Short-Term Electricity Demand Forecasting Using LSTM and GRU Case Study: High Voltage Consumers PT PLN (Persero) West Java

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***Abstract*— This study aims to predict short-term electricity demand for high-voltage consumers (KTT) at PT PLN (Persero) West Java Distribution Main Unit using the Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) models. Accurate prediction is very important for PT PLN to manage electricity supply efficiently and anticipate demand fluctuations. In this study, historical data of daily electricity consumption is used to train and test the prediction model. The data was processed through preprocessing techniques, including outlier removal using the Interquartile Range (IQR) method and normalization using Min-Max Scaler. The data was then grouped by industry type to generate more specific predictions. The LSTM and GRU models were tested with various combinations of epoch and batch size parameters to evaluate their performance. The test results show that LSTM provides good prediction results on customer data from all industries, cement industry, and transportation industry, while GRU shows better results on tire, paper, metal, automotive, and textile industry customer data. Model evaluation is performed using Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) metrics.**

Keywords— Deep Learning, Long Short-Term Memory, Generated Recurrent Unit

I. INTRODUCTION (*HEADING 1*)

Based on the final energy demand analysis using the Low Emission Analysis Platform (LEAP) conducted by (National Energy Council, 2023), it is stated that the total electricity demand from 313 TWh in 2022 is projected to increase to 479 TWh in 2033, equivalent to a Year on Year growth of 3.46%. PT Perusahaan Listrik Negara (PLN) (Persero) as the electricity provider in Indonesia, needs to predict short-term electricity demand to be able to prepare for the projected increase that has been carried out by the National Energy Council. Short-term electricity demand prediction is also important for building strategies to cope with demand variations and adjusting generation supply to meet demand over time [1]. Short-term electricity demand prediction can begin with the prediction of electricity demand from industrial consumers. This is because based on the PLN Sales Report, industrial consumers have contributed 29% of electricity sales in 2023, followed by business consumers by 20%. The majority of electricity sales from industrial consumers come from High Voltage Consumers (KTT), PLN consumers with contract power greater than or equal to 30 Mega Volt Ampere (MVA). So that the prediction of short-term electricity demand for KTT needs to be done by PLN.

PLN is faced with challenges in predicting short-term electricity demand, these challenges are also conveyed by [2] in their research, which includes modelling nonlinear electricity demand patterns and handling long-term historical dependencies. Modelling nonlinear electricity demand patterns is analysing measurable and predictable factors, such as weather conditions, geographic differences, and seasonal changes, to form a linear regression model that can project expected electricity demand [3]. Long-term historical dependence, on the other hand, refers to patterns that continue beyond a season, day, or interval, as seen in electricity demand forecasting [2]. Both challenges are prioritized by PLN to be addressed immediately so that short-term electricity demand prediction can be done.

Machine Learning (ML) models for short-term electricity demand prediction are unable to overcome these challenges. Therefore, the use of Deep Learning (DL) is necessary, as DL models based on Recurrent Neural Networks (RNN) show the highest accuracy in short-term electricity demand forecasting compared to statistical and ML models (Morales-Mareco et al., 2023). Time-series forecasting methods such as Long Short-Term Memory (LSTM) and Gate Recurrent Unit (GRU) with multi-sequence time lags achieve higher performance in electricity demand prediction by capturing important characteristics of complex time series, such as periodicity, from multiple time-scale series [4]. Both the LSTM and GRU models have good accuracy values for predicting the short-term electricity demand of KTT PLN.

The research addresses the following questions: 1) How to develop LSTM and GRU models to help predict the short-term electricity demand of KTT PLN?

This research will focus on the prediction of electricity for Industrial High Voltage Consumers (KTT). The data used in this research is historical data of PLN's customer electricity daily consumption. This research uses the LSTM and GRU models. Evaluation of model performance will be carried out using standard matrices, such as Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE). This study will not consider external factors that may affect electricity demand, such as weather, time of day, special events.

The purpose of this research is to build a prediction model as a solution to the challenges in modelling the short-term electricity demand pattern of KTT PLN. While the benefits of this research are to improve PLN's operational efficiency with more accurate energy supply planning and reduce the risk of power supply shortages with increased accuracy in predicting summit energy consumption.

