Sinkron : Jurnal dan Penelitian Teknik Informatika
Volume 9, Number 2, April 2025
DOI : https://doi.org/10.33395/sinkron.v9i2.14804
e-ISSN : 2541-2019
p-ISSN : 2541-044X

Enhanching Prophet Time Series Forecasting on Sparse Data via Hyperparameter Optimizattion: A Case Study in Retail

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Submitted :May 22, 2025 | **Accepted** : Jun 16, 2025 | **Published** : Jun 23, 2025

Abstract: In today's competitive business landscape, accurate sales forecasting is crucial for retailers to optimize inventory, prevent overstock, and support strategic decision-making. However, many small to medium enterprises operate with sparse and irregular sales data, making conventional forecasting methods less effective. This study aims to evaluate the performance of the Prophet time series model in such non-ideal conditions and to investigate how hyperparameter tuning affects its forecasting accuracy. The research adopts the Prophet algorithm, an additive time series forecasting model developed by Facebook, which incorporates trend, seasonality, and holiday components. The model was implemented in two configurations: one using default parameters, and another with manually tuned hyperparameters, including changepoint prior scale (CP), seasonality prior scale (SP), and seasonality mode. A total of 32 experiments were conducted using historical transaction data from PT Eko Hejo. Results show that the default Prophet model achieved a MAPE of 9.50%, while the best-performing configuration (CP = 0.5, SP = 0.01, additive mode) reduced the MAPE to 6.80%. This indicates that hyperparameter tuning significantly improves forecast accuracy, even in sparse data environments. The study contributes both practically and scientifically by demonstrating that Prophet, when properly configured, is a robust and adaptable tool for business forecasting with limited data. It also highlights the value of manual tuning in enhancing model responsiveness and generalization, offering insights for further research in model comparison, automated optimization, and hybrid forecasting approaches.

Keywords: Sales Forecasting; Time Series; Prophet Algorithm; Hyperparameter Tuning; Sparse Data; Retail Analytics; MAPE; Machine Learning.

INTRODUCTION

Accurate sales forecasting is essential to any successful retail business in today's highly competitive environment, where timely and precise demand prediction directly influences inventory management and operational efficiency (Ensafi et al., 2022). These factors can be identified by analyzing the sales patterns of total revenue or specific product-level data in a retail store. It is worth mentioning that each product has a different level of forecasting complexity some items may be easier to predict, while others fluctuate due to irregular purchase behavior or external influences.

One of the most effective approaches to improve forecasting performance is the use of information technology, particularly through data analysis techniques. By leveraging historical data, businesses can predict future sales more accurately. The application of appropriate analytical methods, such as data mining and machine learning, enables the modeling and prediction of large-scale historical datasets. Among these techniques, time series forecasting plays a key role in understanding trends over time.

This study adopts Facebook Prophet, a time series forecasting model known for its robustness and simplicity. Prophet is designed using an additive model framework where non-linear trends are combined with yearly, weekly, and daily seasonalities, along with special event or holiday effects (Dash et al., 2021). The model decomposes a time series into three core components: trend, seasonality, and holiday effects. Once fitted, Prophet provides high-performance forecasting with relatively low computational cost. Moreover, Prophet is capable of handling missing values and outliers effectively. It can adapt to drastic changes in trend, assign nulls to missing data points, and automatically project future values based on historical patterns (Tanuwidjaja & Widjaja, 2022).

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Prophet is also flexible enough to work even when the data lacks traditional seasonal patterns. In our case, although the dataset does not show strong seasonality, Prophet still performs reliably. This highlights one of Prophet's primary advantages: its automatic, adaptive nature that can accommodate dramatic changes in time series data (Christophorus Beneditto Aditya Satrioa, n.d.)Additionally, the algorithm performs well even on sparse or irregular data, and does not require a large amount of time series entries to generate reasonably accurate forecasts (Kumar Jha & Pande, 2021). Prophet is also suitable for non-daily time intervals, which is advantageous for many real world business cases.

