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Electricity demand forecasting in Ambon using machine learning techniques

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ABSTRACT

This study aims to analyze the impact of electrical load forecasting using Artificial Neural Networks (ANN) to improve power supply reliability and efficiency in Ambon's electric system. The objective is to develop a reliable forecasting model that supports effective energy management, helping to achieve operational excellence in terms of quality, safety, and cost-efficiency. A quantitative approach was utilized, gathering historical electricity load data from 2019 to 2024, alongside relevant environmental and temporal factors. The data were analyzed using ANN within a Python-based framework to predict future electricity demands accurately. The study employs a structured equation modeling to validate the forecasting model and its components. The findings reveal that the ANN model effectively predicts electrical loads with high accuracy, demonstrating substantial improvements in operational efficiency and energy cost reductions. The model's ability to incorporate multiple input variables allows for nuanced understanding and prediction of load variations, thereby facilitating better resource allocation and strategic planning. This research contributes uniquely by applying ANN for electrical load forecasting in the context of Ambon's electrical system, underscoring the integration of AI techniques in improving the operational efficiency of power utilities. The study extends the knowledge on the application of machine learning in the power sector by demonstrating how sophisticated forecasting models can significantly enhance energy management strategies.

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1. INTRODUCTION

Ambon Island, located in the heart of Maluku Province, Indonesia, serves as a population center with 362,639 residents spread across an area of 359.4 km², yielding a population density of 1,163.02 individuals per km² as reported by the Central Bureau of Statistics in 2024 (BPS Provinsi Maluku, 2024). This demographic dynamic underscores a significant rise in electricity demand driven by rapid population growth and intensifying economic activities (Kastanja & Tupalessy, 2017; Fretes, 2020; Sesa, Suyono, & Hasanah, 2015). Currently, the electricity generation system in Ambon entirely relies on diesel fuel, a non-renewable resource with limited availability. The main power plants, including BMPP Nusantara 1 Powership, Ambon Peaker Gas Turbine Power Plant, Poka Diesel Power Plant, and Hative Kecil Diesel Power Plant, all depend on diesel (Kementerian ESDM, 2021).

As of March 2024, the basic cost of electricity production in the Ambon system reached IDR 3,171.87 per kWh, far surpassing the rates set by the National Electricity Company (PLN) between IDR 966.74 and IDR 1,699.53 per kWh (PLN, 2024). This situation imposes a significant economic burden on PT PLN (Persero) Unit Induk Wilayah Maluku & Maluku Utara, exacerbated by soaring global fuel prices due to ongoing geopolitical conflicts in Eastern Europe and the Middle East (Malik, 2022; Damayanti, 2022; Sihombing, 2022; Deny, 2023; Deny, 2024; Masitoh & Hidayat, 2024). In response, PT PLN (Persero) has launched the "Moonshot Transformation 2.0" initiative, with a pivotal strategy titled "Beyond RKAP 2024" aimed at optimizing energy management to not only meet current needs but also to prepare future infrastructure with an emphasis on efficiency, digitization, and energy transition (PLN, 2023; Zahra, 2023; PLN, 2023).

This transformation includes various digitalization initiatives at the generation, transmission, and distribution levels, aimed at enhancing the resilience of the electrical system and reducing operational fragility. The transition from manual to centralized, digitized processes utilizing advanced analytics has expedited decision-making and enhanced service quality. A critical aspect of operational efficiency improvement involves precise electricity load forecasting, enabling optimal resource utilization and minimizing production costs (PLN, 2023; Alamsyah, 2023). Electric load forecasting predicts future energy consumption based on historical data (Nti, Teimeh, Nyarko-Boateng, & Adekoya, 2020; Mamun, et al., 2020; Aminulloh & Kartini, 2020). Advances in computing technology have enabled researchers to develop more effective and efficient methods for predicting electrical load usage (Nti, Teimeh, Nyarko-Boateng, & Adekoya, 2020; Zhang, et al., 2021; Zhao, Zhang, Zhang, Wang, & Li, 2020).