II. LITERATURE REVIEW

A. Deep Learning (DL)

DL is a subset of machine learning that uses multiple levels of representation to automatically discover complex functions in high-dimensional data [5]. DL has a role in fields such as cancer diagnosis, precision medicine, driverless cars, predictive forecasting, and speech recognition due to its scalability, efficiency, and ability to overcome the limitations of previous shallow networks [6]. DL is a subset of ML and a branch of Artificial Intelligence (AI), which utilizes perceptron, neuron, or back propagation methods that can overcome the complexity of high-dimensional data and the limitations of previous shallow networks.

B. Recurrent Neural Network (RNN)

RNNs are commonly used in time-series prediction problems by taking a series of inputs and generating a series of output values as well, so they are particularly useful for applications that require sequential processing of input data according to the time phase [6]. RNNs process a sequence or time series of incoming data with individual vectors at each step, keeping the information recorded at the time the previous steps are hidden. RNNs are a subset of DLs that focus on processing sequential data. RNNs also capture dynamic temporal behavior and dependencies over time.

C. Long Short-Term Memory (LSTM)

LSTM is a type of RNN that has a gate mechanism to learn long-term dependencies [7]. LSTM has three gates on the neuron namely forget gate, input gate, and output gate. Forget gate is used to control the reception of historical information, input gate is in charge of regulating the entry of new information, and output gate controls the extent to which the current state of the unit is filtered [8]. The gate mechanism also mitigates bursting and missing gradients when learning long-term dependencies, and can be improved by incorporating information from internal cell states [9]. LSTM mitigates exploding and missing gradients by using Constant Error Carousel (CEC). CEC prevents the problem of error signaling in LSTMs by maintaining errors in each unit cell, where these cells form a recurrent network with input and output gates to form memory cells, as well as recurrent connections that provide feedback with a one time-step lag [10].

D. Gate Recurrent Unit (GRU)

GRU is a variation of RNN that has a similar gating mechanism to LSTM, but has fewer parameters and a simpler structure [11]. The use of fewer parameters makes GRU lighter and faster in the training process. This simple structure helps reduce computational complexity without sacrificing model performance.

GRU only uses two gates, namely the reset gate and the update gate, to overcome the problem of gradient loss and explosion [12]. The reset gate serves to merge the new input with the previous memory. Meanwhile, the update gate determines how much information from the previous memory will be retained to calculate the new state. Reset gate and update gate in the hidden layer make GRU more computationally efficient compared to LSTM [13]. Reset gate helps in combining new information with existing memory. The update gate allows for more effective information modeling, which makes GRU a more optimal choice in some applications.

E. Model Evaluation

i. *Root Mean Square Error*

Root Mean Square Error (RMSE) is a standard statistical metric used to measure model accuracy by calculating the square root of the mean square of the difference between observed and predicted values. RMSE penalizes larger errors more than smaller errors, so it is very sensitive to outliers. This metric is particularly useful when errors follow a normal distribution, as it gives a clear indication of model performance by reflecting the standard deviation of the prediction error [14].

ii. *Mean Absolute Error*

Mean Absolute Error (MAE) is another widely used metric to evaluate model accuracy, calculated as the average of the absolute differences between observed and predicted values. Unlike the RMSE, MAE gives equal weight to all errors, making it less sensitive to outliers. This characteristic makes MAE a preferred metric in scenarios where all errors are considered equally important, such as in some economic and social science models [14].

III. RELATED WORK

The study, conducted by Felix Morales-Mareco and colleagues [15], had the objective of evaluating the effectiveness of different forecasting models in the context of short-term electricity demand. The methodology used included a comparison between statistical models, namely ARIMAX, ML, namely LR and RF, and DL, namely LSTM and GRU. The data used comes from the time-series of electricity demand of the National Interconnected System (SIN) in Paraguay, covering hourly records from 2009 to 2022. The results of this study demonstrate the feasibility of applying DL models, to help stakeholders achieve accurate prediction results.

