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Analysis of Long Short-Term Memory and Support Vector Regression Methods in Forecasting Electric Energy Sales: Case Study

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Abstract

This study aims to predict the sales of electrical energy of PT PLN (Persero) Greater Jakarta Distribution Unit by using machine learning methods, specifically Long Short-Term Memory (LSTM) and Support Vector Regression (SVR). The data used includes electrical energy sales trends from 2016 to 2023 as well as external data from the Central Statistics Agency (BPS), which includes economic and demographic factors that affect energy demand, such as economic growth, population, and seasonal factors. LSTM was chosen for its ability to handle long-term dependencies in time series data, while SVR was used as a comparison to other regression methods. The resulting model is expected to provide more accurate predictions and be useful for PT PLN in planning the distribution of electrical energy efficiently. This research also contributes to the development of the application of machine learning in forecasting, which is growing in various sectors, including the energy sector, to improve operational efficiency and data-based decision making.

Introduction

The demand for electrical energy in Indonesia, especially in the Greater Jakarta area, continues to increase along with economic and population growth. PT PLN (Persero) Greater Jakarta Distribution Unit, which is responsible for the supply and distribution of electrical energy in the region, has recorded growing energy sales. In 2023, PT PLN UID Greater Jakarta has 5,225,077 customers with a connected power of 21,634,715,305 KVA, and sales of electrical energy reached 36,992,354,101 kWh. This figure shows an increase compared to the previous year's sales, which were 34,578,291,711 kWh in 2022 and 32,709,304,744 kWh in 2021 (PLN, 2024) .

This increase in electrical energy sales reflects changes in demand that are influenced by various factors, such as economic growth, population, and other social and demographic factors (Aryani, 2012; Senjawati et al., 2020) . Therefore, it is important for PT PLN to be able to accurately predict electrical energy demand in order to plan efficient energy distribution and avoid energy shortages or waste. One way to achieve this is by using machine learning technology in energy demand prediction (Muhammad & Syaifuddin, 2022; R. H. Nugraha et al., 2022). Machine learning, especially time series methods such as Long Short-Term Memory (LSTM) and Support Vector Regression (SVR), have been proven effective in modeling complex data with temporal patterns (Novianti et al., 2022; Yanti et al., 2024) . LSTM was chosen for its ability to handle long-term dependencies in time series data (Rahmah, 2024) , while SVR was used to compare the prediction results of other regression methods (Aulia et al., 2022) . By utilizing these methods, it is expected that a more accurate

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prediction model can be obtained, which can help PT PLN in planning the distribution of electrical energy more efficiently and data-driven.

This research also contributes to the development of machine learning applications in forecasting, which are increasingly important in various sectors, including the energy sector. By using the latest methods in machine learning, it is expected that the energy planning process can be done more timely and based on more solid data, supporting operational efficiency and better decision-making in the future. Time series forecasting has experienced significant advances in recent years, thanks to the growing application of Machine Learning (ML) techniques. In many industrial applications, such as stock price forecasting (Meriani & Rahmatulloh, 2024), bitcoin price (Ramadhan et al., 2024), and air pollutant standard index quality forecasting (Perdana & Muklason, 2023), ML methods have shown much better performance compared to traditional forecasting techniques. One technique that has been particularly instrumental in this regard is deep learning, where models such as Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU) have been shown to be effective in capturing long-term dependencies in sequential data, which is one of the main challenges in time series forecasting (Sinurat et al., 2024; Rohadi, 2024) .

In addition, combining machine learning techniques with traditional statistical methods has yielded more optimized results. Hybrid models that combine ARIMA (AutoRegressive Integrated Moving Average) with methods such as Support Vector Machines (SVM) have shown substantial improvements in forecasting accuracy, utilizing the advantages of each approach. This approach not only improves prediction accuracy but also allows the model to be more adaptive to the fluctuations present in the time series data (R. E. Nugraha, 2024) . As data complexity increases, the importance of hyperparameter optimization in machine learning is also becoming more pronounced. Techniques such as Grid Search, Random Search, and Bayesian optimization are now integral in ensuring that machine learning models can deliver optimal results in predicting highly dynamic time series data. Through these optimizations, model performance can be improved, reducing the possibility of overfitting, and ensuring more accurate predictions (Huda & Kom, 2019; Putra et al., 2024) .

