Media Statistika

p-ISSN 1979 – 3693 e-ISSN 2477 – 0647
MEDIA STATISTIKA 17(1) 2024: 93-104
http://ejournal.undip.ac.id/index.php/media_statistika

IMPLEMENTATION OF PROPHET IN AMERICAN ELECTRICITY FORECASTING WITH AND WITHOUT PARAMETER TUNING

Winita Sulandari[1], Yudho Yudhanto[2], Riskhia Hapsari[1], Monica Dini Wijayanti[1], Hilman F. Pardede[3]

[1] Department of Statistics, Universitas Sebelas Maret, Surakarta, Indonesia
[2] Informatics Engineering, Vocational School, Universitas Sebelas Maret, Surakarta, Indonesia
[3] Research Center for Data and Information Sciences National, National Research and Innovation Agency, Jakarta, Indonesia

e-mail: winita@mipa.uns.ac.id

DOI: 10.14710/medstat.17.1.93-104

Article Info:
Received: 14 December 2023
Accepted: 21 December 2024
Available Online: 26 December 2024

Keywords:
Prophet; electricity load forecasting; Box-Cox transformation; holidays; parameter tuning.
.

Abstract: Prophet is one of the machine learning approximation methods that accommodate trends, seasonality, and holiday impacts in time series data. Generally, the performance of machine learning models can be improved by implementing hyperparameter tuning. This study investigates whether hyperparameter tuning can improve the model's performance. To show its effectiveness, the Prophet model constructed by parameter tuning is compared to the one with fixed parameter values (namely the default model) for both the original series and the Box-Cox transformed series in terms of mean absolute percentage error (MAPE). Based on the experimental results of the twenty-four daily electricity load time series in American Electric Power (AEP). This shows that parameter tuning successfully reduces the MAPE of the default model in the range of about 3-8% for training data. However, there is no guarantee for testing data. Although, in some cases, parameter tuning can reduce the MAPE value of the default model by up to 38%, in other cases, it actually increases the MAPE of the default model by almost 15%. The experiments on testing data also show that models built from transformed data do not necessarily produce more accurate forecast values than those built from the original data.

1. INTRODUCTION

Forecasting is the process of predicting how intermittent elements would behave based on historical data or additional factors that are connected to the components (Shohan et al., 2022). Any industry can benefit from forecasting since it allows for better planning and solution selection. For many years, it has been employed in a variety of industries, from predicting the movements of financial markets to accurately forecasting energy load (Aytaç, 2021). Electricity is a crucial source for driving the steady industrial development because it is instantaneous and cannot be stored in huge quantities (Zhao et al., 2023). Financial losses occur when the demand for energy exceeds the supply, or vice versa. Therefore, forecasting the amount of electricity needed is essential for managing the balance between supply and demand (Sulandari et al., 2022). All enterprises in power industry, from generation, transmission, and distribution require load forecasting to plan their scheduling and ensure system dependability. Furthermore, with the advent of smart grids, or smart energy management systems, load forecasting has become even more important, as they require precise predictions to ensure optimal grid functioning (Shohan et al., 2022).

The electrical load fluctuations show a specific pattern of a series of time-based data. The characteristics of the load time series, including those by households, businesses, industries, and the government, are dependent on the time of utilization and typically exhibit a repetition pattern. Seasonal patterns are evident in the utilization of electricity consumption. Daily utilization and weekly load patterns are prone to repetition on specific days (Mado, 2020). Various techniques for electricity load time series forecasting have been discussed in many literatures, such as Multiple Linear Regression, K-Nearest Neighbors Regressor, Epsilon-Support Vector Regression, Random Forest Regressor, Extreme Gradient Boosting Regressor, Singular Spectrum Analysis, Long-Short Term Memory, Box-Jenkins, Exponential Smoothing, etc. (Madrid and Antonio, 2020; Sulandari et al. 2022; Bashir et al., 2022; Kim et al., 2019; Khan et al., 2022)

In the previous decade, Facebook introduced Prophet, a brand-new forecasting technique that has a lot of potential for use in predicting time series (Almazrouee et al., 2020). Prophet is a machine learning method that is quick and easily comprehensible. To fit the smoothing and forecasting functions in Prophet, non-linear trends are fitted with yearly, weekly, and daily seasonality as well as holiday effects (Papacharalampous & Tyralis, 2020). In addition, Prophet strives to create reliable predicting models that need less manual work and tend to be robust to outliers, missing data, and structural changes in time series data (Saeed et al., 2023). In the drought forecasting of a semi-arid climate region of western India, Basak et al. (2022) compared Prophet to support vector regression and multiple linear regression where in this case, Prophet produced the smallest error than two other methods in terms of coefficient of determination (R^2) and Nash-Sutcliffe efficiency (NSE). Besides that, Žunić et al. (2021) also conducted a comparison between Prophet and other methods, Amazon's autoregressive RNN (namely DeepAR+) and Convolution Neural Network based on Quantile Regression (CNN-QR) for sales forecasting in distribution companies. Žunić et al. (2021) showed that Prophet provides better results for products with a longer history and more frequent sales, whereas Amazon's DeepAR+ performs better for products with a short history and products that are infrequently sold.