Ambon's unique weather patterns and consumption behaviors necessitate a forecasting model that accommodates variables such as weather, temperature, and variations between workdays and holidays. Ambon Island's unique geographical location and tropical climate significantly influence its electricity demand, exacerbating challenges in fuel supply and increasing reliance on diesel. High humidity and temperature fluctuations necessitate extensive use of cooling systems, especially during warmer months. Additionally, cultural and economic activities such as local festivals, the fishing industry, and tourism lead to peak electricity usage. Festivals and holidays like Christmas and Eid see extensive use of electrical appliances for public celebrations, while the fishing and tourism sectors require continuous operation of energy-intensive facilities such as cold storage and accommodation services. Ongoing infrastructure developments, including new commercial and residential projects, further drive the electricity demand as Ambon modernizes. Together, these factors necessitate a robust forecasting model that can adapt to the distinct patterns of energy use influenced by both natural conditions and social-economic developments in Ambon. (Latuamury, Marasabessy, Talaohu, & Imlabla, 2020; Kang & Reiner, 2022).

In this research, artificial neural networks (ANN) and linear regression are the primary tools for analysis. ANN is renowned for its capability in time series analysis and learning data patterns and relationships, whereas linear regression is utilized to identify linear relationships between independent and dependent variables (Syahputra, Syahfitra, & Putra, 2020; Irawan, Akil, & Gunadin, 2022). This study also employs time series analysis techniques, enabling forecasting that considers multiple changing criteria over time (Gasparin, Lukovic, & Alippi, 2021; Hussain, Aziz, Hossen, & Aziz, 2022).

All analyses and forecasts in this research are conducted using Python, a programming language known for its straightforward syntax and ease of use, making it a popular choice among researchers and practitioners. Python supports object-oriented programming and comes equipped with an extensive library that supports various programming tasks, from web development to data analysis, particularly in Machine Learning and Deep Learning (Romzi & Kurniawan, 2020; Rodrigo & Ortiz, 2023). A comprehensive review about electricity load forecasting offers an extensive overview of various studies conducted on electrical load forecasting. By systematically analyzing seventy-seven studies over a nine-year period (2010-2020), it highlights the use of Artificial Intelligence (AI), particularly Artificial Neural Networks, for short-term electricity demand forecasting (Nti, Teimeh, Nyarko-Boateng, & Adekoya, 2020).

While it provides deep insights into current trends in load forecasting, the Neural Network models used are limited to short-term projections. Although the study notes that 50% of the forecasts consider weather and economic parameters, it lacks the integration of broader variables such as energy policies, technological innovations, and consumer behavior that can impact energy consumption. Another study, provides an in-depth review of load forecasting techniques using single and hybrid predictive models in the power industry. It highlights the use of various Machine Learning models and points out the advantages of hybrid models that combine more than one predictive algorithm to enhance performance (Mamun, et al., 2020).

Although this study offers a broad overview of load forecasting technologies and details the strengths and weaknesses of various models, it does not focus on the specific needs of any region or system, which could lead to shortcomings in practical applications. Furthermore, the use of hybrid models often requires greater computational resources and higher implementation complexity. The study about short-term electric load forecasting using a fuzzy multi-attribute decision making decomposition feed forward neural network (FMADM-Dec-FFNN) introduces a unique approach to short-term electric load forecasting using a hybrid fuzzy and neural network method. Focused on short-term load predictions for the business and industrial sectors in West Surabaya, it utilizes specific data from BMKG and PLN (Aminulloh & Kartini, 2020).

Although the proposed method shows potential in producing low prediction errors, it is tailored for business and industrial categories, potentially excluding the complexity of energy needs in other sectors like residential or public services. Additionally, this study's focus on short-term forecasting (one week) may not aid in long-term strategic planning needed for effective energy management in regions experiencing sharp fluctuations in energy demand. A review of data mining technologies in building energy systems provides a comprehensive literature review on the use of data mining technologies in building energy systems. This review explores how data mining, both supervised and unsupervised, can be utilized for energy load prediction, pattern identification in building operations, and fault detection and diagnosis (Zhao, Zhang, Zhang, Wang, & Li, 2020).