Overall, the development of machine learning techniques, whether in the form of hybrid models, hyperparameter optimization, or deep learning and CNN techniques, has led to significant advances in time series forecasting. The use of ensemble models, which combine results from multiple models, is also gaining popularity to improve the reliability and accuracy of predictions. The application of these models in sectors such as energy, finance, and economics has further demonstrated their relevance and effectiveness in addressing complex and dynamic forecasting challenges.

The research gap in this study lies in the lack of research that directly compares the performance of Long Short-Term Memory (LSTM) and Support Vector Regression (SVR) models in forecasting electric energy sales, especially in the context of PT PLN (Persero) Greater Jakarta Distribution Unit. Although LSTM and SVR have been widely used in various fields of prediction, no study has comprehensively examined these two methods in the context of electric energy sales forecasting by considering various compositions of training and testing data. This research also fills the gap related to the analysis of the contribution of features used in the forecasting model, which can provide deeper insights into the factors that influence the prediction results, as well as optimization of the selection of a more appropriate division of training data to improve the accuracy of the predictive model.

The purpose of this study is to analyze and compare the performance of two forecasting methods, namely Long Short-Term Memory (LSTM) and Support Vector Regression (SVR), in predicting sales of electrical energy at PT PLN (Persero) Greater Jakarta Distribution Unit. This research aims to determine which method is more effective and accurate in producing

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reliable predictions for operational and planning needs for electrical energy distribution. In addition, this research also aims to explore appropriate data processing techniques, such as cleaning, interpolation, and normalization, which can improve the quality of input data thereby improving the performance of the forecasting model used.

Methods

This research framework is built using the SEMMA (Sample, Explore, Modify, Model, Assess) approach which aims to analyze and model data in a systematic and structured manner. The SEMMA approach provides clear guidance in each stage, from data collection to the final evaluation of the model built. This process is intended to ensure that each step in the research is carried out carefully, and the results obtained are reliable and useful for providing accurate predictions related to electricity sales. SEMMA consists of five main stages: *Sample*, *Explore*, *Modify*, *Model*, and *Assess*. Each stage has specific objectives that support and build on each other to produce an optimal prediction model. In this subchapter, the explanation of each stage will be described in detail, starting from data collection to the evaluation of the resulting model.

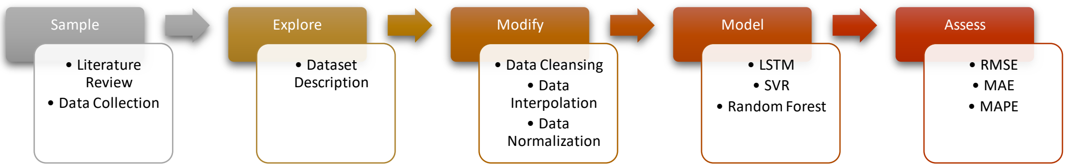

Figure 1. Research Framework

In this first stage, the main step is to collect relevant data for the analysis and prediction of electric energy sales. The data used in this research involves various factors that can affect the sale of electrical energy, including electrical energy sales data (in GWH units) as the main prediction target. In addition, supporting data such as economic indicators, weather conditions and demographic variables are also considered in the model. The economic indicators used include gross domestic product (GDP) and inflation, while the weather factors analyzed include average air temperature and rainfall. Demographic variables considered include population and unemployment rate, as these two factors can influence the pattern of electrical energy consumption.

The data used is secondary data collected from various official sources, such as government publications, statistical databases, annual reports from relevant agencies, and other reliable sources. These data sources were selected to ensure the validity and reliability of the information used. The characteristics of the data used in this study are as follows: 1) Data Period: The data used in this study covers the period from 2016 to Quarter 3 of 2024. The selection of this period is based on the availability of complete and relevant data to analyze past trends in electric energy sales and predict future patterns; 2) Data Frequency: The data collected has varying frequencies, namely monthly, quarterly, and annually. Data with these different frequencies will be integrated through an interpolation method to ensure the data has consistency within the time interval used. The next stage of data exploration aims to analyze and understand the characteristics and structure of the data that has been collected. At this stage, various statistical methods and visualization techniques are used to extract information that can provide deeper insights into the patterns and relationships between variables in the dataset. This data exploration process is essential to ensure that the model built later is based on an accurate understanding of the data.