Since the Prophet is powerful for modeling seasonal and trend time series, we consider this method will be appropriate in modeling hourly or daily electricity time series which has complex patterns, including trend and seasonal with calendar variations (Sulandari et al., 2022). Almazrouee et al. (2020) have shown that Prophet model yields more accurate electrical load forecast values in Kuwait than Holt-Winters model. In the following year, Chaturvedi et al. (2022) have showed that Prophet provided better results in forecasting modeling total and peak monthly energy demand for India compared with recurrent neural networks (RNN) and Box-Jenkins. Discussion on the success of Prophet application in electricity load forecasting can be found in Bashir et al., (2022) and Shohan et al. (2022). Those studies combined Prophet with other methods. So far, there has been limited discussion on the effect of transformation and parameter tuning on the accuracy of forecast values by Prophet model. In general, this treatment is considered to be able to improve model performance (Aytaç, 2021). However, we need to investigate whether it always enhances the performance of the Prophet model.

The objective of this study is to observe the influence of parameter tuning in Prophet model performance for the case of the daily AEP time series for each hour of the day. The Prophet model with parameter tuning constructed from the original and Box-Cox transformed series is compared with those without parameter tuning. It is intended that the findings of this study will aid in developing a better forecasting model for electricity load data utilizing the Prophet method.

2. LITERATURE REVIEW

2.1. Prophet Method

Facebook created the open-source Prophet model algorithmic forecasting tool in 2017. It specializes in handling nonlinear relationship in time series including the seasonal pattern as well as holiday impacts. It also overcome outliers and missing values (Zhao et al., 2023; Zhu, 2021). It almost automates the matching process and makes it work better compared to other approaches (Taylor & Letham, 2018). There are three main model elements in Prophet, which are trend, seasonality, and holidays. These components form Prophet forecasting written in Equation (1), where $g(t)$ is the trend term that can be specified as a linear or a logistic function, $s(t)$ is a seasonality term such as yearly/weekly/daily, $h(t)$ is the holiday effect, and $\varepsilon(t)$ is an error factor that is not fitted by the model (Shohan et al., 2022).

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

Later, in the analysis, we consider a linear trend with changepoints ($c_j, j = 1, 2, \dots, C$) represented in Equation (2)

$$g(t) = (k + \mathrm{a}(t)^{\mathrm{T}}\delta)t + (m + \mathrm{a}(t)^{\mathrm{T}}\gamma) \tag{2}$$

where k is the growth rate, $\mathbf{a}(t) = [a_1(t), a_2(t), \dots, a_C(t)]^{\mathrm{T}} \in \{0,1\}^C$ with C is the number of changepoints and

$$a_j(t) = \begin{cases} 1 & \text{if } t \geq c_j \\ 0 & \text{otherwise} \end{cases}$$

Notation $\boldsymbol{\delta} = [\delta_1, \dots, \delta_C]^{\mathrm{T}} \in \mathbb{R}^C$ is the vector to adjust the rate of growth, m is the offset parameter, and γ_j is set to $c_j\delta_j$ in order to ensure that the function is continuous. Meanwhile, seasonal component $s(t)$ represented as the Fourier function with the number of harmonics n_h and can be written as Equation (3)

$$s(t) = X(t)\beta \tag{3}$$

where $X(t) = \left[\cos\left(\frac{2\pi t}{P}\right), \sin\left(\frac{2\pi t}{P}\right), \dots, \cos\left(\frac{2\pi n_h t}{P}\right), \sin\left(\frac{2\pi n_h t}{P}\right)\right]$ with P denotes the seasonal period, and $\beta = \left[b_1, d_1, \dots, b_{n_h}, d_{n_h}\right]^{\mathrm{T}}$ is assumed to be normally distributed with mean 0 and variance, σ^2.

2.2. Box-Cox Transformation

Box-Cox transformation is a useful family of transformations commonly used in various research fields. It transforms non-normal data into a more normal distribution. In time series analysis, the purpose of the transformation is to simplify the patterns in the historical data by eliminating recognized source of variance or increasing the pattern's consistency over the whole data set. Simpler pattern typically leads to more accurate forecasts (Hyndman & Athanasopoulos, 2018).

Box-Cox transformation depends on the parameter λ, which transforms a given variable y into $y^{(\lambda)}$ by the following equation (Bicego & Baldo, 2016):

$$y^{(\lambda)} = \begin{cases} \frac{y^{\lambda}-1}{\lambda} & \text{for } \lambda \neq 0 \\ \log(y) & \text{for } \lambda = 0 \end{cases} \tag{4}$$

Based on Equation (4), a natural logarithm is employed when $\lambda = 0$ and a power transformation is applied when $\lambda \neq 0$. A suitable value for λ is one that makes the seasonal variation's size roughly consistent across the whole series, as this simplifies the forecasting model.

