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Optimizing short-term energy demand forecasting: a comprehensive analysis using autoregressive integrated moving average method

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ABSTRACT

This study addresses the critical gap in short-term electricity demand forecasting in South Sulawesi, where inconsistencies between projected and actual peak loads hinder daily operational planning, system stability, and investment efficiency. While previous studies have applied approaches such as fuzzy logic, ARIMA-ANN, and hybrid models, few have focused on simple, robust ARIMA-based models validated across different time spans for daily operational use. To address this, the autoregressive integrated moving average (ARIMA) model is implemented within the Box-Jenkins framework, using automated model selection through the *pmdarima* library and Akaike's information criterion (AIC) to identify optimal parameter configurations. The study analyzes daily peak load data from 2018 to 2023, producing realistic forecasts with high accuracy. The selected ARIMA model achieves a mean absolute percentage error (MAPE) of 1.91% and a root mean square error (RMSE) of 38.123, demonstrating its effectiveness in capturing short-term load trends. These results confirm the suitability of ARIMA for short-term forecasting in energy systems and its potential to enhance operational decision-making, reduce forecasting errors, and improve investment planning. The study also establishes a methodological foundation for future development, including the integration of ARIMA with machine learning and the use of extended datasets to support strategic energy management.

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1. INTRODUCTION

Electric power, as one of the main pillars of energy sources in modern human life, plays a crucial role in driving the wheels of development and meeting daily needs [1], [2]. Electricity can be converted into various other forms of energy, such as heat, motion, mechanical, light, and sound [3], [4]. Along with population growth and increased individual demand for electricity, energy providers, particularly PT. PLN (Persero), the state-owned electricity company, face a significant challenge in ensuring an adequate electricity supply at all times [5]. PLN has a major responsibility to plan and execute power generation projects with long lead times, necessitating a long-term power system development plan [6]–[8]. This plan, known as the 2021-2030 electricity supply business plan (RUPTL), serves as PLN's main guideline to ensure investment efficiency, respond to significant electricity consumption growth, and address deviations between projected and actual peak loads [9], [10]. South Sulawesi, as one of Indonesia's provinces experiencing significant electricity growth, is a key focus in the 2021-2030 RUPTL. Despite having established projections for electricity consumption growth, deviations between projected and actual peak loads have become a critical issue. This highlights the need for short-term load forecasting to improve the realism and accuracy of electricity demand projections [11]–[14].

Recent studies on electricity load forecasting have shown rapid methodological advancement driven by the integration of intelligent systems and time series analysis. Liu *et al.* [15] introduced a fuzzy rough set-based feature selection method combined with a multi-kernel extreme learning machine (MKELM) for short-term load forecasting (STLF), achieving high accuracy and robustness against data variability. Similarly, Züge and Coelho [16] proposed a granular weighted fuzzy approach that effectively handled uncertainty in short-term load demand forecasting. Yolcu *et al.* [17] developed a cascade intuitionistic fuzzy time series model integrated with neural networks to enhance nonlinear pattern recognition in electricity load prediction. Park and Yang [18] conducted a comparative analysis of several time-series algorithms—including autoregressive integrated moving average (ARIMA), seasonal ARIMA (SARIMA), long short-term memory (LSTM), and support vector machine (SVM)—for short-term forecasting based on advanced metering infrastructure (AMI) data, where SVM achieved the best performance in modeling nonlinear and volatile demand patterns. Wang *et al.* [19] further improved short-term electrical load forecasting accuracy by combining an extreme learning machine (ELM) with an enhanced optimization algorithm. A fuzzy–swarm intelligence hybrid model was presented in [20], demonstrating superior convergence and stability for dynamic load prediction. Ibrahim and Rabelo [21] proposed a deep learning-based model for peak load forecasting using LSTM, emphasizing its capability in capturing temporal dependencies. Fan *et al.* [22] developed a hybrid model integrating empirical mode decomposition (EMD), support vector regression (SVR), particle swarm optimization (PSO), and AR-GARCH for electricity consumption forecasting, resulting in significant error reduction compared to conventional ARIMA models. In addition, Bose and Mali [23] provided a comprehensive survey of fuzzy time series forecasting models, highlighting their adaptability for nonlinear and uncertain load data. Palomero *et al.* [24] conducted a systematic review of fuzzy-based time series forecasting and modeling from 2017 to 2021, concluding that hybrid fuzzy–machine learning methods consistently outperform classical statistical approaches in terms of MAPE and RMSE metrics.