The idea of the Prophet algorithm is to select a training model that best fits the characteristics of historical data, and then apply it to forecast future observations (Wang et al., 2020). In previous studies, Prophet was shown to outperform other time series forecasting techniques (Ivanko et al., 2020). However, despite these advantages, some research has indicated that using Prophet with default settings does not always result in optimal performance. Even with adjustments to hyperparameters such as changepoint prior scale, seasonality prior scale, seasonality mode, and changepoint range, the improvement in accuracy has been inconsistent. In some cases, hyperparameter tuning did not significantly improve the model's performance (Sulandari et al., 2024). For example, default Prophet models produced a MAPE of 22.62% while some tuned models achieved a MAPE as low as 8.27% (Santoso et al., 2024).

. Based on issues identified in previous studies regarding the use of default parameters in the Prophet algorithm, which can affect prediction accuracy, this research aims to perform sales forecasting using PT Ekko Hejo as a case study.

LITERATURE REVIEW

Prophet is a forecasting algorithm/procedure developed by Facebook to create forecasting models for their in-house projects based on an additive model where non-linear trends are estimated with yearly, weekly, and daily seasonality, plus holiday effects. Prophet aims at producing accurate forecasting models which require minimal manual efforts and are robust to outliers, missing data, and changes in time series data. While having many automation features, Prophet simply uses a decomposable time series model such as the generalized additive model (GAM). Specifically, Prophet uses a generative model with three main components: (1) trend, (2) seasonality, and (3) holidays/events (Saeed et al., 2023).

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

$$g(t) = (k + a(t)\delta)t + (m + a(t)^T\gamma) \qquad (2)$$

Where k is the growth rate, a(t)T is the binary vector for adjusting the growth rate, m is the offset parameter and δ is the growth rate vector for adjusting the growth rate, and γ is a parameter making the trend model continuous. The seasonal component s(t) was constructed by means of a Fourier function:

$$(t) = \sum_{n=1}^{N} \left(a_n \cos\left(\frac{2\pi nt}{p}\right) + b_n \sin\left(\frac{2\pi nt}{p}\right) \right) \qquad (3)$$

Where p (p) is the period of the time series, N (N) is the number of terms in the Fourier series, and a_n (a_n) and b_n (b_n) represent the coefficients of the cosine and sine functions, respectively.The seasonal term $s(t)$ (s(t)) aims to solve the optimal coefficient vector$\beta = (a_1, b_1, \ldots, a_n, b_n)$ and determine appropriate values of p and N(Wei, 2025).

To implement Fb-Prophet, we must first create a Pandas DataFrame with only two columns. The first column contains the dates, and the other contains the corresponding observations, which in our case is the available data. These columns must be renamed to ds and y, respectively, to comply with Prophet's input format. The model is capable of handling seasonal or non-stationary data, so preprocessing steps are minimal. However, we need to configure daily_seasonality, weekly_seasonality, or yearly_seasonality as True depending on the trend patterns present in the dataset. To use Prophet for forecasting, we first define and initialize a Prophet() object, then fit it to the training dataset using the fit() function and supply the prepared dataset. After fitting the model, we can use the predict() function to generate future forecasts. It's important to assess the model's performance by comparing the predictions to actual values, allowing for adjustments in the seasonal parameters if necessary. If the initial model does not perform satisfactorily, we may consider tuning hyperparameters or adding additional regressors to better

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capture the underlying trends and seasonality in the data. Continuous evaluation and refinement of the model can lead to improved forecasting accuracy and more reliable insights (Chhabra et al., 2024).
In Prophet, there are several hyperparameters that can be tuned, including:

Changepoint Prior Scale
The changepoint prior scale is a parameter that determines the flexibility of the trend, specifically how much change is allowed at the changepoints. Higher values of this parameter result in a more flexible model that can adapt to trend shifts more easily. Conversely, lower values may cause the model to underfit, introducing noise due to insufficient sensitivity to trend changes.

Seasonality Prior Scale
The seasonality prior scale controls the flexibility of the seasonal component. Higher values allow the model to capture more complex seasonal patterns, whereas lower values may lead to underfitting with smaller magnitude of seasonal effects.