Previous research by [16] aim to improve the accuracy of short-term electricity consumption predictions at the household level using customized LSTM and GRU models. The methodology applied involved using data from household smart meters to test both models. The data used came from the Waterloo North Hydro portal, a customer portal provided by the utility, which contains the consumption dataset of one of the authors in Canada. The results show that the LSTM model generally provides better results than the GRU model in terms of prediction accuracy. This research discusses how these two models can be integrated into a smart electric grid system to aid load management and demand response.

Research by [17] conducted a study aimed at developing an electricity load prediction model using electricity load data from electricity companies in Palestine. This study used DL algorithms, including LSTM, GRU, and RNN, which were tested and showed that the GRU model provided the best performance with the lowest error rate and R-squared 90.228%. The results of this study are important for power companies to make critical decisions such as the acquisition of electric power and the establishment of transmission and distribution infrastructure.

IV. METHODOLOGY

To overcome the challenges of predicting the short-term electricity consumption of KTT PLN consumers, this research designs the development of LSTM and GRU-based prediction models based on research conducted by [4] as follows:

Fig. 1. Flow of Model Design

A. Dataset

The data used is sourced from Automatic Meter Reading (AMR) of daily industrial customers for the period January 2023 to April 2024. Total instances data is 38,013 with three columns such as Location_Name, Read_Time, kWh_Export_Total. There is no external data that has been used in this research.

B. Preprocessing Data

Data preprocessing is an important step in data analysis to ensure accurate and reliable results. Removing outliers with the Interquartile Range (IQR) method is an effective technique for cleaning data from extreme values that might interfere with the analysis. This process involves calculating the first and third quartile and determining the lower and upper limits to detect and remove outliers from the dataset.

Min-Max Scaler is used to equalize the scale of the various features in the data so that each feature has the same range of values. This method helps machine learning algorithms to work more efficiently and converge faster. By converting the original values to values in the range [0, 1], it ensures that all features contribute proportionally in the machine learning process.

C. Data Split

The data is divided by the historical usage data from January to December 2023 for training and the historical usage data from January to April 2024 for testing. This division should be done to avoid bias in the data distribution that may affect the model evaluation results.

D. Train and Test Model

Training a model involves using training data to learn patterns and adjust parameters to minimize prediction errors. Afterwards, the model is tested with test data to evaluate its performance and ensure generalizability to new data. Testing is important for identifying overfitting or underfitting as well as assessing the model's ability to handle data variability and uncertainty.

LTSM					
A		B		C	
Epoch	Batch Size	Epoch	Batch Size	Epoch	Batch Size
20	1	50	32	100	16
GRU					
A		B		C	
Epoch	Batch Size	Epoch	Batch Size	Epoch	Batch Size
20	1	50	32	100	16

Fig. 2. Testing Scenario

In the context of testing LSTM and GRU models for industrial energy demand prediction, the test scenario was conducted by setting three combinations of epochs and batch sizes for each type of industry. There are seven industry such as tire, paper, metal, automotive, transportation, cement, and textile industries.

V. EXPERIMENTAL RESULTS

A. Experimental Results

The model was evaluated using RMSE and MAE to obtain the accuracy value of the model. LSTM has good results when used in customer data of all industries, cement industry, and transportation industry. While GRU has good results when used in customer data of the tire industry, paper industry, metal industry, automotive industry, and textile industry.