This study introduces machine learning methods as an approach to enhance the accuracy of short-term electricity demand forecasting. Previous research has demonstrated the effectiveness of machine learning in predicting electricity needs, offering new hope in addressing inaccuracies caused by dynamic consumption pattern changes. Specifically, this study employs the ARIMA model within the Box-Jenkins framework to provide a strong theoretical foundation for short-term electricity demand forecasting. The ARIMA model is selected through automated model selection using the Akaike information criterion (AIC) to ensure optimal model performance. The robustness of the model is validated across different data spans to strengthen its applicability.

The aim of this research is to optimize short-term electricity demand forecasting in South Sulawesi, thereby reducing the gap between projected and actual peak loads. More accurate and realistic forecasts are expected to support daily operational planning, improve investment efficiency, and enhance decision-making in the power sector. Furthermore, the findings of this study are anticipated to contribute to the refinement of planning and operational strategies in the development of the next *Rencana Umum Penyediaan Tenaga Listrik* (RUPTL). This will help minimize deviations between projections and actual loads, and optimize investments in the electricity sector.

2. METHOD

2.1. Electrical system

The electrical system is an interconnected unit where electricity produced by power plants is delivered to electricity users (consumers) according to their needs, as illustrated in Figure 1 [25]. Electricity is an energy that can be wasted if not used immediately, and it cannot be stored in large quantities because, to this day, battery storage capacity remains very limited [26]. Therefore, the electricity produced must be adjusted to match the amount of electrical load required by consumers [27].

2.2. Forecasting

Forecasting, or prediction, is a systematic process of estimating what may happen in the future based on past and present information to minimize errors [28]. According to Heizer and Render (2014), forecasting is both an art and a science of predicting future events using historical data and projecting them into the future with various mathematical models [29]. Therefore, forecasting does not guarantee certainty but provides a probability based on solid grounds, aiding decision-making by considering factors such as data sources, modeling methods, and future conditions [30]. Forecasting can be categorized into two types: qualitative forecasting, which uses categorical data from the past, and quantitative forecasting, which employs numerical data under the assumption that certain patterns from the past will continue in the future. In the context of demand forecasting, predicting future electricity consumption is crucial to ensure that energy is available when needed. Accurate forecasting forms the basis for developing investment plans and operational strategies for the power system. Investment plans for power plant development are created by the Indonesian government, executed by state-owned enterprises or private companies, and are based on economic growth projections. Meanwhile, the operational plan for the power system is designed to ensure the continuous availability of electricity, relying on historical usage data from previous periods.

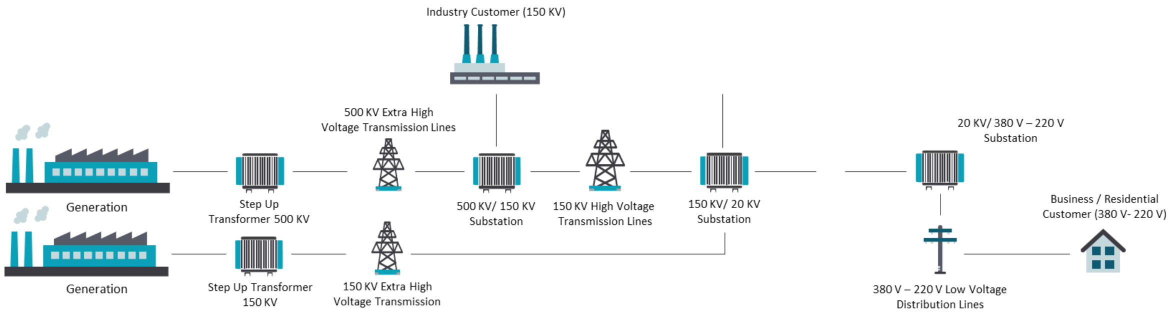


Figure 1. Electrical system

2.3. Time series analysis and forecasting

Time series data is a type of data collected in a specific time order over a certain period. The basic premise of time series is that the current observation (Zt) is influenced by one or more previous observations ($Zt{-}k$) [31]. The purpose of time series analysis is to understand and explain specific mechanisms, forecast a future value, and optimize a control system. Forecasting is the activity of estimating something that will happen in the future over a relatively long period. In contrast, a prediction refers to a condition expected to occur in the future. To make such predictions, accurate past data is required to help determine future situations.