Seasonality Mode
The seasonality mode defines the structure of the seasonal pattern, offering two options: additive or multiplicative. The additive mode assumes that seasonal effects remain constant over time, while the multiplicative mode assumes that seasonal variations change proportionally with the trend. The default mode in Prophet is additive. During hyperparameter tuning, the model selects the most suitable mode based on performance to achieve the best forecasting accuracy.

According to previous comparative studies, Prophet has been shown to perform particularly well in cases involving price fluctuation prediction, especially in the food sector, where it delivered lower prediction error rates than traditional methods such as ARIMA and deep learning approaches like LSTM (Muzakki et al., 2021). Furthermore, those studies recommend using grid search to automatically identify optimal combinations of Prophet's hyperparameters, which has been found effective in improving prediction performance in practical forecasting tasks(Prakoso et al., 2023).

METHOD

The following research involve several steps in developing a Prophet Model to predict. Figure 1 is an illustration of the Prophet model

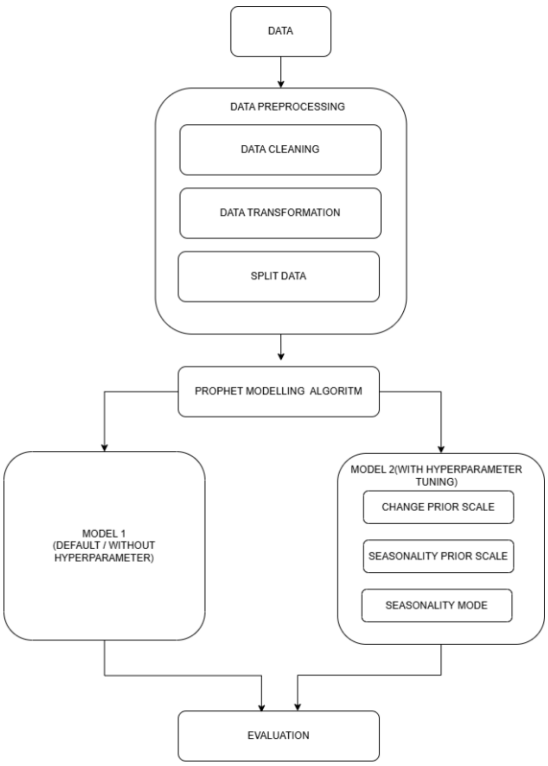

Figure 1. Research stages

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Research techniques are formulated to examine time-related trends and forecast upcoming sales activity using past buying data from PT Eko Hejo. The researchers employ the Prophet algorithm, a predictive model developed by Facebook specifically for time series data. Prophet adopts an additive modeling framework that combines trend, seasonality, and holiday effects to effectively capture complex temporal patterns. This approach aims to evaluate the alignment between forecasted and actual sales figures, identify seasonal fluctuations and long-term trends, and provide a solid foundation for strategic business decisions such as inventory planning and promotional timing.

A key strength of Prophet is its ability to adapt automatically to various data structures and incorporate external regressors when appropriate. However, in this study, the hyperparameter tuning process specifically for changepoint prior scale, seasonality prior scale, and seasonality mode is conducted manually rather than using automated optimization methods like grid search or Bayesian search. This choice is motivated by two factors: (1) manual tuning allows for more controlled exploration of the effect of individual parameters on forecasting behavior, especially important in small or sparse datasets where overfitting is a risk; and (2) it enables a clearer interpretation of how specific settings influence model accuracy, which is valuable for deriving practical insights for similar business forecasting scenarios.

To evaluate model performance, the Mean Absolute Percentage Error (MAPE) is used as the primary error metric. MAPE is widely adopted in business forecasting contexts due to its interpretability in percentage terms, making it intuitive for stakeholders to understand forecast deviations relative to actual values. However, MAPE also presents certain limitations: it can be unstable when actual values approach zero, and it tends to bias toward underpredictions when errors are asymmetric. Despite these drawbacks, MAPE remains a suitable and informative choice for evaluating performance in this case, given the nature of the sales data and the need for a metric that aligns with business decision-making standards.