Data that has been transformed and used for forecasting needs to be returned (or back-transformed) using Equation (5) to obtain forecasts on the original scale (Hyndman & Athanasopoulos, 2018).

$$y = \begin{cases} \left(1 + y^{(\lambda)}(\lambda)\right)^{\frac{1}{\lambda}} & \text{if } \lambda \neq 0 \\ \exp\left(y^{(\lambda)}\right) & \text{if } \lambda = 0 \end{cases} \tag{5}$$

2.3. Validation Approach

In this study, MAPE is used as the validation metrics. The smaller values of these metrics indicate the better forecasting result (Bashir et al., 2022; Ning et al., 2022). MAPE is a scale-independent error that allows comparison of forecast performance across different data sets, so it is commonly used in the evaluation of load forecasting accuracy (Sulandari et al., 2022). The mathematical expressions of these evaluation metrics are presented in Equation (6):

$$\text{MAPE} = \frac{100\%}{T} \sum_{t=1}^{T} \left| \frac{\hat{y}_t - y_t}{y_t} \right| \tag{6}$$

where $\hat{y}_t$ is the predicted value, y_t is true value, and t represents time over a period of T time steps.

3. METHODOLOGY

3.1. Data and Source

This study considered the hourly electricity load of AEP that can be accessed from https://www.kaggle.com/datasets/robikscube/hourly-energy-consumption. This data has also discussed in Kaur et al. (2022), Jin et al. (2021), and Sajjad et al. (2020). The hourly AEP time series from 1 October 2014 00:00 to 2 May 2018 23:00 is divided into twenty-four series with each representing the daily data of each hour, as illustrated in Figure 1.

3.2. Steps Conducted in this Study

Data analysis in this study was carried out with Python software. The steps for the analysis are as follows and presented in Figure 2: (1) Collected AEP data; (2) Prepared the data for input into the model. Prophet simply requires two major data components: the value and time components, indicated by '*ds*' and '*y*'; (3) Divide each time series into two parts: training and testing data sets; (4) Perform Box-Cox transformation on the original training data by using auto λ value, (5) Model the original training data as well as the data transformed in Step 4 using the default Prophet algorithm, the Prophet algorithm with holidays added, and the Prophet algorithm after parameters tuned. Information of the parameters tuned in this work are represented in Table 1; (6) Perform forecasting on testing data sets using each model obtained in Step 5; (7) Evaluate the forecast accuracy based on MAPE; (8) Interpret the results.

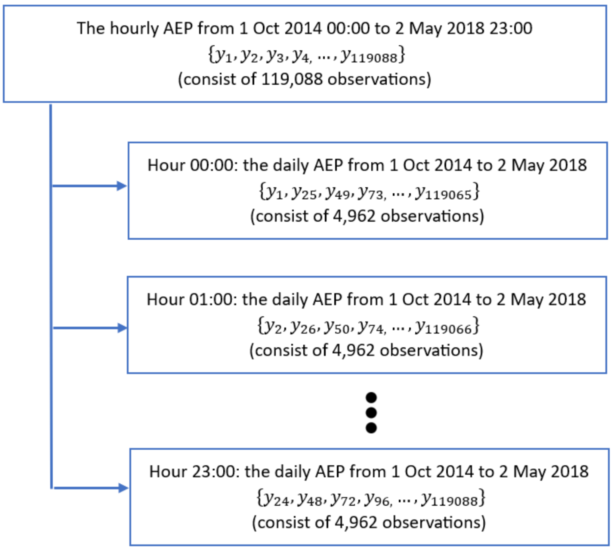

Figure 1. Description of the Twenty-four Daily AEP Time Series Considered In this Study

