). A low value (close to 0) results in a more rigid trend that only detects significant changes, while a high value (close to 1) makes the model more flexible in detecting even small trend changes.
- seasonality_prior_scale: This parameter adjusts the flexibility of the seasonal component (0.01, 0.1, 1.0, 10.0). A high value allows the seasonal component to have more variable amplitudes, while a low value applies stronger regularization to seasonal patterns, resulting in more stable and consistent patterns.
- fourier_order: This parameter determines the complexity of the monthly seasonal pattern (3, 5, 7). A higher value (7-10) allows for modeling of very complex and detailed seasonal patterns, while a lower value (3-5) results in smoother seasonal components and better generalization.

Based on Table 2, the optimal combination of these three parameters is found in simulation 36, which is (changepoint_prior_scale=0.5, seasonality_prior_scale=0.01, fourier_order=3), resulting in a MAPE of 8.58%, which is an improvement from the initial model with a MAPE of 8.70%. This indicates that, although the accuracy improvement is not drastic, the systematic adjustment of parameters still leads to a more precise model for non-oil and gas export forecasting.

After obtaining the optimal parameter combination from the hyper tuning process, the next step is to perform a more comprehensive model validation using cross-validation techniques. The primary goal of this stage is to ensure that the model not only performs accurately at a single point in time but also maintains stable and consistent predictive performance across various testing scenarios. Cross-validation for the Prophet model is conducted by repeatedly splitting the historical data into training and testing segments, then evaluating the model's prediction ability across different time horizons. The three main parameters used in this cross-validation are:

- Horizon: The future time period to be predicted. This parameter determines how far ahead the model forecasts at each validation iteration.
- Period: The time interval between the cutoff points in the data. This parameter controls the frequency of model evaluation in the cross-validation process.
- Initial: The amount of initial data used as the training set. This parameter determines how much historical data is used to train the model before making predictions.

In this study, cross-validation simulations were performed with various parameter combinations: Horizon: 15 days, 20 days, and 30 days; Period: 10 days, 15 days, and 20 days; Initial: 730 days, 1095 days, and 1460 days. The cross-validation results show that the Prophet model with the previously set optimal parameters (changepoint_prior_scale=0.5, seasonality_prior_scale=0.01, fourier_order=3) resulted in an average MAPE value of 8%. This value indicates very good and consistent predictive performance, as the acceptable MAPE threshold for economic forecasting is typically below 10%.

Based on the results from hyperparameter tuning and cross-validation in the previous stages, the optimal parameters (changepoint_prior_scale=0.5, seasonality_prior_scale=0.01, fourier_order=3) were applied to the Prophet model to form the Final Model for generating precise and reliable non-oil and gas export predictions. The implementation of the optimal parameters in the Prophet model resulted in a significant improvement, with the MAPE value drastically decreasing to 4.73%, much lower than the initial model (8.70%) and the post-cross-validation stage (8%). This indicates that the optimal combination of the three parameters successfully enhanced the model's ability to capture complex patterns in Indonesia’s non-oil and gas export data.

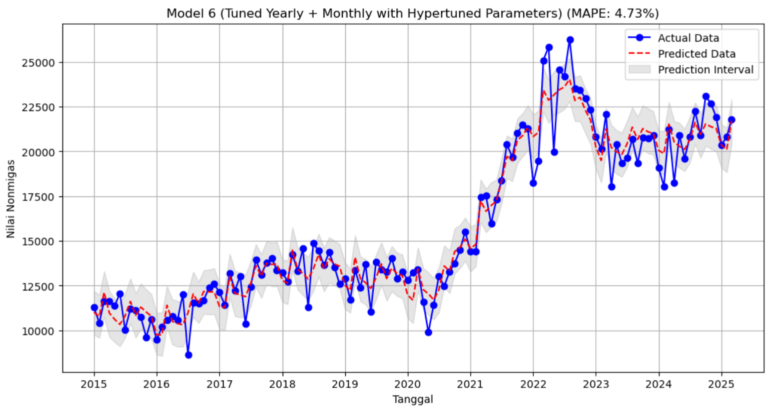

Figure 3 Comparison of Actual vs Predicted Data using the Final Optimized Model (MAPE 4.73%).