2.4. ARIMA method

The ARIMA method is a time series analysis method known as the Box-Jenkins method [32]. This method combines the autoregressive (AR) and moving average (MA) models developed by George Box and Gwilym Jenkins. According to the Box-Jenkins methodology, the ARIMA method consists of four stages: identification of the time series model, estimation of parameters for alternative models, model testing, and forecasting of time series values [33]. The stationarity assumption is a prerequisite for modeling time series. A non-stationary series can be transformed into a stationary series by differencing. To verify stationarity and guide differencing selection, an augmented Dickey-Fuller (ADF) test was conducted on the peak load data. The test results informed the appropriate differencing order (d) applied before model fitting. Non-stationarity in a time series can involve a non-constant mean, a non-constant variance, or both (non-constant mean and variance) [34]. The general form of the ARIMA model equation is:

$$\Phi_p(B)(1-B)^d y_t = \Theta_q(B)\varepsilon_t$$

where B is the backshift operator, $\Phi_p(B)$ is the autoregressive operator, $\Theta_q(B)$ is the moving average operator, and ε_t represents white noise.

2.5. Simulation and implementation detail the implementation of the ARIMA

Models in this study was conducted using Python version 3.10 with the *pmdarima* library version 1.8.5. The dataset used consists of daily peak load data obtained from the South Sulawesi electrical system database managed by PT. PLN (Persero), covering two periods: January 1, 2022 to October 31, 2022 (396 records), and January 1, 2018 to July 14, 2023 (2021 records). The variables extracted include daily maximum peak (DMP), power balance (BP), MV Sent, MV received, capacity available (CAD), and system status, collected for both daytime and nighttime. Data preprocessing included handling missing values using linear interpolation and normalization (min-max scaling) for visualization. The stationarity of the data was verified using the augmented dickey-fuller (ADF) test. Model selection was performed through *auto_arima* from *pmdarima*, which automated the search for optimal (p, d, q) parameters based on the minimum AIC. The search space was set from 0 to 5 for p and q, and up to 2 for d, including seasonal and non-seasonal settings. The model training used the entire dataset for each experimental period, and RMSE was used to evaluate forecasting accuracy. Simulations were run on a standard laptop with Intel Core i7 processor and 16GB RAM, ensuring reproducibility with open-source tools.

2.6. Justification of methodology and conceptual framework

Approach in this study is based on the ARIMA model within the Box-Jenkins framework, consisting of model identification, parameter estimation, diagnostic checking, and forecasting. To ensure rigor in model selection, automated hyperparameter tuning for p, d, and q was performed using the Python-based *pmdarima* library. This tool systematically evaluates multiple ARIMA configurations and selects the optimal model based on the lowest AIC value, thereby balancing model complexity and forecasting accuracy. Bayesian information criterion (BIC) values were also examined to provide additional confirmation during model selection. Cross-validation was not applied in this study due to the sequential dependency inherent in time series data and because the use of information criteria (AIC, BIC) is standard in the Box-Jenkins methodology. The conceptual novelty of this study lies in applying ARIMA across different data spans (short-term and long-term datasets) to validate model robustness for short-term peak load forecasting. This approach provides practical value for daily operational planning and investment efficiency, and offers a foundation for future enhancements through machine learning integration.