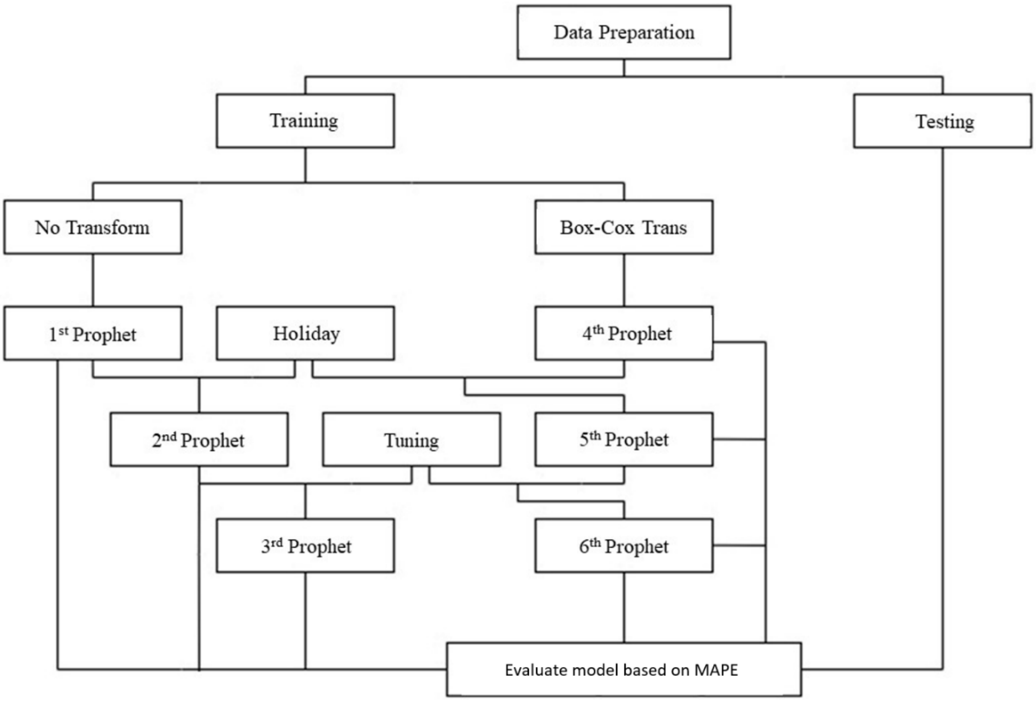

Figure 2. Steps Used in this Study

Table 1. The Default and Optional Setting for Parameters in Prophet Model

Model Configuration	Default	Optional model setting
Changepoint prior scale	0.05	0.01; 0.03; 0.05; 0.07
Seasonality prior scale	10	1; 5; 10; 15
Seasonality mode	Additive	Additive, multiplicative
Changepoint range	0.8	0.6; 0.7; 0.8; 0.9

4. RESULTS AND DISCUSSION

This study discussed the application of Prophet method to modelling and forecasting the twenty-four AEP electricity data. These data sets represent the series for each hour, from 00:00 to 23:00. Each observation consists of 4,962 observations which then divides into two parts, training and testing data. Prophet model is then fitted using the first 4,932 observations from 1 October 2014 to 2 April 2018 as the training data and evaluated the forecasting accuracy performance using the last 30 observations from 3 April to 2 May 2018 as the testing data. The patterns of all series are depicted in Fig 3. In general, all series follow similar patterns, although there are some differences at certain time due to different hours of electricity load. Figure 3 shows that the variance of hours 13:00 to 19:00 are higher the other hours.

Initially, the default Prophet method was used to model both the original and Box-Cox transformed AEP series in the analysis. Then, the data is re-modeled by adding the dummy variable of holidays and tuning parameters. It should be noted that holidays added are the public holidays in United States (US) that are available by Prophet. Table 2 lists the holiday that have a significant impact to the Prophet model. There is an observed holiday when the public holiday falls on the nearest weekday and perhaps the celebration will take place on the preceding or following day. For example, as shown in Table 2, if Christmas Day is on Sunday (25 December 2016), then the observed day is on the following Monday (26 December 2016), or if Veteran's Day is on Saturday (11 November 2017), then observed day on the Friday preceding day (11 November 2017).

For each Prophet model, Table 3 provides the evaluation of errors in terms of MAPE derived from the original series and the Box-Cox transformed series of the training data, respectively, based on the experimental findings. Remarkably, for a number of hour series for the transformed series, the default (denoted by D) Prophet model yields larger MAPE. Furthermore, Prophet models with holidays and parameter tuning yield better results, with the exception of hour 23:00 (see Table 3, for the original series). In this case, we see that the parameter tuning improves the forecasting accuracy. Overall, after evaluating the error in the training data for both the original and transformed series, it can be concluded that parameter tuning provides better Prophet model performance, as indicated by the decreasing of MAPE value. Moreover, the transformation can decrease the MAPE values for all three observed models, i.e., default model (*D*), including holidays (*H*), and including holidays with parameter tuning (*HT*).

Additionally, Table 4 presents the MAPE for all Prophet models derived from the original and transformed series of the testing data. In contrast to what is shown in the training data, the smallest MAPE value is not consistently achieved by the model with parameter tuning. This means that there is no guarantee that parameter tuning can improve the accuracy of the forecast value. In contrast to the training data, there is no guarantee that parameter tuning can reduce the MAPE of the default model for testing data. While parameter tuning can, in some instances, decrease the MAPE value of the default model by as much as 38%, it can also increase it by nearly 15% in other instances. Likewise, for the transformed series, it succeeds in reducing MAPE for some of the models with parameter tuning, but not all cases. And it tends to fail in decreasing MAPE for the default model or the model involving holidays. Different from Aytaç (2021), this work shows that models built from transformed data do not necessarily produce more accurate forecast values than those built from the original data. Therefore, there is no assurance that parameter tuning and transformation can consistently enhance forecast accuracy. Likewise, for the transformed series, it succeeds in reducing MAPE for some of the models with parameter tuning, but not for the default model or the model involving holidays. Therefore, there is no assurance that parameter tuning and transformation can consistently enhance forecast accuracy.

Figure 4 provides a visualization of up to thirty-steps forecast values on test data for the hour 11:00 and the hour 22:00 series, which were obtained by Prophet models constructed from the original and transformed series. From Figures 4(a)-4(d) it can be seen that the forecast values of the default Prophet model tend to coincide with those obtained from the model involving holidays, meaning that there is no increase in forecast accuracy with the addition of holidays to the Prophet model. Meanwhile, the model with holiday and tuning parameters provides a larger error than the other two models for forecast values up to twelve steps ahead. Furthermore, we find that around 60% of thirty-steps forecast values for hour 11:00 series data tend to be overestimated.

