**Building of Informatics, Technology and Science (BITS)**
Volume 4, No 3, Desember 2022 Page: 1671−1678
ISSN 2684-8910 (media cetak)
ISSN 2685-3310 (media online)
DOI 10.47065/bits.v4i3.2690

# Application of Deep Learning LSTM in Online Power Prediction on Three-Phase Power Transformer

**Destra Andika Pratama [1,*], Sinta Nabila[2]**

Study Program Bachelor of Electrical Engineering, Polytechnic State of Sriwijaya, Palembang, Indonesia
Email : [1,*]destra_andika_pratama@polsri.ac.id , [2]sntnblaa@gmail.com
Correspondence Author Email: destra_andika_pratama@polsri.ac.id
Submitted: **06/12/2022**; Accepted: **30/12/2022**; Published**: 30/12/2022**

**Abstract**–Electrical energy plays an important role in daily life, especially companies. The 3 Phase Power Transformer is one of the important electrical components that is very influential in distributing electrical energy to companies as is the case in PT. Semen Baturaja (Persero). 3-phase power transformers require attention because they are one of the components that are prone to interference, this interference can hinder the effectiveness of using electrical energy as a company support for employees to work. As one of the disturbances for 3-phase power transformers is overload or excessive power usage, overload can raise the temperature at the winding and reduce its service life. Artificial intelligence can be one of the keys to predict the use of power transformers in the future, especially deep learning by utilizing the LSTM algorithm. Optimal power prediction requires a lot of maximum input variables so that in this study, it not only adds an offline learning mode but adds a learning mode that can directly access the company's Power Quality Monitoring (PQM) website online with an average accuracy value of 86.62%.

Keywords : Electrical Energy; Power Transformer 3 Phase; Deep Learning; LSTM

## 1. Introduction

The 3-phase power transformer is an important asset of the power grid and monitoring its operating conditions is essential for functional and economic reasons. Regular power monitoring to ensure failures in 3-phase power transformers in the early stages is very important as a protection system because 3-phase power transformers are highly susceptible to interference. Especially overloaded power, in addition to being able to increase the temperature that is in the isolation of a 3-phase power transformer, power overload can reduce the service life of the power transformer. [1][2][3][4][5] 3-phase power transformer in PT. Semen Baturaja (Persero) Tbk Kertapati site has a capacity of 1600KVA with an input voltage of 6KV and an output voltage of 400 volts.

The development of technology plays an important role in all aspects of work. According to Jahromi and R. Piercy in 2019, artificial intelligence technology itself has been widely applied in everyday life such as smart homes, decision support systems, and sensor readings. Without realizing it, information technology is one of the main needs in business development, especially electrical energy that supports the business itself. [6][7][8][9]

Machine learning itself is a branch of artificial intelligence that is useful for predicting power in the future. Machine learning is a branch of evolving computational algorithms designed to mimic human intelligence by learning from the surrounding environment. They are considered working horses in a new era called big data.[10][11][12] In short, machine learning is a field of science that enables a computer program to learn from a set of data

A.A. Ningrum, et al. (A 2021) were able to conduct an analysis to predict the age or feasibility of transformers using the Long Short Term Memory (LSTM) algorithm, but the result of the discussion was a transformer that had not been developed from an IoT perspective, which was the era, and could not be predicted in real time.

LSTM is a Deep Learning algorithm, which is a derivative of machine learning. The LSTM algorithm can be used to predict the use of power consumption to protect the transformer from excess power otherwise known as overload power. [6][13]

Data on Power Quality Monitoring (PQM) in PT. 3-phase power transformer. Semen Baturaja (Persero) Tbk will be inputted and labeled then the data will be trained. The results of the training data will produce a prediction which is then tested first for its suitability with the desired results, if appropriate, it will produce outputs and outputs need to be retested and adjusted through test data so that the output results are more accurate. [14] [15][16]

## 2. Research Methodology

### 2.1 LSTM (Long Short Term Memory)

A Long Short Term Memory Network (LSTM) is a modified version of a recurrent neural network or RNN. There are many changes to the RNN, but LSTM is one of the most popular. LSTM is here to complement the shortcomings of RNN. It cannot predict words based on historical information stored for a long period of time. [17]
Therefore, LSTM can remember long-term stored aggregated information and remove irrelevant information. LSTM is more efficient when processing, predicting, and classifying data based on specific time series.