3. RESULTS AND DISCUSSION

3.1. Dataset

The success of research heavily depends on the quality of the data obtained. Without a thorough understanding of the appropriate data collection techniques, researchers may struggle to obtain data that meets the desired standards of validity and reliability. Therefore, data collection methods are a crucial element in scientific research. To acquire valid and accurate data, researchers must have access to trustworthy and relevant data sources. In this study, the researcher gained access to the electrical system database and Power Balance managed by PT. PLN (Persero). This access allows the researcher to collect the necessary data directly from an authentic source, thereby supporting the validity of the findings and conclusions drawn. The dataset obtained covers two periods: January 1, 2022, to October 31, 2022, consisting of 396 daily peak load records, and January 1, 2018, to July 14, 2023, consisting of 2021 records. The data include detailed operational conditions such as daily maximum peak (DMP), power balance (BP), MV sent, MV received, capacity available (CAD), and System Status, recorded for both day time and night time periods. With data obtained through structured and systematic methods, this research is expected to make a significant contribution to the related field of study and meet the high standards required for publication in reputable scientific journals.

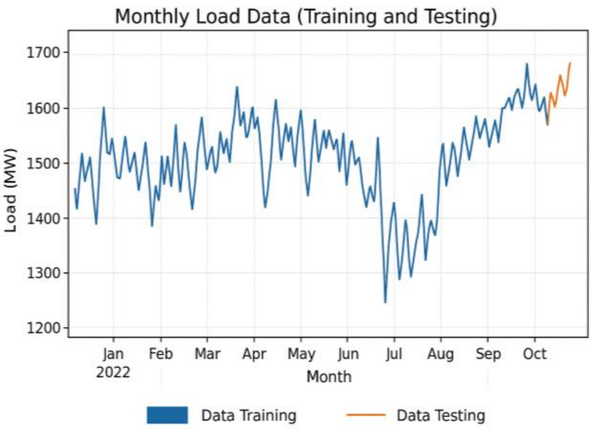
3.2. Data normalization

The data obtained from the web-based application is converted into Excel (*.xlsx) format to facilitate further processing. The first step involves data normalization by separating it into independent and dependent variables. In this study, the independent variables consist of the date and peak load columns, which are used as predictors. The dependent variables include capacity, reserve power, and system status, which represent the outputs to be predicted. After separation, the independent variables are exported into CSV (*.csv) format to ensure compatibility with data analysis and machine learning tools. This format also makes data handling and system integration easier. The CSV file is then checked for anomalies such as missing or zero values to maintain data integrity. Ensuring clean and complete data is critical for the accuracy of the machine learning model. By following these steps, the researcher ensures that the dataset meets high quality standards. This process supports the development of a valid and reliable prediction model, while also meeting the methodological standards required for scientific publication.

3.3. Algorithm implementation

The implementation of ARIMA models in this study builds upon the methodological foundation outlined in the previous section. This approach follows the Box-Jenkins framework for time series forecasting, incorporating model identification, parameter estimation, diagnostic checking, and forecasting. To ensure rigor in model selection, the study employs automated hyperparameter tuning using the Python-based *pmdarima* library. This tool systematically evaluates multiple ARIMA configurations and selects the optimal model based on the lowest AIC score, thereby balancing model complexity and forecasting accuracy. By applying this robust conceptual and technical framework, the results presented in this section aim to provide reliable and practical insights for short-term electricity demand forecasting and energy management. The analysis conducted in this report uses the ARIMA model to forecast peak electrical loads. The testing is carried out in two phases. In the first experiment, the peak load data used comes from the South Sulawesi System for the period from January 1, 2022, to October 31, 2022, with a total of 396 peak load records, as illustrated in Figure 2(a).

Based on the modeling results conducted using the ARIMA method with the help of the Python-based *pmdarima* function, 21 models have been identified as suitable for the “Training” data characteristics. These models have been selected as the most appropriate for forecasting future data. This model selection process was carried out meticulously to ensure that each chosen model could accurately capture the patterns and trends from historical data, thereby providing reliable predictions for future periods. With 21 models available, the researcher has the flexibility to choose the model that best meets specific performance criteria or to combine models to enhance prediction accuracy, as illustrated in Figure 2(b). In the second experiment, the analysis was conducted using peak electrical load data from the South Sulawesi system for a longer period, from January 1, 2018, to July 14, 2023 as shown in Figure 3. In this experiment, a total of 2021 peak load records were obtained, covering a time span of over five years, as illustrated in Figure 3(a).