Dataset

In this study, the transactional information utilized is a time series dataset that reflects sales from PT Eko Hejo. The dataset includes time-related details, comprising the date and year of every transaction, as well as the overall value of items sold on each documented date. In contrast to conventional time series datasets that demand consistent and high-frequency data input, the Prophet algorithm utilized in this research have 115 data does not necessitate a significant volume of data or a perfectly uniform daily frequency. Prophet is built to manage missing values and uneven time intervals, which makes it ideal for real-world datasets that could be sparse or incomplete. Consequently, the dataset employed in this study is deliberately confined and inconsistent, indicating that not each day has a data point. This design decision is taken to assess the strength and predictive ability of the Prophet algorithm in suboptimal data situations. The main objective is to assess if Prophet can continue to generate accurate predictions using limited and irregularly spaced historical information. An Example of the dataset is presented in Table I.

Table 1. Example of Dataset

NO	Historical Data sells	
	Date	**Total Sales**
1	2017-10-04	40000
2	2017-10-30	18300
3	2017-11-15	40000
4	2018-01-22	6000
5	2018-01-30	16000

Data Preprocessing

The data that has been collected is then subjected to a Data Pre-Processing phase to ensure that the Prophet algorithm can accurately interpret the input data. This stage involves several critical steps to prepare the time series dataset for modeling.

1) Data Cleaning
Irrelevant columns are removed, the data is reorganized to include only the date and sales values, and duplicate transactions occurring on the same date are aggregated to produce a single value per day.
2) Data Transformation
The cleaned data is then reformatted into the structure required by Prophet, which includes two primary columns: ds (representing the date in YYYY-MM-DD format) and y (representing the sales value). This transformation ensures the data complies with Prophet's input requirements for time series forecasting.
3) Data Splitting

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Once transformed, the dataset is split into two parts a training set and a testing set. The training dataset is utilized to train the Prophet model, whereas the testing dataset serves to assess the prediction accuracy by contrasting predicted values with real observed information. This division is crucial for assessing the model's effectiveness and its ability to generalize.

Prophet Modelling Algorithm

Prophet modeling is executed in two separate scenarios designed to assess and enhance forecasting effectiveness. The data, once it has been preprocessed, is fed into two distinct model setups:

1) Model 1 (Default Hyperparameters): Prophet is executed using the default settings provided by the Prophet library, with no manual adjustment of hyperparameters.

2) Model 2 (Hyperparameter Tuning*)*: Prophet is executed with customized hyperparameter settings in an effort to improve forecasting accuracy. The adjusted parameters include:
   a. Changepoint Prior Scale, which controls the model's sensitivity to trend changes
   b. Seasonality Prior Scale, which determines the flexibility of the seasonal component
   c. Seasonality Mode, which specifies whether the seasonal component is treated as additive or multiplicative.

Model Evaluation

Each model produces results as forecasted sales figures (yhat) for upcoming time intervals. The results are then analyzed to identify which model offers more precise forecasts. The precision of every model is assessed through the Mean Absolute Percentage Error (MAPE), a widely utilized metric in time series forecasting that quantifies the average size of errors between forecasted and real values, represented as a percentage. A smaller MAPE value signifies a more precise model, serving as a helpful reference for evaluating the effectiveness of both standard and optimized Prophet setups.

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{yi - \hat{y}i}{\hat{yi}}\right| x\ 100 \tag{4}$$

RESULT

In this research, 32 trials were carried out to assess the effect of various hyperparameter settings on the precision of sales predictions using the Prophet algorithm. The adjustment procedure concentrated on three key parameters: Changepoint Prior Scale (CP), Seasonality Prior Scale (SP), and Seasonality Mode (additive or multiplicative). The evaluation measure utilized for each trial was Mean Absolute Percentage Error (MAPE), which assesses the average percentage discrepancy between forecasted values and actual sales figures. The result of both model can be seen in the table II and III.