**Building of Informatics, Technology and Science (BITS)**
Volume 4, No 3, Desember 2022 Page: 1671−1678
ISSN 2684-8910 (media cetak)
ISSN 2685-3310 (media online)
DOI 10.47065/bits.v4i3.2690

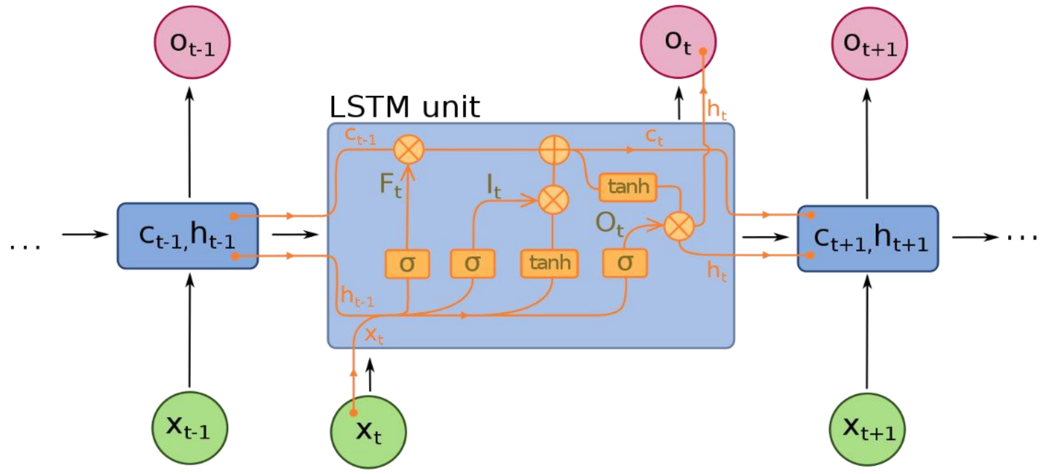


**Figure 1.** LSTM Model

LSTM contains information from the context inside the gate cell. Cells control the write, storage, read, and deletion of data using forget gates, inputs, and outputs implemented by multiplication of elements by sigmoid. Forget The gate studies weights that control the decay rate of values stored in memory cells. [18]
For example, if the input and output gates are off and there is no rollover caused by the forget gate, the memory cell will retain its value over time, so the slope of the error will remain constant as long as the backward propagation increases. This allows the model to remember information longer. Mathematically, each step can be described as:
In the first step, the forget gate layer sees 1 and new inputs to decide which features to remove from the cell state.

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f) \quad (1)$$

In the second step, the decision on what information is stored in the state of the cell is made in two steps. The output gate layer, which is a sigmoid layer, specifies the value to be updated. Then the light brown layer creates a new candidate value vector.

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \quad (2)$$

$$C_t = tanh(W_c[h_{t-1}, x_t] + b_c \quad (3)$$

The old cell state Ct−1 is updated to the new cell Ct summing the output of the forget gate layer functions ft and it × C̃t.

$$c_t = f_t\, X\, c_{t-1} + i_t\, X\, c_t \quad (4)$$

The output is specified in two steps – First, the sigmoid layer decides the parts of the cell to be ejected. The product of the new cell state Ct through tan h and the output from the sigmoid gate produces a selectively defined h t part.

$$C_o = tanh(W_o[h_{t-1}, x_t] + b_o \quad (5)$$

$$h_t = o_t\, X\, tanh\,(c_t) \quad (6)$$

Tuning and optimization of hyperparameters is a difficult and experimental task. LSTM model training is expensive in terms of memory and computing power.

### 2.2 Stages of Research

From the *flowchart* in Figure 2.2 under. The first step is *Data Collection*. The data is a collection of PQM variables in PT. Semen Baturaja (Persero) Tbk. Then these variables are processed so that which variables are selected which influence the prediction of power will later be carried out. Then the dataset is divided into two, namely *Data Train* and *Data Test*. Data Train will train the dataset using the LSTM algorithm and the Data *Test* plays a role in testing the training results that have been carried out by the *Data Train* so that the output results can be in the form of a test score, train score, graph, and *loss* value per *epoch*.