After the data exploration stage, the next step is to prepare the data for use in modeling. Data processing at this stage is very important as the quality of the data used in the model greatly affects the accuracy and effectiveness of the predictions. The data processing stage in this

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study involves several important steps to ensure the quality and consistency of the data used. The first step is data cleaning, which aims to remove any errors, duplications or inconsistencies in the data format that may affect prediction accuracy. Next, data interpolation is performed to harmonize different data frequencies, such as annual or quarterly data, into monthly data using the interpolation method. After that, the data is normalized so that each numerical feature has a uniform scale, so that differences in scale between features do not affect model performance. Normalization is performed using the Min-Max Scaler technique, which changes the value range of each feature to between 0 and 1 to simplify the model training process.

Next is the modeling stage, where the processed data is used to build a prediction model. In this stage, three different machine learning methods are applied to model electric energy sales, namely Long Short-Term Memory (LSTM) and Support Vector Regression (SVR). Each method has its own strengths and weaknesses, and an evaluation is conducted to select the most appropriate method. Furthermore, 5 different compositions between training and testing data were formed in each modeling, namely 50:50, 60:40 70:30, 80:20 and 90:10.

Model evaluation was conducted to measure the accuracy and reliability of the model in predicting electric energy sales. Some of the evaluation metrics used to assess model performance include: 1) Mean Absolute Error (MAE): This metric measures the average absolute error between predicted and actual values, providing an overview of the model's accuracy in predicting electric energy sales; 2) Root Mean Squared Error (RMSE): RMSE penalizes larger errors, so models with large errors will be more affected by this metric. It helps to assess how well the model handles outliers or significant prediction errors; 3) Mean Absolute Percentage Error (MAPE): MAPE measures the error in percentage terms, providing deeper insight into the relative accuracy of the model. MAPE is particularly useful for assessing model reliability in the context of comparisons between time periods.

Each model developed will be evaluated based on these three metrics, and the results will be compared to determine which model provides the best predictions. For model implementation, the Python programming language was used due to its flexibility and extensive library support for data modeling and machine learning. The libraries used include TensorFlow/Keras for LSTM model development and scikit-learn for SVR models, as well as pandas and numpy for data processing. For visualization of data and analysis results, matplotlib and seaborn libraries were used to produce informative graphs and assist in data interpretation.

Results and Discussion

Long Short-Term Memory (LSTM)

LSTM was chosen for its ability to handle time series data that has long-term dependencies, which is very suitable for the characteristics of electric energy sales data. Modeling with Long Short-Term Memory (LSTM) is performed using five different compositions of training and testing data, namely 50:50, 60:40, 70:30, 80:20, and 90:10. Training data process is set as many as 200 epochs with batch size 8 and early stop at epoch without improvement as many as 30 epochs. The following is a graph of the results of training data on LTSM.

The following are the results of LSTM evaluation on various data compositions:

Table 1. Evaluation of LSTM

No	Komposisi	Epoch	RMSE	MSE	MAPE
1	Data Training dan Testing 50:50	112	0.82	0.68	4.21%
2	Data Training dan Testing	45	0.99	0.98	3.14%
3	Data Training dan Testing	115	0.28	0.08	0.77%
4	Data Training dan Testing 80:20	178	0.37	0.14	1.36%

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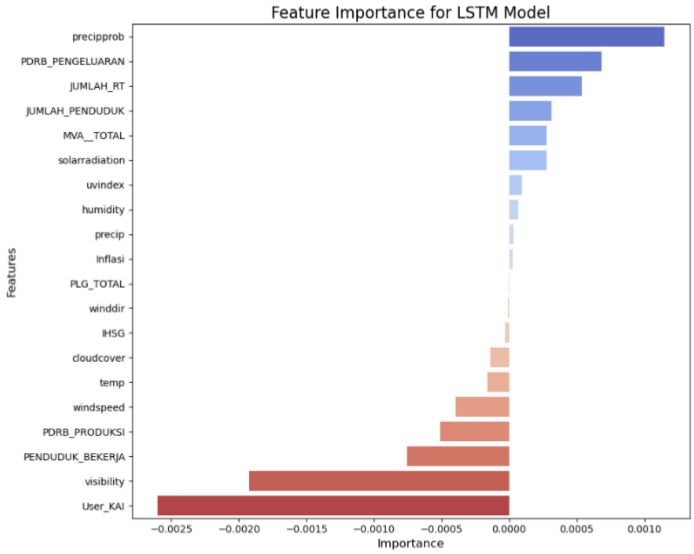
5	Data Training dan Testing	34	0.36	0.13	1.21%

Source: Data Processed (2025)

Based on the model performance table, the 70:30 training and testing data composition provides the best results with an RMSE value of 0.29, MSE 0.08, and MAPE 0.77%. These results show that this data division provides an optimal balance between training and testing data. The 80:20 composition also performed quite well with a MAPE value of 1.36%, but was still slightly worse than 70:30. In contrast, the 50:50 composition produced the largest error (MAPE 4.21%), indicating an inadequate split of training data to build an accurate model.