	LTSM						GRU					
1. Semua Industri	Epoch	Batch Size	Epoch	Batch Size	Epoch	Batch Size	Epoch	Batch Size	Epoch	Batch Size	Epoch	Batch Size
	20	1	50	32	100	16	20	1	50	32	100	16
RMSE	**35906538.64**		55115656.53		38613452.78		**39403819.00**		39910058.22		39637762.15	
MAE	**29635842.69**		45360906.35		29735953.08		**30703754.71**		30991149.42		32347367.82	
	LTSM						GRU					
2. Industri Ban	Epoch	Batch Size	Epoch	Batch Size	Epoch	Batch Size	Epoch	Batch Size	Epoch	Batch Size	Epoch	Batch Size
	20	1	50	32	100	16	20	1	50	32	100	16
RMSE	4221333.46		4126365.81		**3872606.07**		4256473.78		4705394.20		**3747699.83**	
MAE	3552284.41		3485286.67		**3113236.95**		3229333.90		3661250.41		**2861488.40**	
	LTSM						GRU					
3. Industri Kertas	Epoch	Batch Size	Epoch	Batch Size	Epoch	Batch Size	Epoch	Batch Size	Epoch	Batch Size	Epoch	Batch Size
	20	1	50	32	100	16	20	1	50	32	100	16
RMSE	**7922178.67**		8170887.63		8916608.73		**7277748.15**		9035976.19		8044704.61	
MAE	**7413111.61**		7659825.39		8450388.45		**6770691.18**		8539458.98		7467713.85	
	LTSM						GRU					
4. Industri Logam	Epoch	Batch Size	Epoch	Batch Size	Epoch	Batch Size	Epoch	Batch Size	Epoch	Batch Size	Epoch	Batch Size
	20	1	50	32	100	16	20	1	50	32	100	16
RMSE	2033262.81		**1850391.39**		1865108.87		1939898.64		1914068.67		**1847638.63**	
MAE	1674364.37		**1484460.66**		1560652.35		1550339.91		1498845.65		**1510947.34**	
	LTSM						GRU					
5. Industri Otomotif	Epoch	Batch Size	Epoch	Batch Size	Epoch	Batch Size	Epoch	Batch Size	Epoch	Batch Size	Epoch	Batch Size
	20	1	50	32	100	16	20	1	50	32	100	16
RMSE	**1476600.82**		1493945.67		1556650.64		**1241235.12**		1413638.56		1263134.21	
MAE	**1184742.77**		1227205.45		1229590.18		**959252.05**		1124354.63		1008504.18	
	LTSM						GRU					
6. Industri Semen	Epoch	Batch Size	Epoch	Batch Size	Epoch	Batch Size	Epoch	Batch Size	Epoch	Batch Size	Epoch	Batch Size
	20	1	50	32	100	16	20	1	50	32	100	16
RMSE	11798916.95		11528347.46		**11420034.55**		12167087.17		11955967.52		**11691853.31**	
MAE	9719106.73		**9369917.83**		9414034.48		9998666.66		**9620885.19**		9634517.86	
	LTSM						GRU					
7. Industri Tekstil	Epoch	Batch Size	Epoch	Batch Size	Epoch	Batch Size	Epoch	Batch Size	Epoch	Batch Size	Epoch	Batch Size
	20	1	50	32	100	16	20	1	50	32	100	16
RMSE	15967276.73		15258942.58		**13956637.03**		17547302.16		16329080.16		**14866971.83**	
MAE	14873647.36		14216302.62		**12652003.44**		16240425.94		15137970.71		**13722072.40**	
	LTSM						GRU					
8. Industri Transportasi	Epoch	Batch Size	Epoch	Batch Size	Epoch	Batch Size	Epoch	Batch Size	Epoch	Batch Size	Epoch	Batch Size
	20	1	50	32	100	16	20	1	50	32	100	16
RMSE	9595.60		9589.05		**9436.75**		9898.45		9730.19		**9595.60**	
MAE	8524.24		8539.43		**8359.09**		8945.09		8680.31		**8524.24**	