Although it offers deep insights into the application of data mining technologies, the study primarily focuses on building energy systems and does not cover the complexities of large-scale electrical systems, nor does it discuss how data mining technology could be adapted for use in larger systems. The study about potential solar and wind energy forecasting based on neural networks provides important insights into the use of neural networks to predict energy needs based on population dynamics and energy demand growth in Central Java. Although this analysis is crucial, it focuses on the use of Neural Networks with specific neuron configurations without integrating other forecasting methods that could enhance prediction accuracy. This limitation could restrict the model's ability to adapt to data complexity or sudden changes in data patterns (Mustaqim, 2022).

The study relies solely on population growth and energy demand parameters, without considering other significant variables like weather conditions or economic factors that could significantly impact energy needs. By integrating these methods, this research aims to develop a forecasting model that can support PT PLN (Persero) in addressing and overcoming future challenges, as well as supporting the mission to optimize Beyond RKAP 2024. The results of this study are expected to provide robust recommendations for PT PLN (Persero) in making sustainable and efficient strategic decisions, ensuring a reliable energy supply for Ambon's electrical system.

2. RESEARCH METHOD

This chapter outlines the methodology used to forecast electrical load demands in Ambon Island, Indonesia. The input data for this study consists of electrical load, temperature, date & time, and day status (whether it is a holiday or not). These parameters are crucial in understanding and predicting the variations in electrical load due to environmental, temporal, and social factors. The initial step in the research involves the preprocessing of the collected data. This data preprocessing stage includes cleaning, normalization, and transformation processes to ensure data quality and suitability for further analysis. The processed data sets then serve as inputs into the regression models to identify significant predictors and their relationships with electrical load. Subsequently, the study utilizes a neural network to conduct training with electrical load as the target variable. Neural networks are chosen for their ability to model complex nonlinear relationships and their proficiency in handling large datasets with many input variables.

The architecture of the neural network will be designed to accommodate the specifics of the input data, focusing on layers and nodes that can best capture the dynamics of load fluctuations. The parameters used in forecasting the electrical load in Ambon Island include: (a) Load data: Historical data of electricity usage measured in kilowatts (kW). (b) Temperature: Daily temperature data which influences electricity usage patterns, especially in residential and commercial cooling systems. (c) Date and time: Timestamps of data collection that capture consumption patterns across different times of the day and year. (d) Day status: Indicates whether a particular day is a holiday or a regular day, affecting the typical usage patterns due to differences in commercial and domestic activities.

To illustrate the research model and the flow of data through the different stages of analysis, a diagram (Fig 1) will be presented. This diagram visually represents the process from data collection, through preprocessing, to modeling using regression analysis and neural networks, and finally to the output of load forecasts.

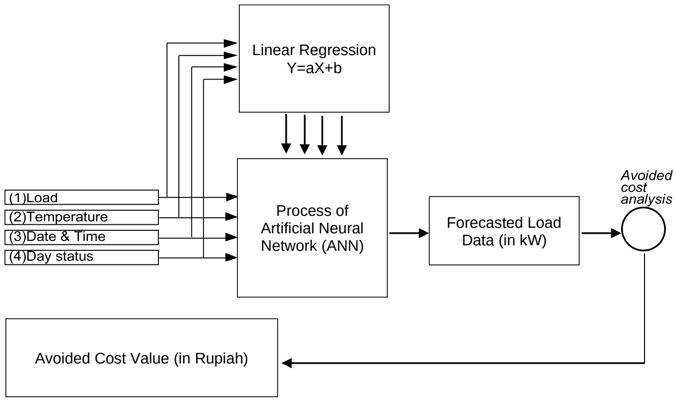

Figure 1. Research Model

Artificial Neural Networks (ANN) are a branch of Artificial Intelligence (AI) that mimics the human biological neural systems in problem-solving through learning processes. This learning occurs through the adaptation of synaptic weights based on processed data. The structure of ANN consists of elements arranged in a way that functions similarly to the human brain, enabling them to analyze and make decisions based on historical data, subsequently processing this data to generate solutions for previously unencountered problems (Sesa, Suyono, & Hasanah, 2015). In the context of energy management, the application of ANN can be incredibly beneficial in making accurate predictions about energy demand based on historical consumption patterns. ANN can be integrated into systems to assist PT PLN (Persero) in forecasting peak loads and adjusting resource distribution more effectively.