Moreover, the current research's hyperparameter tuning is limited to particular values of the changepoint prior scale, seasonality prior scale, seasonality mode, and changepoint range. Consequently, further investigation is needed to enhance the performance accuracy of the Prophet model.

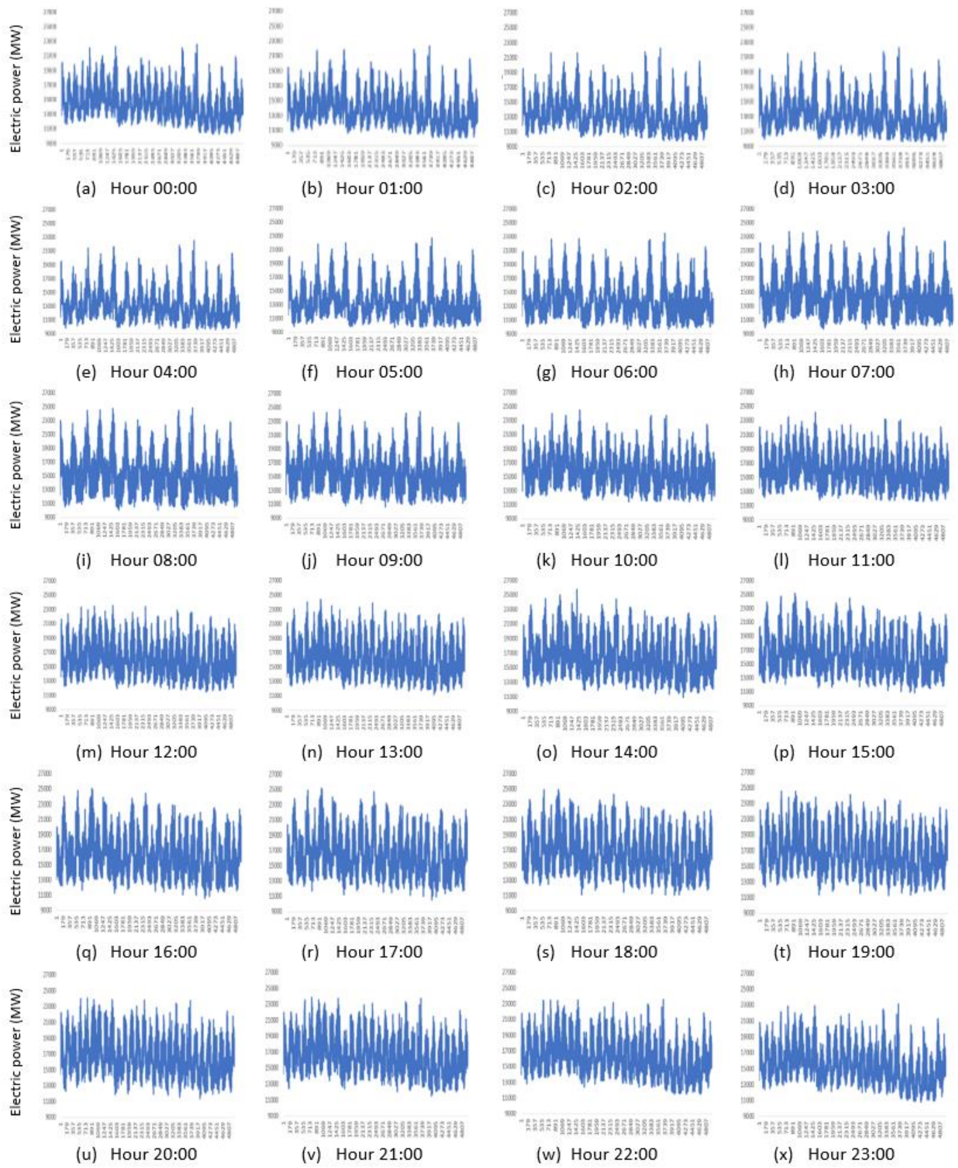

Figure 3. Daily AEP Time Series for Hour 00:00 to 23:00 from 1 October 2014 to 2 May 2018

Table 2. List of Holidays Considered in The Constructed Prophet Model

No	Holiday	Date
1	Martin Luther King Jr. Day	20 Jan 2014, 19 Jan 2015, 18 Jan 2016, 15 Jan 2018
2	Washington's Birthday	17 Feb 2014, 16 Feb 2015, 15 Feb 2016, 16 Jan 2017, 19 Feb 2018
3	Columbus Day	13 Oct 2014, 12 Oct 2015, 10 Oct 2016, 9 Oct 2017
4	Memorial Day	26 May 2014, 25 May 2015, 30 May 2016, 29 May 2017
5	Independence Day	4 Jul in each year
6	Labor Day	1 Sep 2014, 7 Sep 2015, 5 Sep 2016, 4 Sep 2017
7	Veterans Day	11 Nov in each year
8	Thanksgiving Day	27 Nov 2014, 26 Nov 2015, 24 Nov 2016, 23 Nov 2017
9	Chrismast Day	25 Dec in each year
10	Chrismast Day (observed)	26 Dec 2016
12	New Year's Day (observed)	2 Jan 2017
13	Veteran Day (observed)	10 Nov 2017
14	Independence Day (observed)	3 Jul 2015