The visualization of the final model's predictions against the actual data (Figure 4) shows excellent alignment. The predicted line (red dashed line) closely follows the fluctuation pattern of the actual data (blue dots), accurately capturing the stability period (2015-2019), significant surges (2020-2022), and the most recent volatile period (2023-2025). This model also successfully identified important structural changes (changepoints), such as the sharp increase at the beginning of 2021 and the peak in mid-2022.

Table 3 Forecasting Non-Oil and Gas Export Values (in million USD)

Periods	forecast_value	forecast_lower	forecast_upper
4/30/2025	20322.32	19049.48	21531.7
5/31/2025	20221.81	18995.99	21401.45
6/30/2025	20776.25	19508.33	22115.48
7/31/2025	21747.16	20350.27	23112.9
8/31/2025	21125.96	19819.72	22629.37
9/30/2025	21671.2	20394.48	23241.14
10/31/2025	21541.01	20059.14	23224.7
11/30/2025	21391.24	19805.66	23287.85
12/31/2025	20522.33	18756.13	22465.63
1/31/2026	20436.19	18581.56	22418.82
2/28/2026	21760.72	19630.21	24020.7
3/31/2026	20732.1	18582.09	23271.3
4/30/2026	20471.72	18184.44	23249.16

5/31/2026	20371.03	18000.31	23299.24
6/30/2026	20940.89	18112.84	24028.95
7/31/2026	21896.91	18977.75	25245.14
8/31/2026	21279.74	18160.58	24832.52
9/30/2026	21822.38	18403.9	25757.45
10/31/2026	21690.82	18039.83	25953.1
11/30/2026	21535.94	17478.63	25930.75
12/31/2026	20678.06	16492.86	25687.9

The prediction interval (shaded area) provides a realistic range of confidence, indicating relatively low uncertainty in the forecast results. This confirms the model's reliability in projecting Indonesia's non-oil and gas export trends. The MAPE of 4.73% falls into the "very good" category, indicating that models with MAPE values under 10% are considered highly accurate for economic forecasting. This high accuracy achievement demonstrates that the systematic approach to optimizing the Prophet model is effective in generating reliable non-oil and gas export predictions. Furthermore, this model can serve as a valuable tool for policymakers in strategic planning related to Indonesia's international trade. The projected non-oil and gas export values for the period are presented in Table 3, which includes the forecast values (yhat) along with the lower (yhat_lower) and upper (yhat_upper) bounds of the prediction intervals.

This forecasting provides strategic information for policymakers to anticipate seasonal fluctuations in non-oil and gas exports and plan appropriate interventions to maintain or improve export performance. These projections can also serve as a reference for industry players and exporters in their business planning and international market penetration strategies. It should be noted that although the Prophet model with optimal parameters produces very good accuracy (MAPE of 4.73%), unpredictable external factors, such as changes in global trade policies, geopolitical unrest, or economic crises, could cause deviations from this projected outcome.

V. CONCLUSIONS AND SUGGESTIONS

This study analyzes the use of the Facebook Prophet algorithm to forecast Indonesia's non-oil and gas export values, focusing on trends, seasonal patterns, and volatility. The results show that the export trend from 2015 to 2025 has exhibited dynamic growth, despite fluctuations, particularly during 2020-2022. The Prophet model with a combination of annual and monthly seasonality provided the best prediction accuracy, with an initial MAPE of 8.70%, improving to 4.73% after parameter optimization. Projections for 2025-2026 indicate a stable export trend, with values ranging from 20,000 to 22,000 million USD, and a moderate annual growth rate of about 0.7%.

For future research development, several directions can be pursued, such as integrating exogenous variables, such as global economic indicators and trade policies, to enhance model accuracy. A comparison with other machine learning techniques, such as LSTM or XGBoost, could also provide deeper insights into optimal prediction methods. Further research into the changepoints identified by the Prophet model is also important for understanding external factors influencing non-oil and gas exports. Additionally, analysis at the commodity or sector level may provide more detailed predictions useful for sectoral policy. Lastly, developing an early warning system based on this prediction model could assist policymakers in anticipating export trend changes effectively. Overall, this study demonstrates that the Prophet model with optimized parameters can be an effective tool for predicting Indonesia's non-oil and gas exports with a very high level of accuracy. The systematic approach in parameter optimization significantly contributed to improving the model's accuracy from 8.70% to 4.73%.