**Building of Informatics, Technology and Science (BITS)**
Volume 4, No 3, Desember 2022 Page: 1671−1678
ISSN 2684-8910 (media cetak)
ISSN 2685-3310 (media online)
DOI 10.47065/bits.v4i3.2690

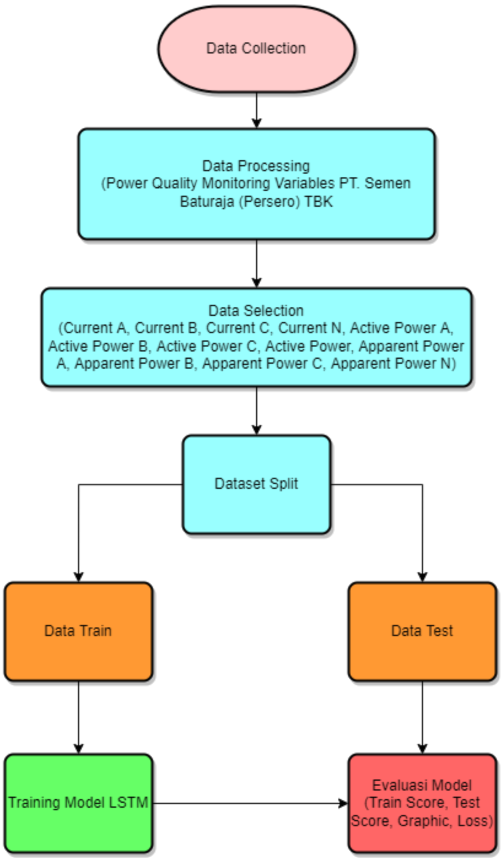


**Figure 2.** Research Stages

### 2.3 Observed variables

Variabel yang diamati adalah data monitoring pada power transformer 3 fasa, baik fitur Current A (A), Current B (A), Current C (A), Current N (A), Active Power A (W), Active Power B (W), Active Power C (W), Active Power (W), Apparent Power A (VA), Apparent Power B (VA), Apparent Power C (VA), Apparent Power (VA), Active energy delivered (Wh), Active energy received (Wh), Active energy delivered + received (Wh), Demand Current Avg (A), Demand Active Power (W), Demand Apparent Power (VA).

## 3. Results and Discussion

To make predictions in *real time*, you need *pseudocode* as stated in table 3.1 below:

**Table 1.** *Pseudocode* Power Prediction in *Realtime* through the *Company's website*

| Order | Process |
|---|---|
| **Step-1** | Preparing the *scaler* |
| **Step-2** | Fixing random seeds to increase productivity |
| **Step-3** | Enter the monitoring dataset and enter the company website URL |
| **Step-4** | Enter the variable you want to predict |
| **Step-5** | Entering the LSTM algorithm and making predictions |
| **Step-6** | Print prediction results |

Before entering the dataset in the algorithm that has been prepared, it's a good idea to prepare the *scaler* first, *scaling* aims to make the numerical data on the dataset have the same range of values (*scale*). There is no longer one data variable dominating the other data variables and then proceeds to fix random seeds to increase predictive productivity. [19][20]

### 3.1 *Realtime* VS Actual Active *Power* A Prediction Results

Ayu Ahadi Ningrum, et al with their scientific journal entitled "Deep Learning Algorithm-LSTM to Predict Transformer Age", *Deep Learning* Algorithm-LSTM using parameters namely *activation* = *linear*, *epoch* = 50, *batch_size* = 64, *verbose* = 2, *optimizer* = Adam, *hidden layer* = 2 and *learning rate* = 0.1 has better performance than 3 other algorithms RMSE value = 0.0004 and *Squared Correlation* value = 0.9690. The results of the discussion

**Building of Informatics, Technology and Science (BITS)**
Volume 4, No 3, Desember 2022 Page: 1671−1678
ISSN 2684-8910 (media cetak)
ISSN 2685-3310 (media online)
DOI 10.47065/bits.v4i3.2690

have not been developed on the basis of IoT (*Internet of Things*) so that they cannot predict the age of *power transformers* in *real time*.

Fausto Valencia, et al with their scientific journal entitled "Comparison of *Machine Learning Algorithms for the Prediction of Mechanical Stress in Three-Phase Power Transformer Winding Conductors*", succeeded in predicting mechanical pressure on 3-phase transformers comparing 4 methods and succeeded in proving that mechanical pressure on 3-phase transformers affects workload to their service life. However, the results of the discussion in this study only compare between four analytical methods in *machine learning*, namely linear regression, *support vector regression, random forests*, and *artificial neural networks* have not yet obtained the best prediction results on mechanical pressure in 3-phase power transformers.