Before processing data through ANN, the data must be normalized. The normalization process involves scaling numerical data to a range of 0 to 1, making the learning process more stable and efficient. The commonly used normalization formula is in Equation (1).

$$X' = \frac{(X - X_{min})}{(X_{max} - X_{min})} \times (BA - BB) + BB \quad (1)$$

Where X' is the normalized value, X_{min} is the minimum value of the data,X_{max} is the maximum value, BA is the upper limit, and BB is the lower limit. After predictions are made and results obtained, the next process is denormalization, which returns the normalized values back to their original scale. The formula for denormalization is shown in the Equation (2).

$$X = X \times (X_{max} - X_{min}) + BB \quad (2)$$

To evaluate the forecasting approach, the mean squared error (MSE) is utilized, which measures the average of the squares of the errors; a lower value indicates smaller errors:

$$MSE = \frac{1}{N} \sum_{i=1}^{N} (y' - y)^2 \quad (3)$$

where y' is the predicted value, y is the actual value, and N is the number of training data points. The data design in this study is a critical aspect that determines how data is organized, processed, and analyzed using the Python programming language. Python, with its extensive capabilities in data processing and visualization, serves as the primary tool in this research for managing and displaying data so that it can be effectively interpreted. This includes creating predictive models using ANN, which are central to this research in analyzing and predicting the electricity load needs on Ambon Island. In developing the application design using Python for this study, the use of block diagrams is essential to detail the prediction system's workflow comprehensively. These diagrams consist of various components such as input parameters used during the training of the ANN, the expected system output, and the relationships between the involved processes.

The presence of these diagrams greatly assists in understanding the system's workflow, facilitating the identification of problem focuses and providing clarity on the designed workflow. This structure is illustrated in Fig. 2, effectively showing how four primary input data are analyzed and processed through the ANN. The data utilized has been normalized to ensure that the developed program can effectively read and process the information.

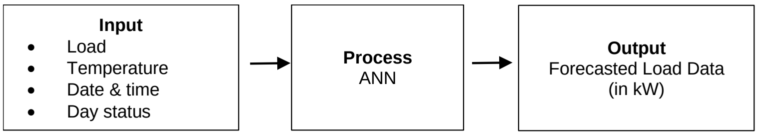

Figure 2. Block diagram of forecasting using artificial neural network

Subsequently, the Neural Network training process begins with the goal of obtaining optimal weights. These weights are represented in the form of matrices which facilitate data visualization and management. After the training phase, the system is tested with test data derived from previous input and output data. The results of these tests are then analyzed to determine the accuracy of the predictions produced, which are key to evaluating the effectiveness of the developed predictive model. Here is the sequence of work in this research: (a) Data Organization: Data collected from various sources such as BPS Maluku, PT PLN (Persero), and related scientific publications are gathered and organized in a format that facilitates further processing. This data includes variables affecting energy consumption, such as historical electric load data, demographic information, economic conditions, and meteorological data. (b) Data Pre-processing: The collected data undergoes a pre-processing stage to ensure it is free from noise or outliers and ready for model creation. This step includes data normalization, where data values are adjusted to the same scale to prevent bias in the predictive model. (c) Model Architecture Design: The use of ANN in this research is designed with a specific architecture to predict electric load considering factors such as temperature, time, and whether it is a holiday or a working day. This model will have several hidden layers, with the number of neurons in each layer varying based on experimental results to achieve the best prediction accuracy (c) Implementation and Model Training: The designed ANN model will be implemented using Python. Python provides various libraries like TensorFlow or Keras that facilitate the implementation of neural networks. This model will then be trained with historical data using the backpropagation method, an algorithm to minimize prediction error by adjusting the network weights based on output error. (d) Model Testing: After the model is trained, it will be tested with a different dataset to verify the model's accuracy. This will provide insights into how well the model predicts electric loads. Metrics used to measure model performance include Mean Squared Error (MSE). (e) Result Visualization: Python is also used for visualizing prediction results to assess the model's effectiveness in an applicative context. Charts and other visualizations created using libraries like Matplotlib or Seaborn will provide a clear visual representation of trends and patterns in the data and the effectiveness of the predictive model.