Feature	Importance
precipprob	0.001148
PDRB_PENGELUARAN	0.000684
JUMLAH_RT	0.000536
JUMLAH_PENDUDUK	0.000311
MVA__TOTAL	0.000279
solarradiation	0.000277
uvindex	0.000096
humidity	0.000069
precip	0.000034
Inflasi	0.000025
PLG_TOTAL	-0.000007
winddir	-0.000012
IHSG	-0.000032
cloudcover	-0.000138
temp	-0.000162
windspeed	-0.000397
PDRB_PRODUKSI	-0.000510
PENDUDUK_BEKERJA	-0.000754
visibility	-0.001923
User_KAI	-0.002602

Figure 2. Feature important in LSTM

Source: Data Processed (2025)

From the feature importance analysis, the features with the highest positive contribution to the model are precipprob (0.001148), GRDP_EXPENDING (0.000684), and NUMBER_RT (0.000536). These features have a significant influence on prediction accuracy and can be considered as key variables in the model. In addition, features such as NUMBER_PENDER (0.000311), MVA__TOTAL (0.000279), and solarradiation (0.000277) also contribute positively, albeit with a smaller influence.

In contrast, some features have negative contributions to model performance, such as User_KAI (-0.002602), visibility (-0.001923), and EMPLOYEE (-0.000754). These features tend to be detrimental to the model and can be considered for removal. In addition, features such as PLG_TOTAL (-0.000007) and winddir (-0.000012) have almost zero influence, which suggests that they may be less relevant for prediction. Based on this analysis, it is recommended to use a 70:30 training and testing data composition to get the best accuracy. Particular focus should be given to features with high positive contributions, such as precipprob, PDRB_EXPENDING, and NUMBER_RT, to improve the prediction accuracy of the model. Re-evaluation of features with negative or near-zero contributions is required to determine if they need to be removed to simplify the model.

Research by Akbar et al. (2023) also used the Long Short-Term Memory (LSTM) method for data forecasting, and the results showed the importance of hyperparameter settings such as the number of LSTM units, number of epochs, and batch size in building the best model. The study was used to predict the temperature level of Semarang city using climate data from January 1, 2019 to December 31, 2021, with a total of 1096 data, and produced the best model with 70% training data, learning rate 0.009, 128 LSTM units, batch size 16, and 100 epochs. This model shows the lowest loss function value of 0.013 and provides excellent evaluation

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results with a MAPE value of 1.896016% and RMSE of 0.725. These results are in line with the findings of the current study, where a balanced composition of training and testing data provides the best performance in forecasting, with relatively low MAPE and RMSE, demonstrating the effectiveness of hyperparameter settings in improving the accuracy of electric energy forecasting models.

Support Vector Regression (SVR)

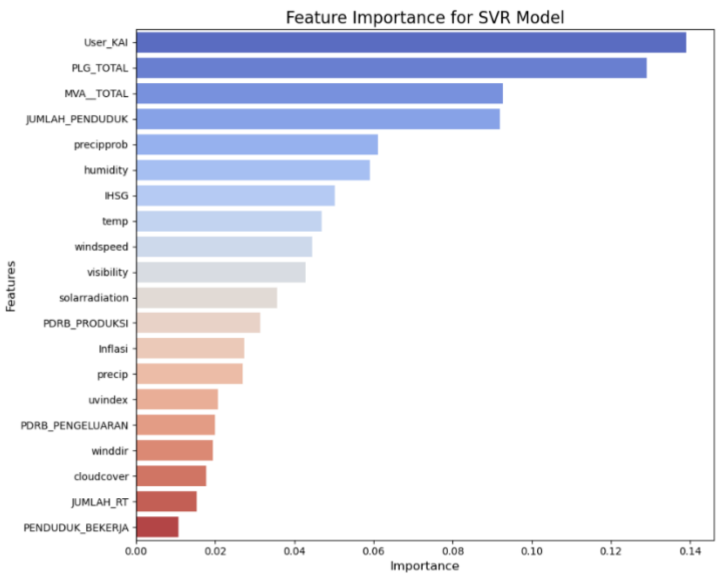
Modeling using Support Vector Regression (SVR) is done in a similar way to LSTM, using five compositions of training and testing data. SVR was chosen because of its ability to model non-linear relationships between input and target variables. Below is a graph of the modeling results on SVR.