After entering the scenario listed in table 3.1 above, the following is the result of prediction data carried out in *real time* and *online* on *active power* A which will later be compared with the actual result. The prediction is to predict the amount of power on active power A for an hour to come.

**Table 2.** Actual VS Prediction Results using LSTM *Active Power* A

| Jam | Prediction (W) | Jam | Actual (W) | Difference(W) |
|---|---|---|---|---|
| 13.00 | 65318,90 | 14.00 | 66424,40 | 1105,49 |
| 14.00 | 61948,63 | 15.00 | 64545,88 | 2597,25 |
| 15.00 | 61416,29 | 16.00 | 60916,06 | 500,23 |
| 16.00 | 61123,64 | 17.00 | 62941,63 | 1817,99 |
| 17.00 | 58798,93 | 18.00 | 57756,01 | 1042,92 |
| 18.00 | 51238,56 | 19.00 | 41694,11 | 9544,45 |

The value of the difference in power prediction on *active power* A between 13.00 – 14.00 is 1105.49. At 14.00 – 15.00 there was a difference of 2597.25. At 15.00 – 16.00 experienced a decrease in the prediction of power returning with a difference of 500.23. At 16.00 – 17.00 the actual result of power increased from the predicted result with a difference of 1817.99. At 17.00 – 18.00 the predicted result was greater than the actual result with a difference of 1042.92. And the last one, at 18.00 – 19.00 gets a power difference of 9544.45.

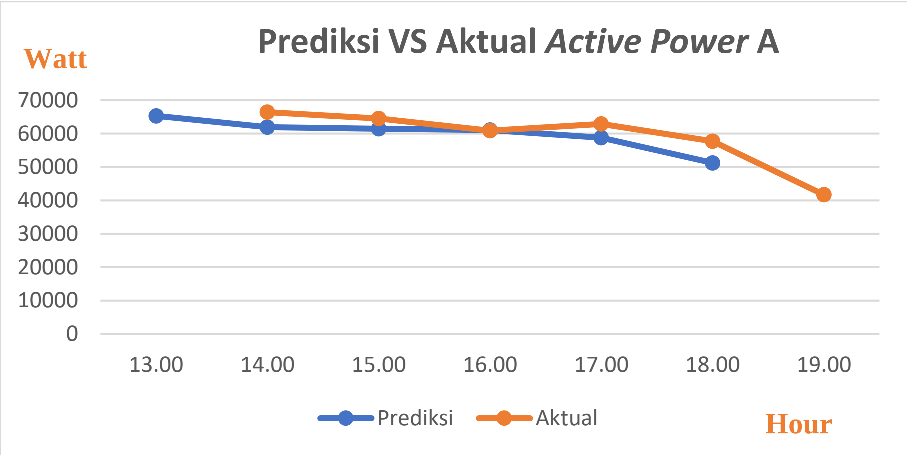


**Figure 3.** Prediction Chart VS Actual Active *Power* A

The following are the accuracy test results obtained by the difference in predictions and actuals that have been listed in table 2.

$$Akurasi = 100\ \% - \left( \frac{\frac{nilai\ selisih\ per-jam}{nilai\ aktual}\ x\ 100\%}{jumlah\ data} \right)$$

$$= 100\ \% - \left( \frac{1{,}6642 + 4{,}0238 + 0{,}8211 + 2{,}8883 + 1{,}8057 + 22{,}8916}{6} \right)$$

Accuracy = 100 % - 12.28 % = 87.72 %

The accuracy of *online* predictions on *active power* A reached 87.72%, which is certainly a good result because it exceeds 50% of the expected results.

### 3.2 *Realtime* VS Actual Active *Power* B Prediction Results

The value of the difference in power prediction on *active power* A between 13.00 – 14.00 is 26.01. At 14.00 – 15.00 there was a difference of 1826.45. At 15.00 – 16.00 experienced a decrease in the prediction of power returning with a difference of 1871.31. At 16.00 – 17.00 the actual result of power decreased from the predicted result with a

**Building of Informatics, Technology and Science (BITS)**
Volume 4, No 3, Desember 2022 Page: 1671−1678
ISSN 2684-8910 (media cetak)
ISSN 2685-3310 (media online)
DOI 10.47065/bits.v4i3.2690

difference of 3785.13. At 17.00 – 18.00 the predicted result was greater than the actual result with a difference of 1301.94. And finally, at 18.00 – 19.00 get a power difference that increases to 6674.48.