REFERENCES

[1] M. Purba, M. Sihombing, and J. Sihotang, "ANALISIS PENGARUH EKSPOR MIGAS, EKSPOR NON MIGAS DAN PENANAMAN MODAL ASING TERHADAP PERTUMBUHAN EKONOMI INDONESIA TAHUN 2000-2019," *J Econ Bus*, 2021, doi: 10.36655/jeb.v2i2.557.

[2] S. Aisyah and T. D. Renggani, "DETERMINANTS OF INDONESIA NON-OIL AND GAS EXPORTS TO NON-TRADITIONAL MARKET," vol. 5, 2021, doi: 10.29040/IJEBAR.V5I3.3310.

[3] Badan Pusat Statistik, "Nilai Ekspor Migas-NonMigas (Juta US$), 2025." Accessed: May 04, 2025. [Online]. Available: https://www.bps.go.id/id/statistics-table/2/MTc1MyMy/nilai-ekspor-migas-nonmigas.html

[4] Badan Pusat Statistik, "Perkembangan Ekspor dan Impor Indonesia Januari 2025," Jakarta, 2025.

[5] K. A. Rijal, A. V. Vitianingsih, Y. Kristyawan, A. Maukar, and S. F. A. Wati, "Forecasting Model of Indonesia's Oil & Gas and Non-Oil & Gas Export Value using Var and LSTM Methods," *Jurnal Teknologi dan Manajemen Informatika*, 2024, doi: 10.26905/jtmi.v10i1.13127.

[6] W. Xie, L. Yu, S. Xu, and S. Wang, "A New Method for Crude Oil Price Forecasting Based on Support Vector Machines," pp. 444–451, 2006, doi: 10.1007/11758549_63.

[7] L. Yu, X. Zhang, and S. Wang, "Assessing Potentiality of Support Vector Machine Method in Crude Oil Price Forecasting," *Eurasia journal of mathematics, science and technology education*, vol. 13, pp. 7893–7904, 2017, doi: 10.12973/ejmste/77926.

[8] H. Awijen, H. Ameur, Z. Ftiti, and W. Louhichi, "Forecasting oil price in times of crisis: a new evidence from machine learning versus deep learning models," *Ann. Oper. Res.*, vol. 345, pp. 979–1002, 2023, doi: 10.1007/s10479-023-05400-8.

[9] L. Jovanovic *et al.*, "Multi-Step Crude Oil Price Prediction Based on LSTM Approach Tuned by Salp Swarm Algorithm with Disputation Operator," *Sustainability*, 2022, doi: 10.3390/su142114616.

[10] M. F. Maulana, S. Sa'adah, and P. E. Yunanto, "Crude Oil Price Forecasting Using Long Short-Term Memory," *Jurnal Ilmiah Teknik Elektro Komputer dan Informatika*, 2021, doi: 10.26555/jiteki.v7i2.21086.

[11] H. Aldabagh, X. Zheng, and R. Mukkamala, "A Hybrid Deep Learning Approach for Crude Oil Price Prediction," *Journal of Risk and Financial Management*, 2023, doi: 10.3390/jrfm16120503.

[12] E. Žunić, K. Korjenić, K. Hodzic, and D. Donko, "Application of Facebook's Prophet Algorithm for Successful Sales Forecasting Based on Real-world Data," *IRPN: Innovation Strategy (Topic)*, 2020, doi: 10.5121/ijcsit.2020.12203.

[13] B. K. Jha and S. Pande, "Time Series Forecasting Model for Supermarket Sales using FB-Prophet," *2021 5th International Conference on Computing Methodologies and Communication (ICCMC)*, pp. 547–554, 2021, doi: 10.1109/iccmc51019.2021.9418033.