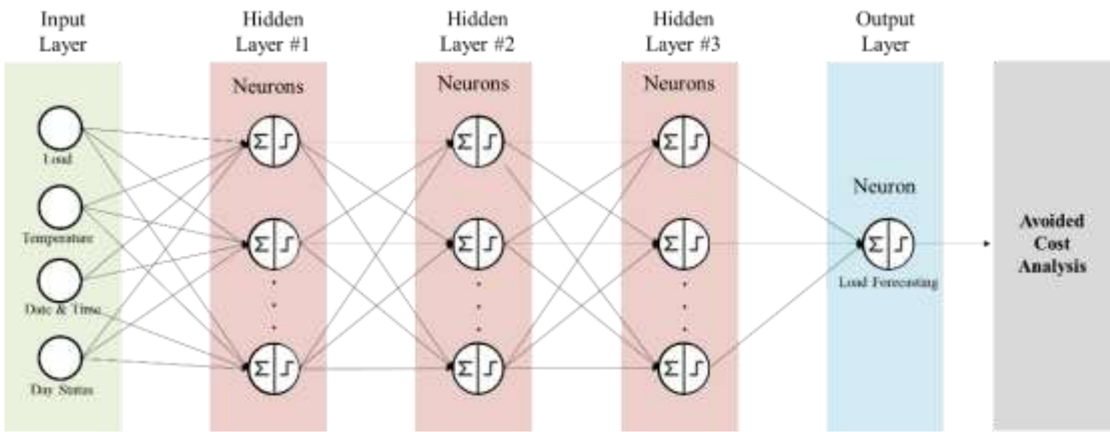

Figure 3. The architecture of the artificial neural network for forecasting

The Neural Network architecture used in this research is designed with four inputs and one output neuron, where the number of neurons in the hidden layers is set as a variable to allow experimentation on its influence on the network output. Using three hidden layers with variable neuron numbers ranging from 1 to 15 allows adjustments to be made to meet the specific needs of this research, providing flexibility in testing and optimizing the model. The output from this system is the predicted electric load for a specified period, taking into account variables such as load, temperature, date and time, and day status (holiday or not). This architecture is detailed in Fig. 3, which shows how each layer of neurons is interconnected and how information is processed through the network to produce an estimated avoided cost using more accurate forecasting techniques.

This research begins by establishing a research framework, a crucial step in formulating the methods and approaches to be adopted. Once the framework is set, the next step involves identifying the necessary data, which includes electric load data, temperature, date and time of data collection, and the status of the day. This data forms the foundation for training the ANN models to forecast electrical loads. The training process of the ANN uses the specified historical data, which involves testing and validation phases to determine the model's accuracy in predicting electric loads. After the model is trained, an evaluation is conducted to determine if the developed algorithmic model meets the set criteria. If the model is found to be unsatisfactory, iterations are performed by adjusting parameters or selecting different data features for retraining the model.

Once the algorithmic model is deemed appropriate, the next step is to carry out electric load forecasting using the trained ANN model. This model will be applied to estimate future electric loads assuming conditions learned from historical data. Following the forecasting results, the potential for avoided cost savings in electric production is calculated. This critical stage of the research aids in identifying the extent of cost efficiency that can be achieved through the implementation of an accurate forecasting model. These potential savings indicate the effectiveness of the ANN model in a real operational context and provide significant added value in the management of electric energy.

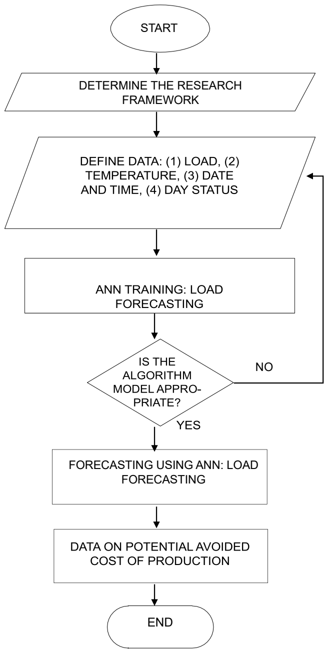

Figure 4. Research Flowchart Model

3. RESULTS AND DISCUSSIONS

The dataset utilized in this study encompasses historical electricity load data for the Ambon system, spanning from January 1, 2019, at 00:30 to December 31, 2023, at 23:30, recorded at 30-minute intervals. This extensive dataset includes several critical variables: the timestamp, electricity demand, temperature, date, and holiday status.