TABLE 3. EVALUATION RESULT WITH HYPERPARAMETER TUNING

Number TRIAL	CP: Changepoint Prior Scale SP: Seasonality Prior Scale			
	CP	SP	SEASONALITY MODE	MAPE
1	0.5	0.01	additive	6.80%
2	0.5	0.01	Multiplicative	6.90%
3	0.5	0.1	Additive	7.14%
4	0.001	0.01	Multiplecative	7.41%
5	0.1	0.1	Multiplecative	7.41%

TABLE 4 . EVALUATION RESULT WITHOUT HYPERPARAMETER TUNING

MAPE :	**9.50%**	

The trials revealed that Trial 25, utilizing CP = 0.5, SP = 0.01, and the additive mode, achieved the minimum MAPE score of 6.80%, signifying the greatest forecasting accuracy among all setups. Conversely, the least effective outcome was noted in Trial 32 (CP = 0.5, SP = 10.0, multiplicative mode) with a MAPE of 10.47%. Furthermore, the model that lacked any hyperparameter tuning achieved a MAPE of 9.50%. These results indicate that using a larger changepoint prior scale alongside a smaller seasonality prior scale enhances Prophet's capability

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to detect slight trend shifts while reducing the risk of overfitting to seasonal elements. Moreover, the additive seasonality model had a slight edge over the multiplicative model in the majority of low-SP situations.

