Comparison of Deep Learning using Neural Networks with Long Short Term Memory and Prophet Algorithm In Forecasting Electricity Consumption

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Abstract : Electricity has become one of the main human needs today because all environments, whether at home, at work, or in factories, use electrical energy. Every year the use of electricity always increases, this cause an increase in electricity prices which in turn makes electricity expensive. With the increase in tariffs, this should be an impetus for the public to be aware of saving electricity use. This study aims to compare the two models using two algorithms, namely LSTM and Prophet, then measure the level of accuracy and draw conclusions using the statistical metrics Mean Absolute Error (MAE) method to forecast electricity consumption in a period of thirty days or about one month. The datasets used are the consumption of electricity use in Germany during the period 2006 – 2017. This data includes the total daily consumption of electricity in GWh, daily column in day – month – year format, wind power production in GWh, production solar power in GWh, as well as the total sum of wind and solar power production in GWh. In this case, the researcher only uses daily column data in the format of days - months - years and data on total daily consumption of electricity as parameters to estimate electricity use for the next month. This data is provided by Open Power System Data (OPSD) and is available on the “kaggle.com” website. The data used in this study is very useful for time series analysis. Based on the results of testing with the LSTM algorithm with the SGD optimizer, the MAE value is 133.311. The test results with the Prophet algorithm produce an MAE with a value of 54.62.

Keyword : LSTM, Prophet, MAE, Datasets, Forecast Electricity

1. INTRODUCTION

In this era, electricity has become one of the most important needs or even one of the basic needs for the community [1]. Irregular use of electricity will certainly have an impact on the high use of electricity, because the need for the use of electrical energy is greater than its supply, so uncontrolled use causes waste of use of electrical energy [2]. In addition, an accurate predict of electricity consumption is very effective because it contributes to understanding trends and sectors of economic development in a country. By reason of electricity has a big role for society, it is very important to have a credible predict of electricity consumption. The level of accuracy of the estimated electricity consumption is influenced by several factors including population size, economic development, electricity facilities, and weather factors, which make the project more complex [3].

There are several studies related to this research regarding the forecasting of electricity consumption.

Research by Alfa Saleh in 2015 on the implementation of the naïve Bayes classification method in predicting the amount of household electricity use. This study aims to predict the amount of electricity use, from 60 household electricity usage data tested using the naïve Bayes method, the percentage results are 78.3333% for prediction accuracy, of which from 60 data there are 47 data that have been classified correctly[2].

Research by Kangji Li, Chenglei Hu, Guohai Liu, and Wenping Xue in 2015 regarding Prediction of Electricity Use in Buildings with Optimized ANN Algorithms and Using Principal Component Analysis. This study presents a kind of ANN model that is optimized for prediction of building electricity consumption per hour. Improved Particle Swarm Optimization (iPSO) was applied to adjust the ANN structure weights and threshold values. Principal Component Analysis (PCA) is used to select significant modeling inputs and simplify the model structure. The investigation used two different datasets, for performance comparison, two other prediction models, the ANN model and the Hybrid Model Genetic Algorithm - ANN (GA-ANN) were also used in this study. The comparison results show that the iPSO-ANN and GA-ANN models have better accuracy than the ANN models. From the perspective of timeframe, the iPSO-ANN model has a shorter modeling time than the GA-ANN method [4].

Research by Yi-Chung Hu in 2016 regarding Prediction of Electricity Consumption Using the Neural Network Gray Model (NNGM) Approach. The data used in this case is data from the Turkish Ministry of Energy and Natural Resources and The Asia-Pacific Economic Cooperation energy database. In this study, NNGM has been tested for its predictive ability and the experimental results show that NNGM has good performance [5].

Research by Aaron Zeng, Hodde Ho, and Yao Yu in 2019 regarding Prediction of Electricity Use in Buildings Using the Gaussian Process Regression (GPR) Algorithm. Specifically, this study uses large-scale data collected from building energy management systems that are used to estimate energy consumption online. The credibility and efficiency of the algorithm used shows the comparison between the actual data and the predicted results. The results prove that the Gaussian Process Regression algorithm gets a balance of data prediction accuracy with an average deviation of below 15% and low computation time [6].

Research by Yoga Tri Nugraha, M Fitra Zambak, and Arnawan Hasibuan in 2020 regarding Estimates of Electrical Energy Consumption in Aceh in 2028 Using the Adaptive Neuro Fuzzy Inference System Method. This study was conducted to estimate long-term electrical energy consumption using the Adaptive Neuro Fuzzy Inference System method. The results obtained for estimating electricity consumption in the next 10 years in the city of Aceh are 5578.02 GWh or with an increase of 2.07% every year until 2028 [7].