Table 3. Comparison of MAPE Values for The Training Data Obtained by Prophet Model Constructed From The Original and Transformed Series

Hours	Original Series			Transformed Series		
	D	*H*	*HT*	*D*	*H*	*HT*
00:00	6.62	6.52	6.43	6.02	5.94	**5.80**
01:00	6.78	6.68	6.59	6.26	6.08	**5.93**
02:00	6.95	6.83	6.73	6.33	6.25	**6.09**
03:00	7.06	6.93	6.83	6.46	6.30	**6.20**
04:00	7.15	7.01	6.91	6.54	6.40	**6.27**
05:00	7.21	7.04	6.95	6.61	6.47	**6.32**
06:00	7.23	7.04	6.93	6.70	6.50	**6.38**
07:00	7.24	6.96	6.87	6.83	6.55	**6.46**
08:00	6.88	6.53	6.45	6.53	6.18	**6.10**
09:00	6.63	6.31	6.23	6.20	5.88	**5.82**
10:00	6.45	6.19	6.11	6.02	5.75	**5.65**
11:00	6.36	6.15	6.07	5.86	5.65	**5.57**
12:00	6.41	6.24	6.16	5.85	5.68	**5.60**
13:00	6.59	6.44	6.34	5.98	5.82	**5.76**
14:00	6.74	6.59	6.51	6.15	7.07	**5.88**
15:00	6.89	6.73	6.64	6.30	6.10	**6.01**
16:00	7.01	6.84	6.75	6.41	6.24	**6.10**
17:00	7.11	6.94	6.85	6.49	6.31	**6.18**
18:00	7.16	6.98	6.89	6.53	6.34	**6.23**
19:00	7.04	6.86	6.77	6.42	6.20	**6.12**
20:00	6.82	6.64	6.56	6.20	6.01	**5.92**
21:00	6.60	6.42	6.34	6.01	5.85	**5.75**
22:00	6.51	6.33	6.25	6.00	5.86	**5.68**
23:00	6.54	6.39	**6.30**	8.37	8.01	7.71

D: default Prophet model, *H*: Prophet with holidays, *HT*: Prophet with holiday and parameter tuning. Bold values represent the lowest value in a row of each accuracy.

Table 4. Comparison Of MAPE Values For The Testing Data Obtained By The Prophet Model Constructed From The Original And Transformed Series

Hours	Original Series			Transformed Series		
	D	H	HT	D	H	HT
00:00	6.44	6.38	6.49	7.85	6.77	**5.65**
01:00	6.91	6.84	7.03	6.89	7.69	**6.43**
02:00	7.55	7.47	7.69	8.88	7.56	**7.04**
03:00	7.76	7.70	7.86	7.86	8.32	**7.61**
04:00	8.08	**8.01**	8.07	8.12	8.43	8.05
05:00	8.26	**8.17**	8.24	8.42	8.22	8.31
06:00	8.21	**8.11**	8.21	8.36	8.20	8.64
07:00	7.86	**7.72**	7.75	8.14	7.88	8.43
08:00	7.66	**7.48**	7.56	7.72	7.52	7.82
09:00	6.94	6.76	6.96	7.12	6.84	**6.65**
10:00	6.22	6.14	6.22	6.11	6.15	**5.78**
11:00	5.64	5.55	5.57	6.53	6.20	**4.62**
12:00	5.71	5.59	5.57	7.31	6.40	**4.51**
13:00	5.93	5.87	5.60	6.84	6.81	**4.67**
14:00	6.14	6.09	5.82	6.43	5.96	**5.63**
15:00	6.21	6.19	5.99	6.76	7.76	**5.77**
16:00	6.58	6.52	6.56	7.27	6.24	**6.12**
17:00	6.48	6.48	6.58	7.71	6.80	**5.91**
18:00	6.58	6.59	6.46	7.36	7.26	**6.27**
19:00	6.48	6.48	6.35	6.58	7.41	**5.11**
20:00	6.43	6.42	6.34	7.34	7.51	**5.18**
21:00	6.13	6.10	6.03	6.96	6.00	**5.12**
22:00	5.91	5.89	5.82	5.66	5.62	**5.17**
23:00	6.13	6.12	**6.05**	7.06	**5.80**	6.57

D: default Prophet model, *H*: Prophet with holidays, *HT*: Prophet with holiday and parameter tuning. Bold values represent the lowest value in a row of each accuracy.