**Table 3.** Prediction Results VS Actual using LSTM *Active Power* B

| Jam | Prediction(W) | Jam | Actual(W) | Difference(W) |
|---|---|---|---|---|
| 13.00 | 48173,56 | 14.00 | 48147,55 | 26,01 |
| 14.00 | 45431,47 | 15.00 | 47257,92 | 1826,45 |
| 15.00 | 45503,22 | 16.00 | 47374,53 | 1871,31 |
| 16.00 | 45270,55 | 17.00 | 41485,42 | 3785,13 |
| 17.00 | 41614,03 | 18.00 | 40312,09 | 1301,94 |
| 18.00 | 39261,73 | 19.00 | 32587,25 | 6674,48 |

The following are the accuracy test results obtained by the difference in predictions and actuals that have been listed in table 3.3.

$$Akurasi \; = \; 100\ \% \; - \left( \frac{\frac{nilai\ selisih\ per - jam}{nilai\ aktual}\ x\ 100\%}{jumlah\ data} \right)$$

$$= \; 100\ \% \; - \left( \frac{0{,}0540 + \ 3{,}8648 + \ 3{,}9501 \ + \ 9{,}1240 + 3{,}2296 + \ 20{,}4818}{6} \right)$$

Accuracy = 100 % - 10.27 % = 89.73%

The accuracy of *online* predictions on active power B reached 89.27%, which is even better than the previous predictions of *active power* A.

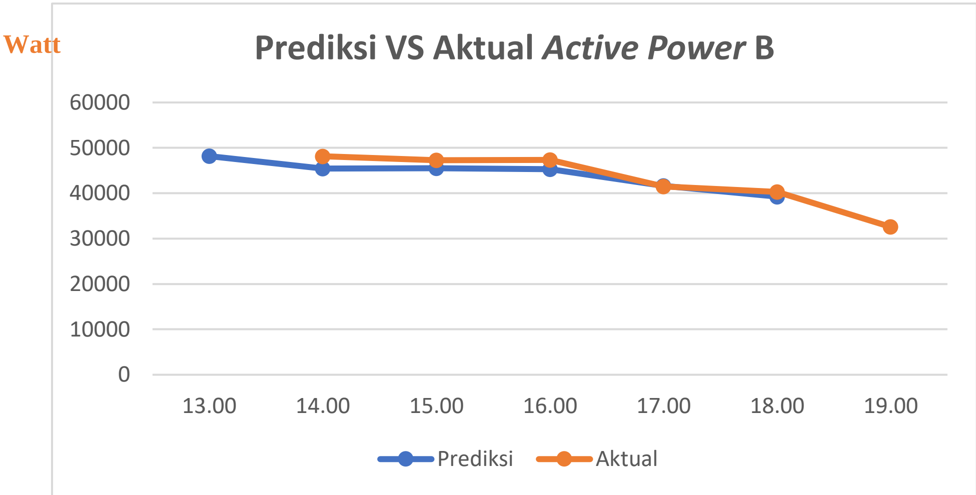


**Figure 4.** Prediction Graph VS Actual Active *Power* B

### 3.3 *Realtime* VS Actual Active *Power* C Prediction Results

The value of the difference in power prediction on *active power* A between 13.00 – 14.00 is 3770.16. At 14.00 – 15.00 there was a difference of 3011.98. At 15.00 – 16.00 experienced a decrease in the prediction of power returning with a difference of 1641.46. At 16.00 – 17.00 the actual result of power decreased from the predicted result with a difference of 7987.11. At 17.00 – 18.00 the predicted result was greater than the actual result with a difference of 2528.02. And finally, at 18.00 – 19.00 get a power difference that increases to 6012.18.

**Table 4.** Actual VS Prediction Results using LSTM *Active Power* C

| Jam | Prediction(W) | Jam | Actual(W) | Difference(W) |
|---|---|---|---|---|
| 13.00 | 52356,78 | 14.00 | 56126,94 | 3770,16 |
| 14.00 | 50782,47 | 15.00 | 53794,45 | 3011,98 |
| 15.00 | 51216,02 | 16.00 | 49574,55 | 1641,46 |
| 16.00 | 49673,66 | 17.00 | 41686,55 | 7987,11 |
| 17.00 | 41582,93 | 18.00 | 39054,91 | 2528,02 |
| 18.00 | 36208,66 | 19.00 | 30196,48 | 6012,18 |

The following are the accuracy test results obtained by the difference in predictions and actuals that have been listed in table 4. 4.