Table 2. SVR evaluation

No	Komposisi	RMSE	MSE	MAPE
1	Data Training dan Testing 50:50	0.95	0.90	2.76%
2	Data Training dan Testing	1.24	1.53	3.77%
3	Data Training dan Testing	0.87	0.76	1.46%
4	Data Training dan Testing 80:20	0.97	0.94	1.65%
5	Data Training dan Testing 90:10	0.54	0.29	0.40%

Source: Data Processed (2025)

From the model evaluation results based on various proportions of training and testing data, the 90:10 proportion provides the best performance with an RMSE value of 0.54, MSE of 0.29, and MAPE of 0.40%. This shows that the model is able to predict with a high level of accuracy when most of the data is used for training. In contrast, the 60:40 proportion showed the worst performance with an RMSE of 1.24, MSE of 1.53, and MAPE of 3.77%, indicating that the model has a higher error rate at this proportion. In general, the larger the proportion of training data, the better the model accuracy.



Feature	Importance
User_KAI	0.139084
PLG_TOTAL	0.129055
MVA__TOTAL	0.092651
JUMLAH_PENDUDUK	0.091981
precipprob	0.061144
humidity	0.059029
IHSG	0.050173
temp	0.046868
windspeed	0.044464
visibility	0.042811
solarradiation	0.035558
PDRB_PRODUKSI	0.031330
Inflasi	0.027327
precip	0.026922
uvindex	0.020773
PDRB_PENGELUARAN	0.020023
winddir	0.019367
cloudcover	0.017670
JUMLAH_RT	0.015408
PENDUDUK_BEKERJA	0.010757

Figure 3. Feature important in SVR

Source: Data Processed (2025)

From the feature importance analysis, the User_KAI, PLG_TOTAL, and MVA_TOTAL features are the three most dominant features with contributions of 13.91%, 12.91%, and 9.27%, respectively. These features indicate that customer data and electricity capacity have a significant influence on the model's prediction results. In addition, population-related

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features such as NUMBER_PENDING and weather variables such as precipprob and humidity also make important contributions in building an accurate model.

In contrast, features such as EMPLOYEE, cloudcover, and several other variables have very little influence, each less than 2%. Therefore, these features can be considered to be ignored or given a lower weight if a model simplification process is required.

In conclusion, to obtain optimal prediction results, it is recommended to use a proportion of training and testing data of 90:10 and to focus mainly on features with a high level of importance. This step is expected to increase the efficiency of the model while producing more accurate predictions as needed.

Research conducted by Purnama & Hendarsin (2020)shows that the results of forecasting data on the number of passengers departing through air transportation in Central Sulawesi using SVR show good forecasting accuracy with a MAPE value of 7.28 percent for *training* data and 18.67 percent for *testing* data. This shows that SVR can be used to predict in various sectors.

Comparison of LSTM and SVR Results

Table 3. Comparison of LSTM and SVR evaluation

NO	Model	Train:Test	RMSE	MSE	MAPE
1	LSTM	50:50	0.82	0.68	4.21%
	SVR	50:50	0.95	0.90	2.76%
2	LSTM	60:40	0.99	0.98	3.14%
	SVR	60:40	1.24	1.53	3.77%
3	LSTM	70:30	0.28	0.08	0.77%
	SVR	70:30	0.87	0.76	1.46%
4	LSTM	80:20	0.37	0.14	1.36%
	SVR	80:20	0.97	0.94	1.65%
5	LSTM	90:10	0.36	0.13	1.21%
	SVR	90:10	0.54	0.29	0.40%

Source: Data Processed (2025)

Based on the model performance and feature importance data provided, this analysis aims to provide an overview of the advantages of each model, the effect of training data sharing on performance, and features that contribute significantly to prediction. The following are the results of the analysis based on the table and data provided.