2. MATERIALS

2.1 Neural Networks (NN)

Neural Networks is a machine learning technique that is inspired by the human nervous system and resembles the structure of the brain. This technique consists of organized processing units at the input, hidden, and output layers. The inner nodes or units in each layer are connected to the nodes in the adjacent layer. Each connected node or unit has a certain weight value. An input is multiplied by the respective weights and added to each unit. Then, after the addition process, it will undergo a transformation based on the activation function, which in most cases uses a sigmoid function, hyperbolic tan, and rectified linear unit (ReLU). These functions are used mathematically because they are advantageous for derivatives and make it easier to calculate the partial derivative of the delta error associated with the individual weights. The sigmoid function and hyperbolic tan also suppress input into output with a narrow range with values of 0/1 and 1/+1, respectively. On the other hand, ReLU shows saturating and non-saturating behavior with the function $f(x) = \max(0, x)$. The output of the function is then given as input to the next unit in the next layer. Thus, the result of the final layer output is used as a solution to the problem [8].

2.2 Long Short Term Memory (LSTM)

Long Short Term Memory (LSTM) is an application of Recurrent Neural Network (RNN), LSTM can retain knowledge of previous states and can be trained for jobs that require memory or states of consciousness. LSTM mostly addresses part of RNN.

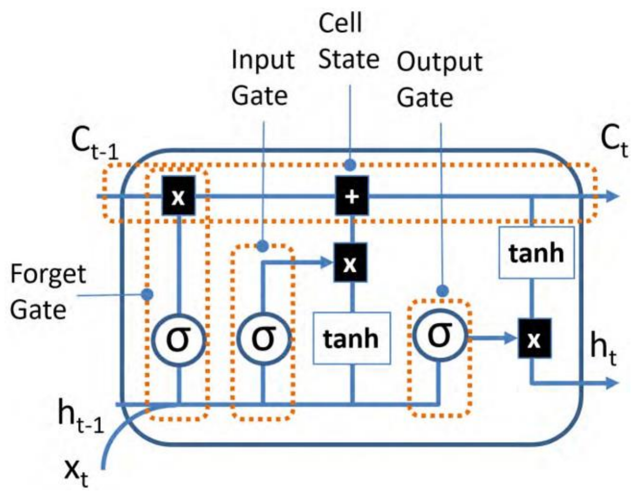

FIGURE 1. LSTM block with memory cell and gates[8].

As shown in figure 1, the LSTM consists of several blocks of memory cells in which the signal flows when set by the input and ignores the output gate as it passes through it. C, x, h represent cells between input and output. The text below the t line shows the value of the time step, that is, t – 1 the value of the previous LSTM block and t indicates the value of the current block. The symbol is a sigmoid function (sigmoid function) and tanh is a hyperbolic tangent function. The + operator is the summing element and x is the multiplier element. The calculation of this gate is written in the following equation :

$$f_t = \sigma(W_f x_t + w_f h_{t-1} + b_f) \tag{3}$$

$$i_t = \sigma(W_i x_t + w_i h_{t-1} + b_i) \tag{4}$$

$$o_t = \sigma(W_o x_t + w_o h_{t-1} + b_o) \tag{5}$$

$$c_t = f_t \otimes c_{t-1} + i_t \otimes \sigma_c(W_c x_t + w_c h_{t-1} + b_c) \tag{6}$$

$$h_t = \sigma_t \otimes \sigma_h(c_t) \tag{7}$$

where f, i, o ignore the input and output of the vector gate, respectively. W, w, b, represent the weight of the input, the weight of the output, bias, and multiplier elements. LSTM can track long-term dependencies, therefore LSTM is good for studying data from consecutive inputs and models that rely on context and previous state[8].

2.3 Prophet

Prophet or FBprophet is an open source forecasting framework developed by the Facebook data sciencetist team. Prophet is used to estimate data analysis in a time series based on a simple linear equation that can simplify the prediction and access process. Prophet includes three parameters, namely trend, seasonality, and holidays[9]. Basically the Prophet is indeed used for time series analysis which can predict events in the next 4 months. In addition, Prophet uses a simple linear equation with the formula :

$$y(t) = g(t) + s(t) + h(t) + \varepsilon t \tag{8}$$

yang terdiri dari 3 komponen :

- g(t) : represents piecewise or logical growth to match non-periodic changes in values from time series data.
- s(t) : represents changes periodically from week to week or year to year.
- h(t) : represents the effects of holidays that occur on an irregular basis every day or even more.
- εt : represents abnormal changes where the changes are not in accordance with the designed model [9].