**Building of Informatics, Technology and Science (BITS)**
Volume 4, No 3, Desember 2022 Page: 1671−1678
ISSN 2684-8910 (media cetak)
ISSN 2685-3310 (media online)
DOI 10.47065/bits.v4i3.2690

$$Akurasi = 100\,\% - \left( \frac{\frac{nilai\ selisih\ per - jam}{nilai\ aktual}\ x\ 100\%}{jumlah\ data} \right)$$

$$Akurasi = 100\,\% - \left( \frac{6{,}7172 + 5{,}5991 + 3{,}3111 + 19{,}1599 + 6{,}4729 + 19{,}9102}{6} \right)$$

Accuracy = 100 % - 13.31% = 86.69%

The accuracy of *online* predictions on *active power* C reached 86.69%, where this result is already good because it remains consistently exceeding the 80% mark.

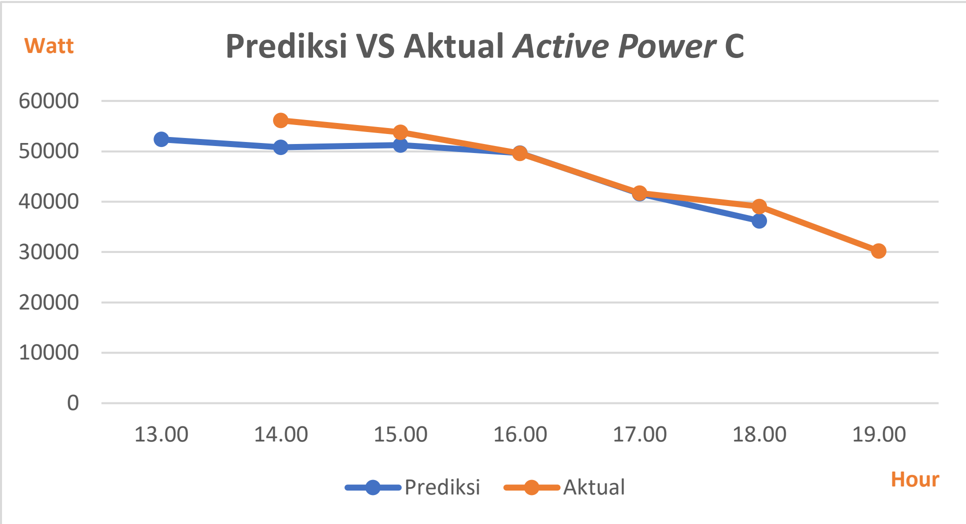


**Figure 5.** Prediction Graph VS Actual Active *Power* B

### 3.4 *Realtime* VS Actual Active *Power* Prediction Results

The value of the difference in power prediction on *active power* A between 13.00 – 14.00 is 14048.64. At 14.00 – 15.00 there was a difference of 9673.39. At 15.00 – 16.00 experienced a decrease in the prediction of power returning with a difference of 12426.82. At 16.00 – 17.00 the actual power result decreases from the predicted result with a difference of 10120.21. At 17.00 – 18.00 the predicted result was greater than the actual result with a difference of 9506.51. And finally, at 18.00 – 19.00 get a power difference that increases to 26097.31.

**Table 6.** Prediction VS Actual Results using LSTM *Active Power*

| Jam | Prediction(W) | Jam | Actual(W) | Difference(W) |
|---|---|---|---|---|
| 13.00 | 161822,89 | 14.00 | 175871,53 | 14048,64 |
| 14.00 | 159661,63 | 15.00 | 169335,03 | 9673,39 |
| 15.00 | 159820,23 | 16.00 | 172247,05 | 12426,82 |
| 16.00 | 154294,92 | 17.00 | 144174,71 | 10120,21 |
| 17.00 | 140021,83 | 18.00 | 130515,31 | 9506,51 |
| 18.00 | 121609,92 | 19.00 | 95512,61 | 26097,31 |

The following are the accuracy test results obtained by the difference in predictions and actuals that have been listed in table 3.5.

$$Akurasi = 100\,\% - \left( \frac{\frac{nilai\ selisih\ per - jam}{nilai\ aktual}\ x\ 100\%}{jumlah\ data} \right)$$

$$Akurasi = 100\,\% - \left( \frac{7{,}9881 + 5{,}7125 + 7{,}2145 + 7{,}0194 + 7{,}2838 + 27{,}3234}{6} \right)$$

Accuracy = 100 % - 17.66% = 82.34%

The accuracy of *online* predictions on *active power* reached 82.34%, where this result is already good because it remains consistently exceeding the 80% mark.