Fig. 3. Testing Result of RMSE and MAE

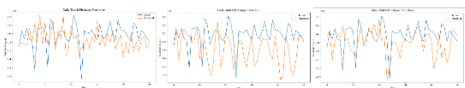

Fig. 4. LSTM A, B, C All Industry

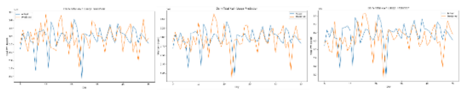

Fig. 5. GRU A, B, C All Industry

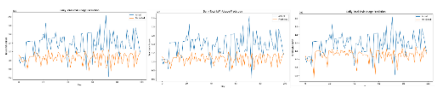

Fig. 6. LSTM A, B, C Tire Industry

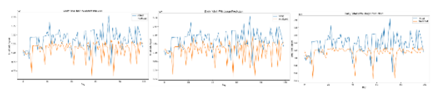

Fig. 7. GRU A, B, C Tire Industry

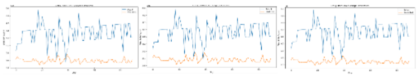

Fig. 8. LSTM A, B, C Paper Industry

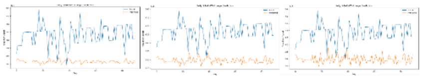

Fig. 9. GRU A, B, C Paper Industry

Fig. 10. LSTM A, B, C Metal Industry

Fig. 11. GRU A, B, C Metal Industry

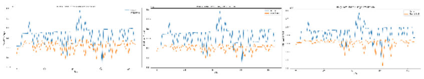

Fig. 12. LSTM A, B, C Automotive Industry

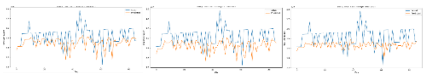

Fig. 13. GRU A, B, C Automotive Industry

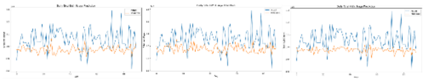

Fig. 14. LSTM A, B, C Cement Industry

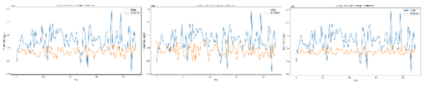

Fig. 15. GRU A, B, C Cement Industry

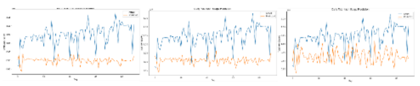

Fig. 16. LSTM A, B, C Textile Industry

Fig. 17. GRU A, B, C Textile Industry

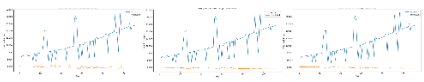

Fig. 18. LSTM A, B, C Transportation Industry

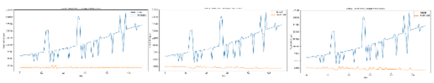

Fig. 18. GRU A, B, C Transportation Industry

B. *Evaluation and Analysis*

From the visualization, it can be seen that the transportation industry and the paper industry have different patterns of real and estimated usage. There is a significant difference in the pattern between the real and predicted usage values. This may be due to industry-specific factors that are not captured by the model. Visualizations for the textile, cement, automotive, metal, tire, and all industries have similar patterns, although the values are significantly different.

Overall, both LSTM and GRU have their own advantages and disadvantages that should be considered when choosing a model for electricity demand prediction in a particular industry. LSTM is more suitable for data with very complex patterns, but requires more careful parameter tuning. GRU, with its better stability, can be a more reliable choice in situations where precise parameter tuning is difficult or the data has simpler patterns.

To ensure the model works well not only on the training data but also on the validation data, it is necessary to evaluate the model fit through cross-validation. In addition, it is important to perform hyperparameter tuning on the LTSM and GRU models to find the best configuration that can provide more accurate predictions. This effort can be improved by applying data augmentation techniques or collecting additional relevant data to enrich the training data, so that the performance of the model can be improved.

VI. Conclusions and Future Work

Based on the test results, several conclusions can be drawn. First, the LSTM model shows good prediction results for customer data from all industries, the cement industry, and the transportation industry. Conversely, the GRU model performs better on customer data from the tire, paper, metal, automotive, and textile industries. Second, the selection of parameters such as epoch and batch size significantly affects the model's performance. Different parameter combinations can yield optimal performance depending on the type of industry analysed. Third, preprocessing techniques, such as outlier removal using the Interquartile Range (IQR) method and data normalization using Min-Max Scaler, help improve model accuracy. Fourth, clustering data by industry type enhances the specificity and accuracy of predictions according to the energy consumption characteristics of each industry.

Based on these conclusions, several recommendations are suggested. Based on the conclusions described, several suggestions can be conveyed. Firstly, it is recommended to implement the best LSTM and GRU models according to the type of industry at PT PLN (Persero) UID West Java. Secondly, integrating external data, such as weather conditions and specific times that affect electricity demand, can enhance prediction accuracy. Lastly, exploring the use of other deep learning models, such as Transformer or hybrid models, is suggested to further improve prediction performance.

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PERNYATAAN

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Jakarta, 8 Juni 2024

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