The performance of electric energy sales forecasting models using LSTM and SVR is measured based on three main metrics, namely RMSE (Root Mean Squared Error), MSE (Mean Squared Error), and MAPE (Mean Absolute Percentage Error). The performance comparison analysis between LSTM and SVR models shows that LSTM consistently outperforms SVR on all training and testing data shares, from 50:50 to 90:10, with lower RMSE, MSE, and MAPE values. On a 70:30 data split, LSTM achieved the best performance with an RMSE of 0.28, MSE of 0.08, and MAPE of only 0.77%. Although SVR showed the best performance at 90:10 data split, it still could not surpass the accuracy achieved by LSTM. Both models showed a significant improvement in performance as the proportion of training data increased, where at 50:50 both had the lowest performance, while at 70:30, 80:20, and 90:10, the prediction results became more accurate.

The features used in the models contribute differently to the prediction. The following is a detailed analysis of the feature importance for each model. In the LSTM model, feature importance analysis shows that the precipprob feature (0.001148) has the largest positive influence on model performance, followed by PDRB_PENGELUARAN (0.000684) and

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JUMLAH_RT (0.000536), indicating an important role in improving prediction accuracy. Economic features such as GRDP_PENGELUARY and NUMBER_PENDING also make significant contributions in aiding prediction. In contrast, some features negatively affect the model, including visibility (-0.001923) and User_KAI (-0.002602), which have the most significant impact. In addition, some climate features such as windspeed (-0.000397), temp (-0.000162), and cloudcover (-0.000138) also show a negative influence, albeit smaller.

In the SVR model, the feature User_KAI (0.139084) has the most influence on model performance, followed by PLG_TOTAL (0.129055) and MVA__TOTAL (0.092651), which show significant contributions in improving prediction accuracy. In addition, population-related features such as NUMBER_PENDING (0.091981) also have an important impact. However, some features have a relatively small contribution to the model, such as EMPLOYER (0.010757) and cloudcover (0.017670), which have only minimal influence in improving prediction accuracy.

Based on the analysis of model performance and feature importance, it can be concluded that the LSTM model is superior to SVR in all performance metrics (RMSE, MSE, MAPE). LSTM is suitable for prediction with larger training datasets (at least 70% for training). In addition, the important features that influence the two models are different, where LSTM is more influenced by economic and weather features such as precipprob and GRDP_EXPENDING, while SVR is more dependent on transportation features (User_KAI) and population indicators (PLG_TOTAL). The effect of training data sharing also shows that a larger proportion of training data (such as 70:30 or 80:20) gives more accurate prediction results in both models. As a recommendation, if accuracy is a top priority, an LSTM model with a sizable training data share (at least 70%) is recommended. However, for simpler analysis or interpretation of the influence of certain features, SVR can be used, especially if the focus is on transportation and population features. Research conducted by Arfan & Lussiana (2020) in comparing the performance of LSTM and SVR in predicting gold prices. The findings show that LTSM is able to predict stock prices in 2017-2019 with good performance and a relatively small error rate. While testing using the Support Vector Regression (SVR) method, LSTM has a better loss value than the SRV algorithm. The data range in LSTM affects the training time used, the larger the data range, the longer the training time used. The data range in SVR affects the loss value, the larger the data range, the greater the resulting loss value.

Conclusion

The results showed that the LSTM method consistently provided more accurate results than SVR in all data testing scenarios. Using a 70:30 proportion of training and testing data, LSTM achieved an RMSE of 0.29, MSE of 0.08, and MAPE of 0.77%, indicating that it is capable of capturing complex and dynamic data patterns. On the other hand, SVR has a relatively lower performance although it still produces acceptable predictions, especially on data compositions with a larger proportion of training. The feature importance analysis identified that some variables such as precipprob, GRDP_EXPENDING, and NUMBER_RT have significant influence on the LSTM, while variables such as User_KAI and PLG_TOTAL dominate the SVR model.

To improve prediction accuracy, it is recommended that the LSTM method be applied to the real-time electric energy sales forecasting system at PT PLN (Persero). The use of training data with a proportion of at least 70% can improve model efficiency. In addition, variables that contribute negatively or insignificantly, such as visibility and winddir, should be re-evaluated to simplify the model without sacrificing accuracy. Further research can be done by exploring hybrid models that combine LSTM with other machine learning methods or expanding the dataset to improve the reliability of the prediction results. The implementation

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of this model can also support strategic decision-making related to energy planning and distribution in the Greater Jakarta area.

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