3. METHODOLOGY

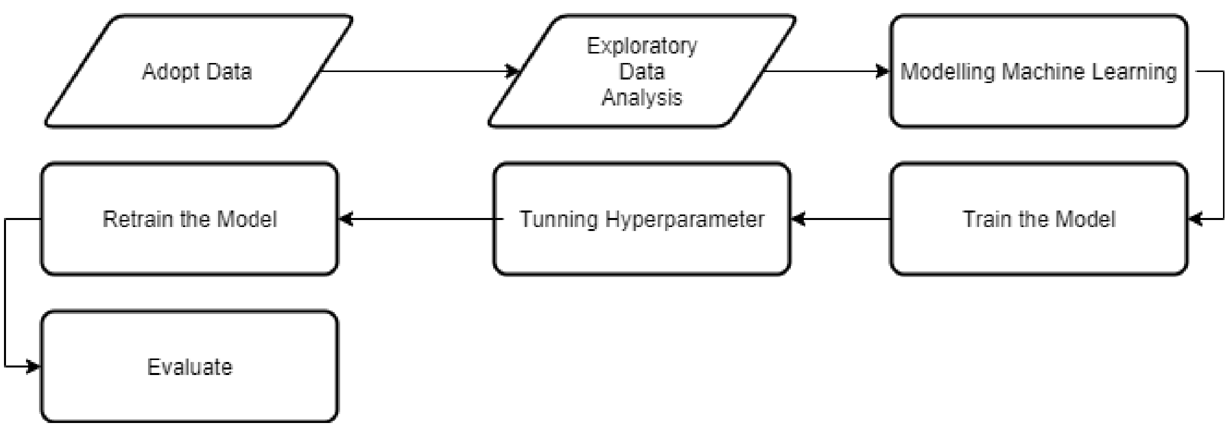

FIGURE 10. Research Overview

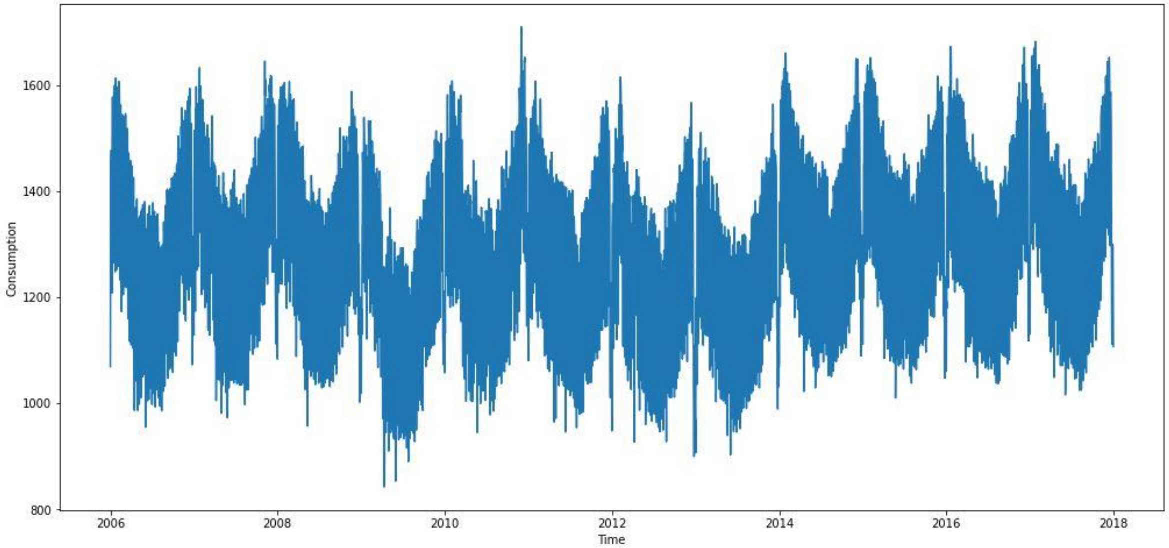

FIGURE 2. Actual data of Electricity Consumption in Germany 2006 – 2017.

1	Date	Consumption	Wind	Solar	Wind+Solar
4377	2017-12-24	1141.7572999999998	812.422	9.949	822.371
4378	2017-12-25	1111.2833799999999	587.8100000000001	15.764999999999999	603.5749999999999
4379	2017-12-26	1130.1168300000002	717.453	30.923000000000002	748.3759999999999
4380	2017-12-27	1263.9409099999996	394.50699999999995	16.53	411.0369999999999
4381	2017-12-28	1299.86398	506.424	14.161999999999999	520.586

FIGURE 3. last 10 actual data from OPSD Germany Electricity Power in 2006 – 2017

3.1 Data

To support this research, datasets of electrical energy consumption in Germany in the period 2006 - 2017 were obtained from a website called "kaggle.com". These datasets amounted to 4383 of the total data that contain the use of electrical energy in GWh, wind power production, solar power production and a combination of wind and solar power production in Germany in 2006 – 2017. The use of data in this study only involved data on the use of electrical energy over a span of thirteen years. This study aims to compare prediction models that match the case of forecasting the use of electrical energy, use forecasting models that involve trends and seasonality and use neural networks models with long short term memory as a comparison of the two models to ensure the model fits the actual data.