(a)

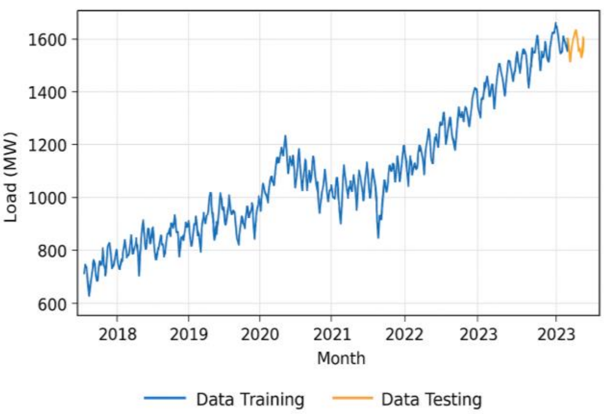
```
automodel = arimamodel(train)
print(automodel.summary())

ARIMA(0,1,0)(0,0,0)[1] intercept : AIC=2983.609, Time=0.03 sec
ARIMA(0,1,1)(0,0,0)[1] intercept : AIC=2980.217, Time=0.14 sec
ARIMA(0,1,2)(0,0,0)[1] intercept : AIC=2960.950, Time=0.21 sec
ARIMA(0,1,3)(0,0,0)[1] intercept : AIC=2960.987, Time=0.28 sec
ARIMA(0,1,4)(0,0,0)[1] intercept : AIC=2957.305, Time=0.38 sec
ARIMA(0,1,5)(0,0,0)[1] intercept : AIC=2957.117, Time=0.56 sec
ARIMA(1,1,0)(0,0,0)[1] intercept : AIC=2982.498, Time=0.05 sec
ARIMA(1,1,1)(0,0,0)[1] intercept : AIC=2960.415, Time=0.22 sec
ARIMA(1,1,2)(0,0,0)[1] intercept : AIC=2959.063, Time=0.30 sec
ARIMA(1,1,3)(0,0,0)[1] intercept : AIC=2960.511, Time=0.43 sec
ARIMA(1,1,4)(0,0,0)[1] intercept : AIC=2958.467, Time=0.58 sec
ARIMA(2,1,0)(0,0,0)[1] intercept : AIC=2972.013, Time=0.09 sec
ARIMA(2,1,1)(0,0,0)[1] intercept : AIC=2959.762, Time=0.80 sec
ARIMA(2,1,2)(0,0,0)[1] intercept : AIC=inf, Time=1.594 sec
ARIMA(2,1,3)(0,0,0)[1] intercept : AIC=inf, Time=2.08 sec
ARIMA(3,1,0)(0,0,0)[1] intercept : AIC=2973.847, Time=0.19 sec
ARIMA(3,1,1)(0,0,0)[1] intercept : AIC=2961.426, Time=0.47 sec
ARIMA(3,1,2)(0,0,0)[1] intercept : AIC=inf, Time=0.66 sec
ARIMA(4,1,0)(0,0,0)[1] intercept : AIC=2966.965, Time=0.25 sec
ARIMA(4,1,1)(0,0,0)[1] intercept : AIC=2959.186, Time=0.59 sec
ARIMA(5,1,0)(0,0,0)[1] intercept : AIC=2953.416, Time=0.30 sec

Best model: ARIMA(5,1,0)(0,0,0)[1] intercept
Total fit time: 10.277 seconds
SARIMAX Results
```

(b)

Figure 2. Comparison of actual and predicted peak load patterns for the South Sulawesi system during 2022: (a) peak load of the South Sulawesi system for the period January–December 2022 and (b) ARIMA modeling results