Table 1. Input Data Parameters

Time	Demand	Temperature	Date	Holiday
01/01/2019 00:30	46800	26.1	01/01/2019	TRUE
01/01/2019 01:00	46200	26.8	01/01/2019	TRUE
01/01/2019 01:30	45600	26.4	01/01/2019	TRUE
01/01/2019 02:00	45000	27.2	01/01/2019	TRUE
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.
31/12/2023 23:00	50776	29.7	31/12/2023	FALSE
31/12/2023 23:30	49257	28.8	31/12/2023	FALSE

Source: PLN (2024)

However, for the purpose of this paper, only the first ten rows of the dataset are presented as a preview, providing a snapshot of the initial segment of the data. The dataset's initial entries, as shown in the table, start with a demand of 46,800 kW at 00:30 on January 1, 2019, with a corresponding temperature of 30.1°C and a holiday status marked as true, indicating that the data point falls on a public holiday. This pattern continues for the subsequent time intervals, illustrating a decreasing trend in electricity demand from 46,200 kW at 01:00 to 40,800 kW at 05:00, while the temperature remains constant at 30.1°C, and the holiday status remains true throughout.

This detailed dataset is crucial for developing a robust forecasting model, as it captures the variations in electricity demand relative to time, temperature, and holiday status. The granular 30-minute interval data allows for precise modeling of demand fluctuations, which is essential for accurate load forecasting. By incorporating temperature and holiday status, the model can account for external factors that influence electricity consumption patterns, thereby enhancing the forecast's accuracy. The inclusion of temperature data provides insight into the correlation between weather conditions and electricity demand, which is particularly relevant for regions where climate significantly impacts energy consumption. Similarly, the holiday status helps identify deviations in demand due to non-working days, which typically exhibit different consumption patterns compared to regular working days.

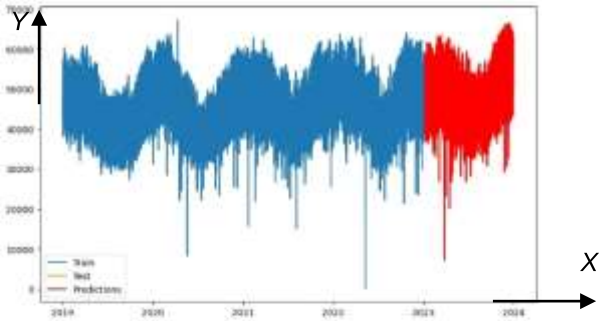

Figure 5. Actual data Electricity demand forecasting (train in blue, test in red)
Source: Analysis result in Python with matplotlib.pyplot library

In the subsequent sections, this dataset will be utilized to train and validate various machine learning models aimed at predicting future electricity demand. The results from these models will be evaluated based on their accuracy and reliability, with the goal of identifying the most effective approach for load forecasting in the Ambon system. This comprehensive analysis will contribute to optimizing energy management strategies and improving operational efficiency within the electrical grid. Fig 5 presents a comprehensive visualization of the electricity demand data for the Ambon system over a specified period, segregated into training and test datasets along with the model's predictions. The visualization is pivotal in understanding the model's performance and the underlying patterns within the data. Fig 5 delineates the division between the training and test datasets, with the training set represented in blue and the test set in red.

The training set covers the initial segment of the data, from January 1, 2019, up to approximately 80% of the entire dataset. This portion of the data was utilized to train the model, enabling it to learn the patterns and relationships within the data. The test set comprises the remaining 20% of the data, used to evaluate the model's predictive performance. This division ensures that the model is tested on unseen data, providing a realistic assessment of its generalizability and accuracy. Fig 6 presents a detailed comparison between the actual electricity demand and the model's future predictions over a specific period, highlighting the model's forecasting capabilities. This visualization is crucial for assessing the accuracy and reliability of the model's predictions in capturing the demand dynamics. The blue line in the graphic represents the actual electricity demand, while the red line indicates the model's future predictions. The x-axis denotes the time intervals from December 30 to January 1, covering a span of approximately two days, while the y-axis represents the electricity demand in units. This timeframe provides a focused view of the model's performance in predicting short-term demand fluctuations. The graphic demonstrates that the model has successfully captured the overall trend and patterns in electricity demand. The actual demand exhibits significant variability, including sharp rises and falls within the observed period.