**Building of Informatics, Technology and Science (BITS)**
Volume 4, No 3, Desember 2022 Page: 1671−1678
ISSN 2684-8910 (media cetak)
ISSN 2685-3310 (media online)
DOI 10.47065/bits.v4i3.2690

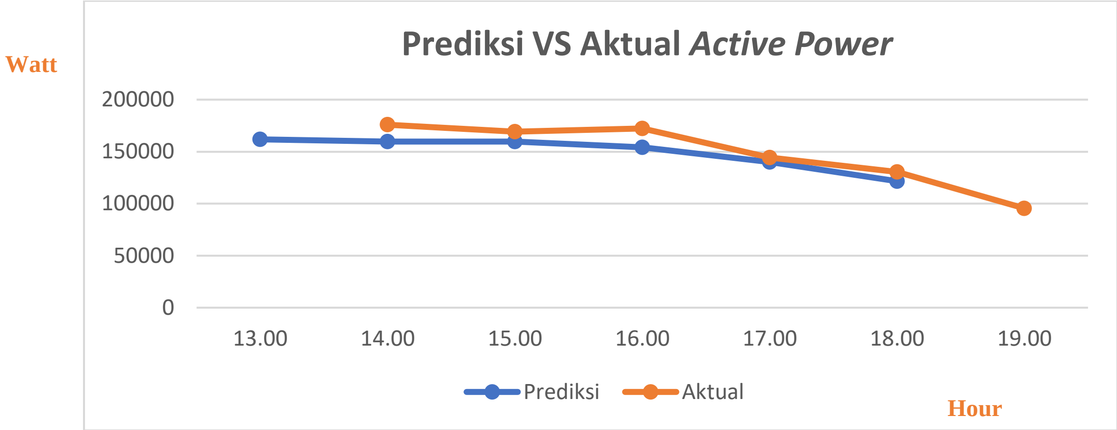


**Figure 6.** Prediction Graph VS Actual *Active Power*

From the results of the four online predictions that have been carried out on the actual results, the results of *online* predictions are more optimal than predictions that are only carried out *offline*, as for the thing that affects it, it is a double *dataset* consisting of *training* and *testing monitoring* data for 6 months and *realtime* data which is accessed directly through the company's *website*.

## 4. Conclusion

The software studied in this study obtained satisfactory results on the dataset derived from 6 months monitoring data on *Power Quality Monitoring* (PQM) at PT. Semen Baturaja (Persero) Tbk. after being re-observed, features were re-selected that are relevant to the prediction of power in 3-phase *power transformers* into: *Current*, *Apparent* Power, and *Active Power*. 3.Online prediction results get satisfactory results with average accuracy = 86.62% this is because the dataset consists of monitoring data for 6 months and main data that is connected to the company's website directly.