(a)

```
automodel = arimamodel(train)
print(automodel.summary())

ARIMA(0,0,0)(0,0,0)[1] intercept : AIC=27120.657  | Time=0.11 sec
ARIMA(0,0,1)(0,0,0)[1] intercept : AIC=25014.012  | Time=0.74 sec
ARIMA(0,0,2)(0,0,0)[1] intercept : AIC=23804.112  | Time=1.11 sec
ARIMA(0,0,3)(0,0,0)[1] intercept : AIC=23248.379  | Time=2.12 sec
ARIMA(0,0,4)(0,0,0)[1] intercept : AIC=22687.770  | Time=6.97 sec
ARIMA(0,0,5)(0,0,0)[1] intercept : AIC=22332.354  | Time=2.80 sec
ARIMA(1,0,0)(0,0,0)[1] intercept : AIC=21342.274  | Time=0.17 sec
ARIMA(1,0,1)(0,0,0)[1] intercept : AIC=21186.832  | Time=1.46 sec
ARIMA(1,0,2)(0,0,0)[1] intercept : AIC=21060.250  | Time=2.72 sec
ARIMA(1,0,3)(0,0,0)[1] intercept : AIC=21036.674  | Time=3.02 sec
ARIMA(1,0,4)(0,0,0)[1] intercept : AIC=21031.705  | Time=6.16 sec
ARIMA(2,0,0)(0,0,0)[1] intercept : AIC=21251.602  | Time=0.49 sec
ARIMA(2,0,1)(0,0,0)[1] intercept : AIC=21030.774  | Time=3.33 sec
ARIMA(2,0,2)(0,0,0)[1] intercept : AIC=21031.389  | Time=3.85 sec
ARIMA(2,0,3)(0,0,0)[1] intercept : AIC=21041.322  | Time=2.08 sec
ARIMA(3,0,0)(0,0,0)[1] intercept : AIC=21186.189  | Time=0.76 sec
ARIMA(3,0,1)(0,0,0)[1] intercept : AIC=21037.274  | Time=3.83 sec
ARIMA(3,0,2)(0,0,0)[1] intercept : AIC=21043.046  | Time=5.63 sec
ARIMA(4,0,0)(0,0,0)[1] intercept : AIC=21154.150  | Time=1.82 sec
ARIMA(4,0,1)(0,0,0)[1] intercept : AIC=21043.691  | Time=6.04 sec
ARIMA(5,0,0)(0,0,0)[1] intercept : AIC=inf        | Time=1.20 sec

Best model: ARIMA(2,0,1)(0,0,0)[1] intercept
Total fit time: 61.738 seconds
```

(b)

Figure 3. Comparison of historical and predicted peak load patterns for the South Sulawesi system: (a) peak load of the South Sulawesi system for the period 2018–2023 and (b) ARIMA modeling results based on long-term data

The modeling results using the ARIMA method with the help of the Python-based *pmdarima* function produced 21 models that fit the characteristics of the “Training” data. These models have been identified as the most suitable for forecasting future data. Each model was selected based on its ability to capture patterns and trends from historical data, allowing for more accurate and reliable predictions for future periods. With these 21 models, the researcher has a broad selection to determine the best model or to combine several models to enhance prediction accuracy, as illustrated in Figure 3(b). Using two datasets with different periods allows the author to compare and validate the performance of the ARIMA models in predicting peak electrical loads with varying data coverage, providing deeper insights into electricity consumption trends over a longer time frame. The AIC is a mathematical method used to evaluate how well a model fits the data it produces. In statistics, AIC is used to compare different statistical models and choose the one that best fits the data. Introduced by Japanese statistician Hirotugu Akaike in 1974, it has become an essential tool in statistical modeling for balancing model complexity with its ability to explain the data. AIC provides a numerical score based on two main aspects: model complexity (determined by the number of parameters in the model) and model fit to the data. The goal of AIC is to find the simplest model that still explains the data well. In other words, AIC aims to minimize the information loss due to adding parameters to the model while maintaining a good fit to the data. A lower AIC value indicates a better model in describing the data. Therefore, among the models tested, the model with the lowest AIC is considered the most appropriate. In the first experiment, Automodel selected the ARIMA(5,1,0)(0,0,0)[1] model as the best for the characteristics of load growth, with an AIC value of 2953.416, which was the lowest compared to other models. This model was chosen for its best balance between complexity and the ability to explain the data. In the second experiment, auto model selected the ARIMA(2,0,1)(0,0,0)[1] model as the best with an AIC value of 21030.774. Although this model differs in structure from the one selected in the first experiment, the selection criteria remain the same, *i.e.*, the lowest AIC value indicating the most efficient and accurate model in representing the characteristics of load data over a longer period. This result underscores the importance of AIC in the model selection process, particularly in the context of complex data modeling such as peak load forecasting. Root mean square error (RMSE) is a measure for evaluating the accuracy of forecasting results by calculating the average of the squared prediction errors. The calculation process involves squaring the difference between predicted values and observed values, averaging these squared values, and then taking the square root. A smaller RMSE value indicates a more accurate model in predicting the data, as a lower RMSE shows that the model's variance is closer to the variance of the observations. This unitless RMSE is very useful in determining the quality of forecasting models, as presented in Tables 1 and 2.