3.2 LSTM Model

LSTM is a particular type of RNN capable of handling multiple information reminders for longer time. In LSTM, each node is used as a memory cell that can store other information that is different from the simple neural network, where each node is a single activation function. Specifically, LSTMs have their own cell state. LSTM has three gates: input gate i_t, forget gate f_t and output gate o_t. Sigmoid function is applied to the inputs s_t and the previous hidden state h_{t-1}[10]. The following is the LSTM model used in this study.

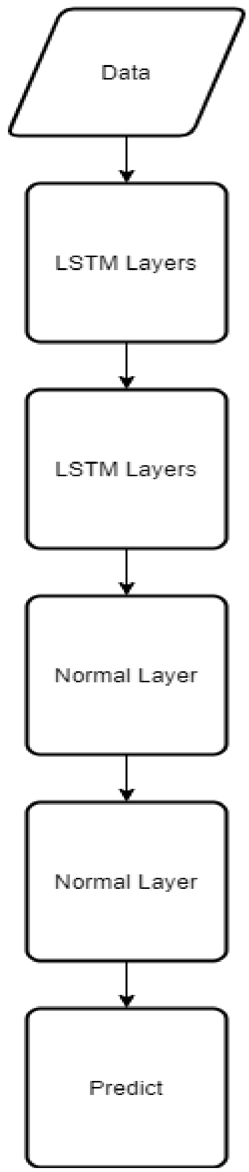

FIGURE 11. LSTM Architecture

The model of the machine learning used consist of 2 LSTM layers and 2 normal layer. The activation function used in the normal layer is RelU (Rectified Linear Unit) activation function cause RelU is a common activation in neural networks. The purpose of training algorithms is to get the optimal value to solve a problem. This study uses a training algorithm model, namely Stochastic Gradient Descent (SGD). Stochastic Gradient Descent is the most common variation for training algorithms and implementing gradient descent. In SGD, updates are applied after running a mini batch of n samples, whereas in GD all samples are processed into training datasets before being implemented into updates. Because SGD updates more often than GD, so SGD can get convergent results much faster [8]. The last layer is a normal layer which has 1 neuron to indicate only 1 output value that comes out.

The goal of the LSTM is to generate the current hidden state at time *t*. The hidden state h_t^j of LSTM unit is defined as :

$$h_t^j = o_t^j \tanh(c_t^j)$$

where o_t^j modulates the memory influence on the hidden state. The output gate is computed as :

$$o_t^j = \sigma(W_o x_t + U_o h_{t-1} + v_o ct)^j$$

where σ is the logistic sigmoid function and V_o is a diagonal matrix. The memory cell c_t^j is updated partially following the equation

$$c_t^j = f_t^j c_{t-1}^j + i_t^j \tilde{c}_t^j$$

where the memory content is defined by a hyperbolic tangent function :

$$c_t^j = \tanh(W_c x_t + U_c h_{t-1})^j$$

Forget gate f_t^jcontrols the amount of old memory loss. Instead, input gate i_t^jcontrols new memory content that is added to the memory cell. Gates are computed by:

$$f_t^j = \sigma(W_f x_t + U_f h_{t-1} + v_f c_{t-1})^j$$

$$i_t^j = \sigma(W_i x_t + U_i h_{t-1} + v_i c_{t-1})^j$$

LSTM can convey information captured at an early stage and easily retains memory of this information for the long term, which allows opportunities to generate potential long-distance dependency[10].

3.3 Prophet Model

The trend model of the prophet algorithm can be represented by two functions according to its growth nature :

- If the growth is logistic, the trend is determined by the saturated growth model with the following equation :

$$tr(t) = \frac{CC_t}{1 + \exp(-(gr + b(t)^T \partial)\big(t - (d + b(t)^T \pi)\big))}$$

Where: CC is the support capability, gr is the growth rate, and d represents the offset parameter.

- If the growth is linear, the trend is measured by a Piecewise linear model and is defined as the following equation :

$$gr(t) = (gr + b(t)^T \partial)t + (d + \; b(t)^T \pi)$$

Where: gr is the rate of growth, d is the rate of change, and d also represents displacement.

- The effect of daily, weekly, and yearly periodic changes of the datasets is determined by the following equation :

$$se(t) = \sum_{t=i}^{J} (a_n \cos\left(\frac{2\pi i t}{R}\right) + b_n \sin\left(\frac{2\pi i t}{R}\right))$$

Then, the holiday impact can be calculated by the equation:

$$Y(t) = [1(t \in P), \dots \dots \dots, 1(t \in PL)]$$
$$ho(t) = Y(t)\, \text{ꞓ}$$

where : is a constant parameter for holiday which represents a change in a prediction[11].

3.4 Model Evaluate

To evaluate the final results in terms of accuracy, this study uses statistical metrics model, namely the mean absolute error (MAE) which can be described as the following equation :

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n} |yi - \hat{y}i|$$

where : y and represent measured and predicted[12].

4. RESULT

4.1 LSTM Result

Training on the datasets was carried out using the stochastic gradient descent (SGD) optimizer model.