## REFERENCES

[1] R. S. De Andrade Ferreira, P. Picher, H. Ezzaidi, and I. Fofana, “Frequency Response Analysis Interpretation Using Numerical Indices and Machine Learning: A Case Study Based on a Laboratory Model,” IEEE Access, vol. 9, pp. 67051–67063, 2021, doi: 10.1109/ACCESS.2021.3076154.
[2] I. Soedibyo and M. Mt, “Evaluasi Penentuan Kelayakan Minyak Transformator Daya Berdasarkan Metode Interval Fuzzy Type 2 B-115 B-116,” vol. 7, pp. 115–120, 2015.
[3] Z. Kazemi, F. Naseri, M. Yazdi, and E. Farjah, “An EKF-SVM machine learning-based approach for fault detection and classification in three-phase power transformers,” IET Sci. Meas. Technol., vol. 15, no. 2, pp. 130–142, 2021, doi: 10.1049/smt2.12015.
[4] C. Zhang, Y. He, B. Du, L. Yuan, B. Li, and S. Jiang, “Transformer fault diagnosis method using IoT based monitoring system and ensemble machine learning,” Futur. Gener. Comput. Syst., vol. 108, pp. 533–545, 2020, doi: 10.1016/j.future.2020.03.008.
[5] R. B. ROSLI, “Parameter Identification for Fault Detection of Power,” 2015.
[6] A. A. Ningrum, I. Syarif, A. I. Gunawan, E. Satriyanto, and R. Muchtar, “Algoritma Deep Learning-LSTM untuk Memprediksi Umur Transformator,” J. Teknol. Inf. dan Ilmu Komput., vol. 8, no. 3, p. 539, 2021, doi: 10.25126/jtiik.2021834587.
[7] R. Soni and K. Chaudhari, “An approach to diagnose incipient faults of power transformer using dissolved gas analysis of mineral oil by ratio methods using fuzzy logic,” Int. Conf. Signal Process. Commun. Power Embed. Syst. SCOPES 2016 - Proc., pp. 1894–1899, 2017, doi: 10.1109/SCOPES.2016.7955775.
[8] A. Tavakoli, L. de Maria, B. Valecillos, D. Bartalesi, S. Garatti, and S. Bittanti, “A Machine Learning approach to fault detection in transformers by using vibration data,” IFAC-PapersOnLine, vol. 53, no. 2, pp. 13656–13661, 2020, doi: 10.1016/j.ifacol.2020.12.866.
[9] M. I. Dahlan, “Analisa Respon Tegangan Uji Surja,” 2017.
[10] I. El Naqa and M. J. Murphy, “What Is Machine Learning ?,” pp. 3–11, doi: 10.1007/978-3-319-18305-3.
[11] M. Ukkelberg, “Utilisation of Machine Learning in Power Transformer Asset Management,” no. June, 2018.
[12] “Project Report On Condition Monitoring of Distribution Transformer Using Machine Learning Submitted in partial fulfilment of the requirement for the award of the Degree of BACHELOR OF TECHONOLOGY In ELECTRICAL ENGINEERING By AHMAD HASAN ( 1615105001 ) AJI,” no. 1615105002.
[13] L. Malviya, J. Shreemali, R. Ojha, P. Chakrabarti, and S. Poddar, “Transformer prediction in the supply chain using machine learning,” Mater. Today Proc., no. xxxx, 2021, doi: 10.1016/j.matpr.2020.12.625.
[14] F. Valencia, H. Arcos, and F. Quilumba, “Comparison of Machine Learning Algorithms for the Prediction of Mechanical Stress in Three-Phase Power Transformer Winding Conductors,” J. Electr. Comput. Eng., vol. 2021, 2021, doi: 10.1155/2021/4657696.
[15] K. Mahmudah et al., “Pengembangan Sistem Informasi Dissolved Gas Analysis ( Dga ),” vol. 12, pp. 54–59, 2016.
[16] S. . Arismunandar, Artono M.A, Teknik Tenaga Listrik Jilid III, no. 0806365412. 2004.

**Building of Informatics, Technology and Science (BITS)**
Volume 4, No 3, Desember 2022 Page: 1671−1678
ISSN 2684-8910 (media cetak)
ISSN 2685-3310 (media online)
DOI 10.47065/bits.v4i3.2690

[17] Y. Sun, X. Wang, and J. Yang, “Modified Particle Swarm Optimization with Attention-Based LSTM for Wind Power Prediction,” Energies, vol. 15, no. 12, 2022, doi: 10.3390/en15124334.
[18] X. Zhang, S. Wang, Y. Jiang, F. Wu, and C. Sun, “Prediction of dissolved gas in power transformer oil based on LSTM-GA,” IOP Conf. Ser. Earth Environ. Sci., vol. 675, no. 1, 2021, doi: 10.1088/1755-1315/675/1/012099.
[19] J. Lin, L. Su, Y. Yan, G. Sheng, D. Xie, and X. Jiang, “Prediction method for power transformer running state based on LSTM-DBN network,” Energies, vol. 11, no. 7, pp. 1–14, 2018, doi: 10.3390/en11071880.
[20] H. Song, J. Dai, L. Luo, G. Sheng, and X. Jiang, “Power transformer operating state prediction method based on an LSTM network,” Energies, vol. 11, no. 4, 2018, doi: 10.3390/en11040914.