[14] Y. Liu, G. Feng, K. Chin, S. Sun, and S. Wang, "Daily tourism demand forecasting: the impact of complex seasonal patterns and holiday effects," *Current Issues in Tourism*, vol. 26, pp. 1573–1592, 2022, doi: 10.1080/13683500.2022.2060067.

[15] I. Önder, U. Gunter, and S. Gindl, "Utilizing Facebook Statistics in Tourism Demand Modeling and Destination Marketing," *J Travel Res*, vol. 59, pp. 195–208, 2020, doi: 10.1177/0047287519835969.

[16] S. Bouhaddour, C. Saadi, I. Bouabdallaoui, M. Sbihi, and F. Guerouate, "A Novel Hybrid Approach for Daily Tourism Arrival Forecasting: The PROPHET-Bayesian Gaussian Process-Forward Neural Network Model," *Ingénierie des systèmes d information*, 2023, doi: 10.18280/isi.280404.

[17] A. B. Sinaga, R. P. Sari, and N. Nurviana, "Forecasting The Amount Of Oil and Non-Oil and Gas Exports In Indonesia Using The Box-Jenkins Method," *Mathline : Jurnal Matematika dan Pendidikan Matematika*, 2023, doi: 10.31943/mathline.v8i4.403.

[18] N. Nairob, E. Russel, A. Ambya, A. Darmawan, M. Usman, and W. Wamiliana, "DYNAMIC MODELING DATA EXPORT OIL AND GAS AND NON-OIL AND GAS BY ARMA(2,1)-GARCH(1,1) MODEL: STUDY OF INDONESIAN'S EXPORT OVER THE YEARS 2008-2019," *International Journal of Energy Economics and Policy*, vol. 10, pp. 175–184, 2020, doi: 10.32479/ijeep.9892.

[19] Bustami, A. Yolanda, and N. Thahira, "Forecasting Non-Oil and Gas Exports in Indonesia Using Double and Triple Exponential Smoothing Methods," *International Journal of Industrial Engineering and Engineering Management*, 2023, doi: 10.24002/ijieem.v5i1.6211.

[20] M. S. Borahima, H. Sain, I. Setiawan, and F. Fadri, "Implementation of the Fuzzy Time Series Singh Method for Forecasting Non-Oil and Gas Export Values in Indonesia," *BERKALA SAINSTEK*, 2024, doi: 10.19184/bst.v12i3.52663.

[21] M. Firdaus and Suwanda, "Pemodelan Metode Fuzzy Time Series Stevenson-Porter pada Nilai Peramalan Ekspor Non-Migas di Indonesia," *Bandung Conference Series: Statistics*, 2023, doi: 10.29313/bcss.v3i2.9512.

[22] S. A. W. Dinata, A. A. Purbosari, and P. Hasanah, "Forecasting Indonesian Oil, Non-Oil and Gas Import Export with Fuzzy Time Series," *IJCCS (Indonesian Journal of Computing and Cybernetics Systems)*, 2022, doi: 10.22146/ijccs.78399.

[23] B. H. Winarno, D. Kusumawati, H. A. Triyanto, and B. H. Winarno, "PENERAPAN MACHINE LEARNING (MODEL PROPHET) DALAM PREDIKSI PERMINTAAN PRODUK UNTUK MENGOPTIMALKAN INVENTORI," no. November, pp. 168–174, 2024.

[24] A. Subashini, K. Sandhiya, S. Saranya, and U. Harsha, "Forecasting Website Traffic Using Prophet Time Series Model," *International Research Journal of Multidisciplinary Technovation*, vol. 1, no. 1, pp. 56–63, 2019, doi: 10.34256/irjmt1917.

[25] S. J. Taylor and B. Letham, "Business Time Series Forecasting at Scale," *PeerJ Preprints 5:e3190v2*, vol. 35, no. 8, pp. 48–90, 2017.

[26] F. B. Wijaya, D. P. Putra, M. Azzahra, F. Arina, and F. Ikhsan, "Forecasting the Open Unemployment Rate in Banten Province Using the FB Prophet Method in Python Programming Language," *Tirtayasa Journal of Statistics*, vol. 01, no. 01, 2025.