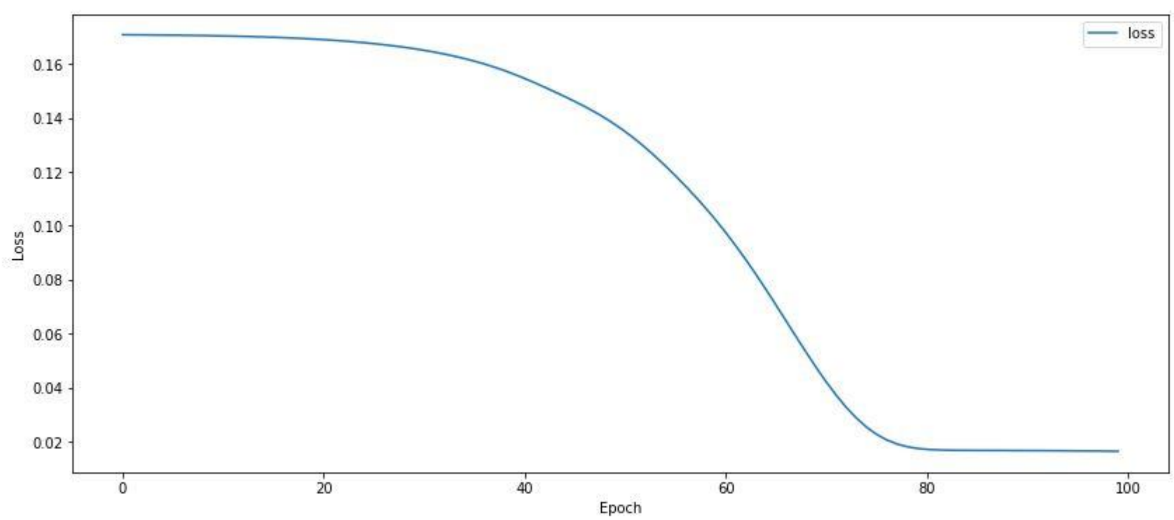

FIGURE 4. epoch and loss metrics using LSTM Methods with SGD Optimizer

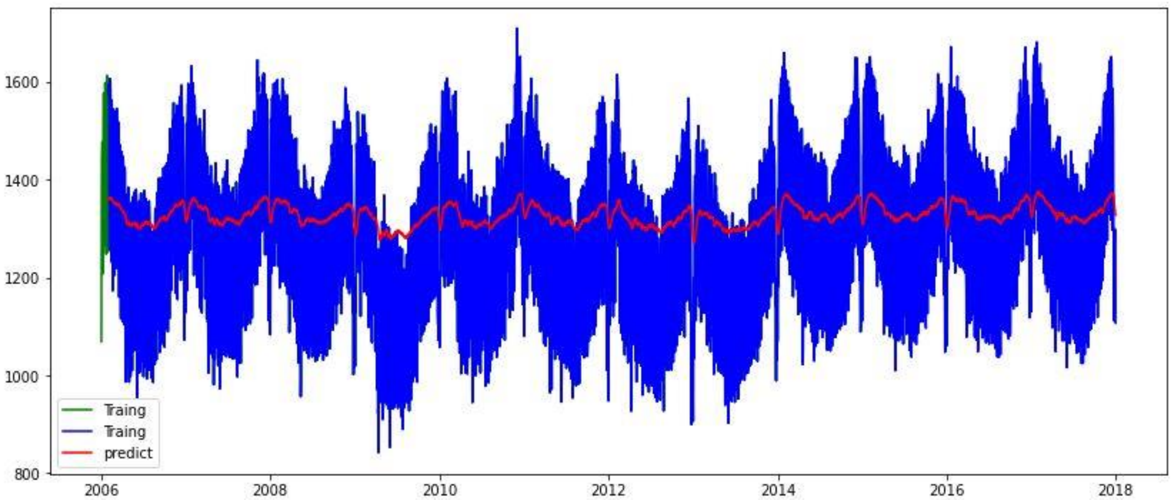

FIGURE 5. Data Training and Predict of Electricity Forecasting Consumption

	Consumption	Predictions
Date		
2017-12-02	1391.85405	1364.418579
2017-12-03	1330.26226	1364.740601
2017-12-04	1620.97758	1363.364014
2017-12-05	1643.72307	1363.463257
2017-12-06	1639.08265	1364.734009
2017-12-07	1628.47979	1366.550171
2017-12-08	1618.05658	1368.447021
2017-12-09	1415.34531	1370.302612
2017-12-10	1318.10964	1370.569458
2017-12-11	1614.15862	1369.015625
2017-12-12	1647.36346	1368.580078
2017-12-13	1651.90418	1369.294678
2017-12-14	1636.54375	1370.569336
2017-12-15	1576.93197	1372.090210
2017-12-16	1382.87708	1373.278320
2017-12-17	1297.21916	1372.742188
2017-12-18	1578.69079	1370.378052
2017-12-19	1586.48230	1369.032104
2017-12-20	1559.68569	1368.662476
2017-12-21	1520.37206	1368.597168
2017-12-22	1423.23782	1368.439941
2017-12-23	1272.17085	1367.412964
2017-12-24	1141.75730	1364.567139
2017-12-25	1111.28338	1359.548340
2017-12-26	1130.11683	1353.090698
2017-12-27	1263.94091	1346.104736
2017-12-28	1299.86398	1340.138794
2017-12-29	1295.08753	1335.445312
2017-12-30	1215.44897	1331.709717
2017-12-31	1107.11488	1328.023804