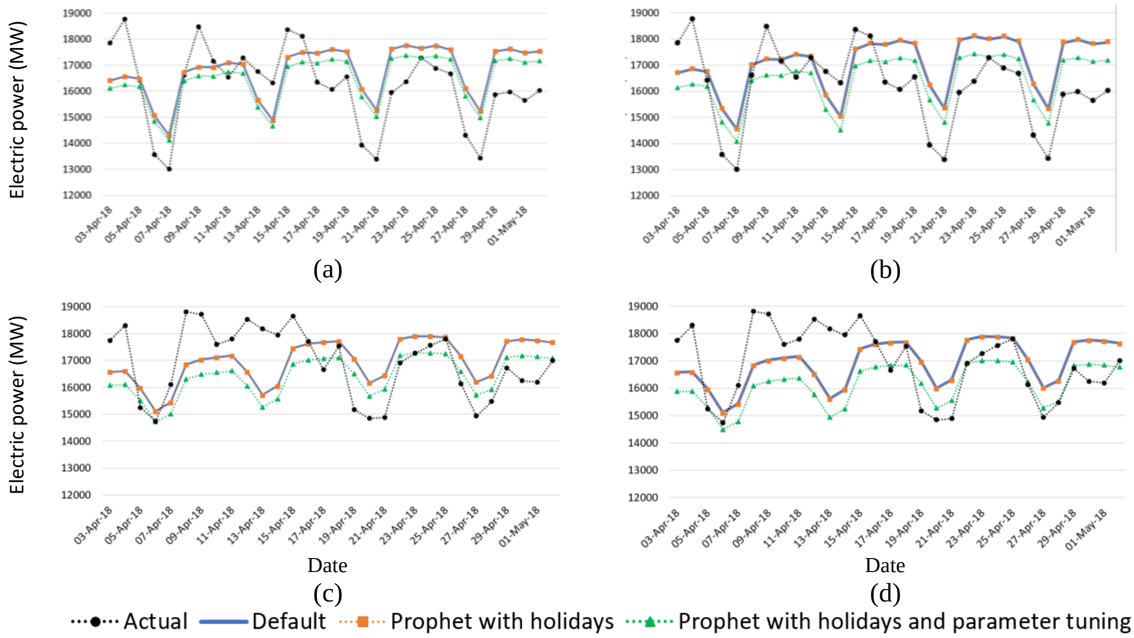

Figure 4. The Actual and Forecast Values Obtained from The Three Prophet Models for The Testing Data (a) The Original Series of Hour 11:00 (b) The Transformed Series of 11:00 (c) The Original Series Hour 22:00 (d) The Transformed Series Hour 22:00

5. CONCLUSION

This study investigates the influence of tuning parameter and the involvement of the holidays to the Prophet model performance. We observe twenty-four daily AEP time series data with and without Box-Cox transformation and model them by the Prophet model with default and hyperparameter tuning, namely changepoint prior scale, seasonality prior scale, seasonality mode, and changepoint range. In the analysis, three different Prophet models, namely the default model, the model with holidays, and the model with holidays and parameter tuning constructed from the original and Box-Cox transformed data are evaluated by MAPE. In conclusion, parameter tuning and transformation do not substantially improve the Prophet model's performance. For future research, the optional model settings in hyperparameter tuning can be expanded so that the more accurate forecast values can be achieved.

ACKNOWLEDGMENT

We thank to DRTPM for their financial support under National Competitive Basic Research Grant Number SP DIPA-023.17.1.690523/2023 with the contract number 055/ES/PG.02.00.PL/2023 (12 April 2023) and 1380.1/UN27.22/PT.01.03/2023 (13 April 2023). We also thank to LPPM Universitas Sebelas Maret.

REFERENCES

Almazrouee, A. I., Almeshal, A. M., Almutairi, A. S., Alenezi, M. R., & Alhajeri, S. N. (2020). Long-Term Forecasting of Electrical Loads in Kuwait Using Prophet and Holt-Winters Models. *Applied Sciences (Switzerland)*, 10(16). https://doi.org/10.3390/app10165627

Aytaç, E. (2021). Forecasting Turkey's Hazelnut Export Quantities with Facebook's Prophet Algorithm and Box-Cox Transformation. *ADCAIJ: Advances in Distributed Computing and Artificial Intelligence Journal*, 10(1), 33–47. https://doi.org/10.14201/adcaij20211013347

Basak, A., Rahman, A. T. M. S., Das, J., Hosono, T., & Kisi, O. (2022). Drought Forecasting Using The Prophet Model in A Semi-Arid Climate Region of Western India. *Hydrological Sciences Journal*, 67(9), 1397–1417. https://doi.org/10.1080/02626667.2022.2082876

Bashir, T., Haoyong, C., Tahir, M. F., & Liqiang, Z. (2022). Short Term Electricity Load Forecasting Using Hybrid Prophet-LSTM Model Optimized by BPNN. *Energy Reports*, 8, 1678–1686. https://doi.org/10.1016/j.egyr.2021.12.067

Bicego, M., & Baldo, S. (2016). Properties of the Box–Cox transformation for pattern classification. *Neurocomputing*, 218, 390–400. https://doi.org/10.1016/j.neucom.2016.08.081

Chaturvedi, S., Rajasekar, E., Natarajan, S., & McCullen, N. (2022). A Comparative Assessment of SARIMA, LSTM RNN and Fb Prophet Models to Forecast Total and Peak Monthly Energy Demand for India. *Energy Policy*, 168. https://doi.org/10.1016/j.enpol.2022.113097

Hyndman, R. J., & Athanasopoulos, G. (2018). *Forecasting: Principles and Practice* (2nd ed.). Australia: OTexts.