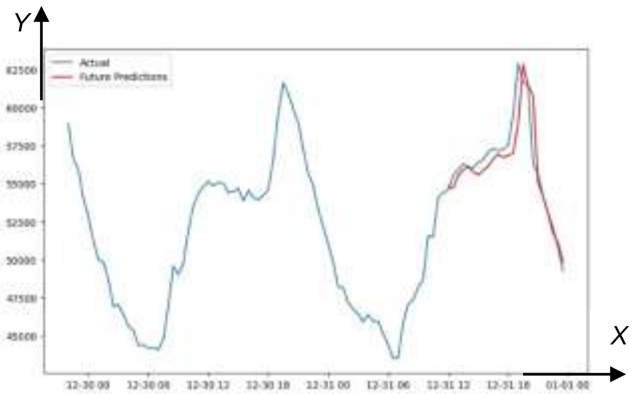

Figure 6. Comparison of actual electricity demand (blue) and model's future predictions (red)
Source: Analysis result in Python with matplotlib.pyplot library

According to Fig 6, the model's predictions (red line) closely follow the actual demand (blue line), indicating that the model has effectively learned the underlying patterns and is capable of forecasting future demand with a reasonable degree of accuracy. During the early hours of December 30, the actual electricity demand exhibits a declining trend, dropping from approximately 57,000 units to around 45,000 units. The model's predictions closely mirror this downward trajectory, which demonstrates its proficiency in anticipating decreases in demand. As the day progresses, the demand undergoes notable midday fluctuations. Around midday on December 30, there is a significant rise in demand, peaking at over 60,000 units. The model accurately predicts this rise, although there are minor deviations in capturing the precise peak value.

Further bolstering the credibility of our findings, the advanced linear regression analysis provides a quantitative measure of the model's performance. The analysis reveals a Mean Squared Error (MSE) of 2,425,054.87, a Mean Absolute Error (MAE) of 919.72, and a Mean Absolute Percentage Error (MAPE) of 1.96%, underscoring the model’s precision. These metrics reflect the model's robustness, with the MAE indicating an average absolute deviation of approximately 919.72 kW from actual electricity demands. This deviation highlights areas for potential refinement in the model, particularly in predicting sudden demand surges more accurately.The computation of avoided costs based on these metrics further quantifies the financial benefits of accurate demand forecasting.

This consistent performance across various demand patterns highlights the model's robustness and reliability in forecasting electricity demand, making it a valuable tool for energy management. The proximity of the red line (predictions) to the blue line (actual demand) across various time intervals indicates that the model has a high level of accuracy in predicting future electricity demand. This close alignment is a testament to the model's robustness and reliability. The minor deviations observed, particularly during peak demand periods, suggest potential areas for further refinement, such as incorporating additional external variables or using more advanced modeling techniques to improve peak prediction accuracy. The close alignment between the actual demand and the model's predictions demonstrates the model's effectiveness and reliability. These results are encouraging, indicating that the model can be a valuable tool for predicting electricity demand, aiding in efficient energy management and strategic planning for the Ambon system.

4. CONCLUSION

In conclusion, the predictive model developed in this study effectively forecasts electricity demand within the Ambon system, enhancing energy management and strategic planning. The model showed improvements in accuracy, with a Mean Absolute Error (MAE) of 919.72 kW and Mean Absolute Percentage Error (MAPE) of 1.96%, indicating reliable predictions compared to previous methods. However, it sometimes underperforms during peak periods due to its limited ability to integrate external variables like sudden weather changes. Future research will focus on incorporating broader datasets and advanced machine learning algorithms to improve prediction accuracy and address current limitations. These enhancements aim to support PT PLN (Persero)'s goals for optimizing operational efficiency and reducing costs, ultimately refining electricity demand forecasting tools and contributing to energy management practices.

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