TABEL 1. Actual Data Consumption and Predict last 30 days using LSTM Methods

	0	1	2	3	4
0	Explained variance	MAE	MSE	RMSE	R^2
1	0.0980412	133.311	24846.9	157.629	0.0940048

FIGURE 6. Mean Absolute Error using LSTM Methods

The final result of the estimation of electrical energy consumption using the LSTM method produces predictions that are less accurate when compared to the actual data as shown in FIGURE 5. In TABLE 1, the comparison between the actual data and the prediction results is shown, the prediction results using the LSTM method indicate that the prediction does not get close to the actual data. In FIGURE 6 displays the results of the Mean Absolute Error (MAE) with a value of 133,311, of course, the resulting value does not get results that match the actual data.

4.2 Prophet Result

Estimated Electrical Energy Consumption using the prophet algorithm shows trend graphs that represent the predicted level of electricity usage from year to year, weekly graphs depict estimated electricity consumption within one week, and yearly graphs indicate estimated electricity usage over a period of one year.

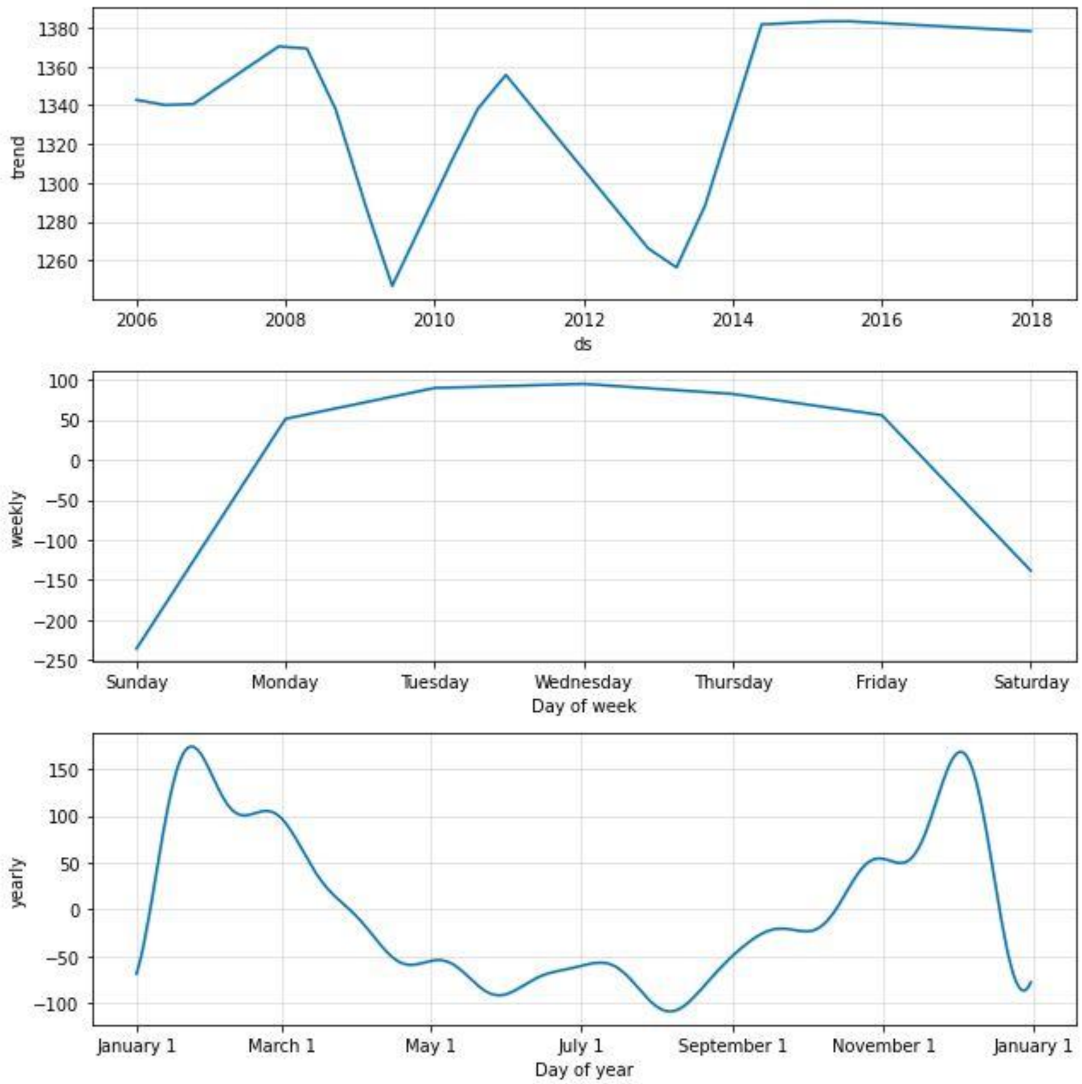

FIGURE 7. trend, weekly, and yearly of Electricity Forecasting Consumption using Prophet Algorithm

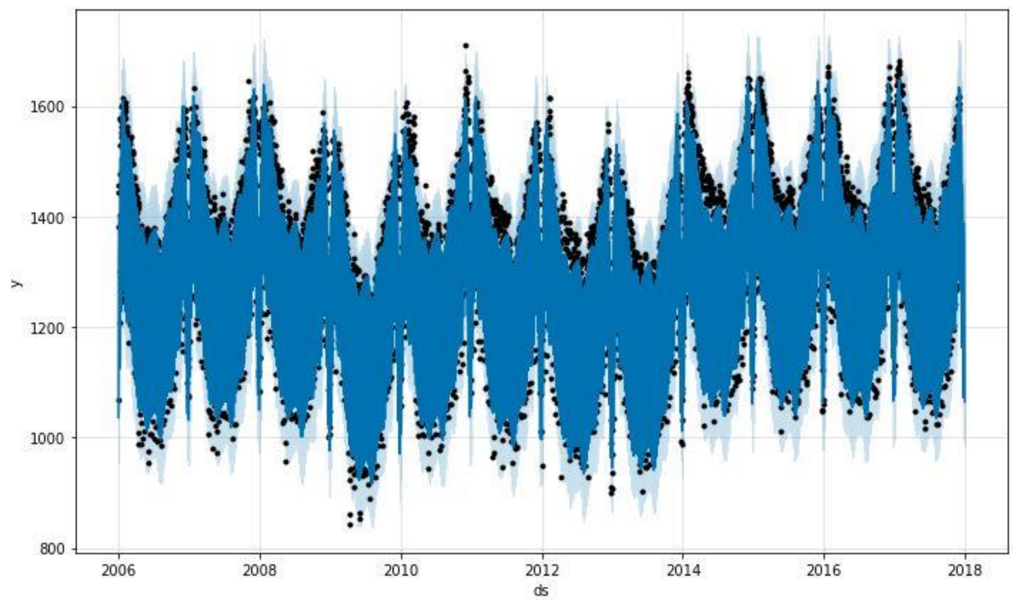

FIGURE 8. Electricity Forecasting Consumption using Prophet Algorithm

	ds	yhat	yhat_lower	yhat_upper
4353	2017-12-02	1408.696760	1324.367466	1489.986719