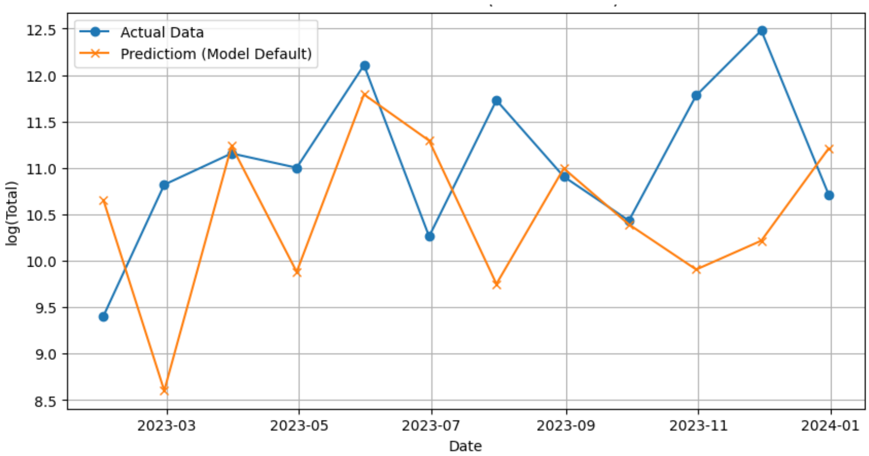

Figure 2. Prophet Model Default Forecasting Plot

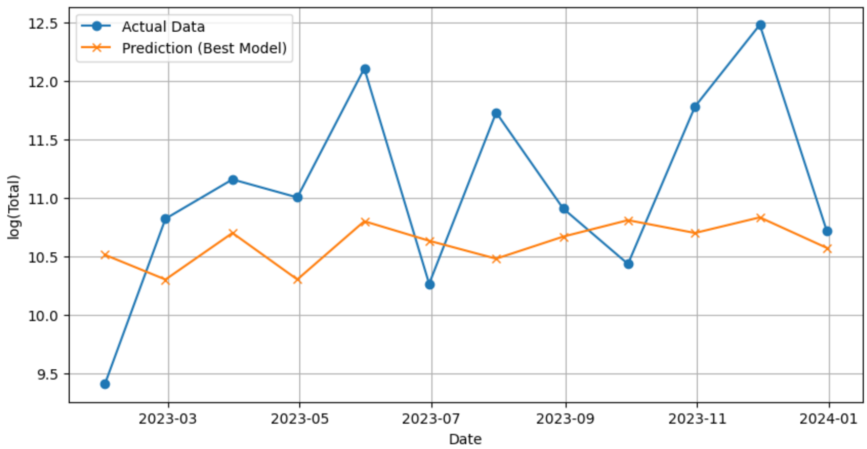

Figure 2. Prophet Model Forecasting Plot with Hyperparameter

DISCUSSIONS

The visual comparison between the two models, shown in Figure 2 (Default Model) and Figure 3 (Best Model), clearly demonstrates the benefits of hyperparameter tuning. While both models attempt to follow the general sales trend, the tuned model shows a closer alignment with actual values and smaller prediction errors throughout the forecast period. This suggests that careful adjustment of Prophet's parameters can significantly improve accuracy, even when working with limited and irregular data. The optimal configuration identified in this study Changepoint Prior Scale (CP) of 0.5 and Seasonality Prior Scale (SP) of 0.01 proved to be the most effective in reducing MAPE. The CP value allows the model to respond adequately to significant changes in trend, which is particularly important in retail data where demand patterns can shift abruptly. At the same time, a low SP value limits the flexibility of the seasonal component, reducing the risk of overfitting to minor or irregular fluctuations. This balance enables the model to generalize better in sparse datasets where noise is more prominent than signal. Compared to findings reported in previous studies, this result reinforces the notion that manual tuning of key hyperparameters can meaningfully enhance Prophet's forecasting performance. Prior research has also observed that default configurations often fail to capture the nuances in real-world business data, especially when the data is irregular, incomplete, or affected by external variability. The current study extends this understanding by validating that tuning remains beneficial even in the absence of rich seasonal patterns. Nonetheless, Prophet is not without its limitations particularly when applied to sparse time series data. The algorithm assumes the presence of recurring patterns and sufficient historical information to extract trend and seasonality components. In cases where such patterns are inconsistent or the data coverage is minimal, the model may underperform or exhibit unstable behavior. Prophet is also less suited for capturing sudden, irregular shocks that do not follow a consistent pattern across time. Future improvements could involve combining Prophet with other approaches that handle nonlinear dependencies more effectively, such as machine learning or deep learning models. Additionally, the

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implementation of automated tuning techniques, like grid search or optimization frameworks, may help identify better parameter combinations systematically, reducing manual trial-and-error. In conclusion, this study confirms that even with sparse data, Prophet remains a valuable forecasting tool provided that its configuration is carefully adjusted to match the characteristics of the data.

CONCLUSION

This research was carried out to assess whether the application of the Prophet algorithm, combined with hyperparameter tuning, can effectively forecast future sales figures based on historical time series data. Throughout the study, 32 model trials were conducted using different combinations of changepoint prior scale, seasonality prior scale, and seasonality modes, both additive and multiplicative. Among these configurations, the best-performing model using a changepoint prior scale of 0.5 and a seasonality prior scale of 0.01 in additive mode achieved a MAPE of 6.80%, which was significantly better than the default Prophet configuration that produced a MAPE of 9.50%.

This study demonstrates that tuning Prophet can significantly improve forecasting accuracy, even under non-ideal conditions such as sparse and irregular datasets. The findings imply that Prophet, when properly adjusted, is a practical and reliable tool for forecasting in real-world business environments where data completeness and frequency cannot always be guaranteed. The ability of the tuned model to closely track actual sales patterns indicates that appropriate parameter selection enhances model responsiveness without compromising generalizati on. Nonetheless, this study also acknowledges several limitations. Prophet's performance may decline in the presence of extreme irregularity, highly volatile sales behavior, or when the dataset contains very limited historical information. Additionally, while the use of logarithmic transformation can stabilize variance and normalize the data distribution, it also introduces challenges in interpretation and may affect the clarity of the forecasting outputs for stakeholders. Looking ahead, future research may benefit from conducting comparative evaluations between Prophet and other time series models such as ARIMA and LSTM, particularly when applied to sparse and noisy retail datasets. Moreover, further exploration into model robustness across different degrees of data sparsity would provide a deeper understanding of Prophet's limitations and strengths. Automated hyperparameter tuning methods, such as grid search or Bayesian optimization, could also be implemented to enhance efficiency and consistency in model configuration. Finally, the development of hybrid forecasting models that combine Prophet with other machine learning techniques could offer new pathways for improving predictive accuracy in complex forecasting scenarios. In conclusion, this study reinforces the potential of Prophet as a flexible and interpretable forecasting tool, and highlights the importance of thoughtful parameter tuning in maximizing its predictive performance under imperfect data conditions.

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