Jin, X. B., Zheng, W. Z., Kong, J. L., Wang, X. Y., Bai, Y. T., Su, T. L., & Lin, S. (2021). Deep-Learning Forecasting Method for Electric Power Load Via Attention-Based Encoder-Decoder with Bayesian Optimization. *Energies*, 14(6), 1596.

Kaur, D., Islam, S. N., Mahmud, M. A., Haque, M. E., & Dong, Z. Y. (2022). Energy Forecasting in Smart Grid Systems: Recent Advancements in Probabilistic Deep Learning. *IET Generation, Transmission & Distribution*, 16(22), 4461-4479.

Khan, Z. A., Ullah, A., Ul Haq, I., Hamdy, M., Maria Maurod, G., Muhammad, K., Hijji, M., & Baik, S. W. (2022). Efficient Short-Term Electricity Load Forecasting for Effective Energy Management. *Sustainable Energy Technologies and Assessments*, 53. https://doi.org/10.1016/j.seta.2022.102337

Kim, Y., Son, H., & Kim, S. (2019). Short Term Electricity Load Forecasting for Institutional Buildings. *Energy Reports*, 5, 1270–1280. https://doi.org/https://doi.org/10.1016/j.egyr.2019.08.086

Mado, I. (2020). Electric Load Forecasting an Application of Cluster Models Based on Double Seasonal Pattern Time Series Analysis. In A. A. Jaoude (Ed.), *Forecasting in Mathematics* (p. Ch. 6). IntechOpen. https://doi.org/10.5772/intechopen.93493

Madrid, E.A., and Antonio, N. (2020). Short-Term Electricity Load Forecasting with Machine Learning. *Information*, 12(2), 50. https://doi.org/10.3390/info12020050

Ning, Y., Kazemi, H., & Tahmasebi, P. (2022). A Comparative Machine Learning Study For Time Series Oil Production Forecasting: ARIMA, LSTM, and Prophet. *Computers and Geosciences,* 164. https://doi.org/10.1016/j.cageo.2022.105126

Papacharalampous, G., & Tyralis, H. (2020). Hydrological Time Series Forecasting Using Simple Combinations: Big Data Testing And Investigations On One-Year Ahead River Flow Predictability. *Journal of Hydrology*, 590. https://doi.org/10.1016/j.jhydrol.2020.125205

Saeed, N., Nguyen, S., Cullinane, K., Gekara, V., & Chhetri, P. (2023). Forecasting Container Freight Rates Using The Prophet Forecasting Method. *Transport Policy*, 133, 86–107. https://doi.org/10.1016/j.tranpol.2023.01.012

Sajjad, M., Khan, Z. A., Ullah, A., Hussain, T., Ullah, W., Lee, M. Y., & Baik, S. W. (2020). A Novel CNN-GRU-based Hybrid Approach For Short-Term Residential Load Forecasting. *IEEE Access*, 8, 143759-143768.

Shohan, M. J. A., Faruque, M. O., & Foo, S. Y. (2022). Forecasting of Electric Load Using a Hybrid LSTM-Neural Prophet Model. *Energies*, 15(6). https://doi.org/10.3390/en15062158

Sulandari, W., Yudhanto, Y., & Rodrigues, P. C. (2022). The Use of Singular Spectrum Analysis and K-Means Clustering-Based Bootstrap to Improve Multistep Ahead Load Forecasting. *Energies*, 15(16). https://doi.org/10.3390/en15165838

Taylor, S. J., & Letham, B. (2018). Forecasting at Scale. *The American Statistician,* 72(1), 37–45. https://doi.org/10.1080/00031305.2017.1380080

Zhao, Y., Guo, N., Chen, W., Zhang, H., Guo, B., Shen, J., & Tian, Z. (2023). Multi-Step Ahead Forecasting for Electric Power Load Using An Ensemble Model. *Expert Systems with Applications*, 211. https://doi.org/10.1016/j.eswa.2022.118649

Zhu, S. (2021). Prophet-Based Research on the Medium and Long-Term Forecast Method of the F10.7 Flux of the Sun. *Journal of Physics: Conference Series*, 2026, 1–5.

Žunić, E., Korjenić, K., Delalić, S., & Šubara, Z. (2021). Comparison Analysis of Facebook's Prophet, Amazon's DeepAR+ and CNN-QR Algorithms for Successful Real-World Sales Forecasting. *International Journal of Computer Science and Information Technology*, 13(2), 67–84. https://doi.org/10.5121/ijcsit.2021.13205