4354	2017-12-03	1311.189771	1227.785049	1389.035827
4355	2017-12-04	1596.631743	1515.628151	1676.703020
4356	2017-12-05	1631.873949	1546.545275	1711.282974
4357	2017-12-06	1632.057664	1552.246848	1713.403115
4358	2017-12-07	1612.932882	1534.447434	1686.779585
4359	2017-12-08	1578.265990	1494.499660	1652.358419
4360	2017-12-09	1374.218097	1289.336509	1459.996646
4361	2017-12-10	1265.694052	1187.858148	1345.115210
4362	2017-12-11	1540.398051	1457.906410	1624.298938
4363	2017-12-12	1565.398845	1487.300113	1649.818034
4364	2017-12-13	1556.051209	1474.819833	1637.607600
4365	2017-12-14	1528.309835	1447.669344	1606.606735
4366	2017-12-15	1486.132315	1405.418942	1565.304408
4367	2017-12-16	1275.852999	1200.000435	1356.167834
4368	2017-12-17	1162.527884	1083.744201	1240.626557
4369	2017-12-18	1433.986555	1354.705673	1514.169880
4370	2017-12-19	1457.394238	1372.161929	1534.697054
4371	2017-12-20	1448.170753	1367.876370	1529.424630
4372	2017-12-21	1422.302570	1336.163106	1504.809813
4373	2017-12-22	1383.744684	1300.545605	1467.942087
4374	2017-12-23	1178.794140	1098.922658	1251.562551
4375	2017-12-24	1072.435360	996.089147	1152.790372
4376	2017-12-25	1352.393307	1274.759915	1432.376419
4377	2017-12-26	1385.697504	1309.137885	1464.914839
4378	2017-12-27	1387.603669	1308.500026	1469.096578
4379	2017-12-28	1373.909097	1297.887283	1453.897223
4380	2017-12-29	1348.358439	1265.860643	1429.879020
4381	2017-12-30	1157.021610	1078.040494	1240.665629
4382	2017-12-31	1064.643890	985.061370	1147.050906

TABLE 2. Predicted last 30 days of Electricity Consumption using Prophet Algorithm

	Consumption
Date	
2017-12-02	1391.85405
2017-12-03	1330.26226
2017-12-04	1620.97758
2017-12-05	1643.72307
2017-12-06	1639.08265
2017-12-07	1628.47979
2017-12-08	1618.05658
2017-12-09	1415.34531
2017-12-10	1318.10964
2017-12-11	1614.15862
2017-12-12	1647.36346
2017-12-13	1651.90418
2017-12-14	1636.54375
2017-12-15	1576.93197
2017-12-16	1382.87708
2017-12-17	1297.21916
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2017-12-26	1130.11683
2017-12-27	1263.94091
2017-12-28	1299.86398
2017-12-29	1295.08753
2017-12-30	1215.44897
2017-12-31	1107.11488

TABLE 3. Actual data last 30 days of Electricity Consumption

	horizon	mse	rmse	mae	mape	mdape	coverage
0	37 days	7061.739536	84.034157	54.766619	0.043344	0.026494	0.809994
1	38 days	7023.179836	83.804414	54.905566	0.043382	0.027117	0.805484
2	39 days	6859.391209	82.821442	55.001301	0.043199	0.027595	0.800853
3	40 days	6607.008599	81.283508	54.746863	0.042635	0.027678	0.797319
4	41 days	6461.878415	80.385810	54.620158	0.042266	0.027798	0.792687

FIGURE 9. Mean Absolute Error (MAE) using prophet algorithm

The final result of the estimation of electrical energy consumption using the prophet algorithm produces predictions that are close to the actual data as shown in FIGURE 8. In TABLE 2, it is shown that there is an upper limit and a lower limit to show that the consumption prediction results have a predetermined limit. In TABLE 3 explaining the original data used in this study as a comparison for the results in TABLE 2, with the existing results in FIGURE 9, it appears that the prediction results in TABLE 2 get results that are close to the original data in TABLE 3 with a Mean Absolute Error value. (MAE) which reached 54.62.

4.3 Comparison

	Consumption	Predictions
Date		
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FIGURE 12. LSTM Predictions

	ds	yhat	yhat_lower	yhat_upper
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4356	2017-12-05	1631.873949	1546.545275	1711.282974
4357	2017-12-06	1632.057664	1552.246848	1713.403115
4358	2017-12-07	1612.932882	1534.447434	1686.779585
4359	2017-12-08	1578.265990	1494.499660	1652.358419
4360	2017-12-09	1374.218097	1289.336509	1459.996646
4361	2017-12-10	1265.694052	1187.858148	1345.115210
4362	2017-12-11	1540.398051	1457.906410	1624.298938
4363	2017-12-12	1565.398845	1487.300113	1649.818034
4364	2017-12-13	1556.051209	1474.819833	1637.607600
4365	2017-12-14	1528.309835	1447.669344	1606.606735
4366	2017-12-15	1486.132315	1405.418942	1565.304408
4367	2017-12-16	1275.852999	1200.000435	1356.167834
4368	2017-12-17	1162.527884	1083.744201	1240.626557
4369	2017-12-18	1433.986555	1354.705673	1514.169880
4370	2017-12-19	1457.394238	1372.161929	1534.697054
4371	2017-12-20	1448.170753	1367.876370	1529.424630
4372	2017-12-21	1422.302570	1336.163106	1504.809813
4373	2017-12-22	1383.744684	1300.545605	1467.942087
4374	2017-12-23	1178.794140	1098.922658	1251.562551
4375	2017-12-24	1072.435360	996.089147	1152.790372
4376	2017-12-25	1352.393307	1274.759915	1432.376419
4377	2017-12-26	1385.697504	1309.137885	1464.914839
4378	2017-12-27	1387.603669	1308.500026	1469.096578
4379	2017-12-28	1373.909097	1297.887283	1453.897223
4380	2017-12-29	1348.358439	1265.860643	1429.879020
4381	2017-12-30	1157.021610	1078.040494	1240.665629
4382	2017-12-31	1064.643890	985.061370	1147.050906

FIGURE 13. Prophet Predictions

5. CONCLUSION

This study aims to compare the Deep Learning method using Neural Networks with LSTM and the Prophet algorithm to estimate the use of electrical energy. As a result, prophet obtained a Mean Absolute Error (MAE) value of 54.62 which was smaller than the LSTM's Mean Absolute Error (MAE) of 133,311. The reason is because Prophet is an algorithm developed to analyze time series data, this model also has several parameters such as trend, seasonality, and holidays which are designed for time series data. Meanwhile, LSTM is better used to study data from sequential inputs and models that rely on previous contexts and states.

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