Table 1. Testing forecasting results using RMSE in the first experiment

Variable	Speed (rpm)	Power (kW)	$(At - Ft)^2$
10/2/2022	1539.13	1.561.143.233	484.5824271
10/3/2022	1537.3	1.583.352.539	2120.836348
10/4/2022	1599.22	159.526.917	15.60905769
10/5/2022	1595.35	1.602.683.109	53.77448761
10/6/2022	1521.77	159.974.597	6080.251897
10/7/2022	1595.27	1.591.816.961	11.92347834
10/8/2022	1544.75	1.587.346.254	1814.440855
10/9/2022	1539.65	158.812.921	2350.233802
10/10/2022	1572.2	1.590.855.819	348.0395826
10/11/2022	1577.69	1.594.943.058	297.6680104
10/12/2022	1619.9	1.598.116.051	474.540434
10/13/2022	1577.14	1.598.937.232	475.1193229
10/14/2022	1562.83	1.598.625.095	1281.288826
10/15/2022	1561.95	1.598.502.658	1336.096807
10/16/2022	1539.47	1.598.785.587	3518.338861
10/17/2022	1638.16	1.599.787.748	1472.429724
10/18/2022	1580.14	1.601.326.007	448.8468926
10/19/2022	1582.11	1.602.755.734	426.2463324
10/20/2022	1663.46	1.603.850.058	3553.345185
10/21/2022	1654.65	1.604.725.643	2492.441422
10/22/2022	1531.75	1.605.458.934	5433.006951
10/23/2022	1530.46	1.606.210.781	5738.180822
10/24/2022	1636.71	1.607.118.944	875.6305952
10/25/2022	1617.3	1.608.135.375	83.99035139
10/26/2022	1658.25	1.609.170.111	2408.835504
10/27/2022	1590.25	1.610.184.689	397.3918255
10/28/2022	1667.6	1.611.148.231	3186.802223
10/29/2022	1576.04	1.612.064.436	1297.759989
10/30/2022	1608.42	1.612.975.726	20.75463939
10/31/2022	1627.48	161.390.627	184.2461461
		RMSE	40.28343448

Table 2. Testing forecasting results using RMSE in the second experiment

Variable	Speed (rpm)	Power (kW)	(At - Ft)^2
7/1/2023	1590.27	1.596.605.199	40.13474637
7/2/2023	1604.84	1.599.318.388	30.48819908
7/3/2023	1563.81	1.600.416.407	1340.029033
7/4/2023	1618.24	1.600.726.908	306.7083914
7/5/2023	1667.61	1.600.653.587	4483.161242
7/6/2023	1660.73	1.600.393.353	3640.510971
7/7/2023	1656.3	1.600.042.248	3164.93466
7/8/2023	1634.6	159.964.712	1221.70382
7/9/2023	1602.43	1.599.230.817	10.23477187
7/10/2023	1653.47	1.598.804.484	2988.31864
7/11/2023	1636.46	1.598.373.557	1450.57714
7/12/2023	1633.19	1.597.940.686	1242.514137
7/13/2023	1576.82	1.597.507.164	427.9587544
7/14/2023	1596.53	1.597.073.621	0.2955237916
		RMSE	38.1234555

4. CONCLUSION

This study presents a comprehensive analysis aimed at optimizing short-term energy demand forecasting using the ARIMA method within the Box-Jenkins framework. By leveraging daily peak load data from South Sulawesi, the ARIMA model was successfully applied to produce realistic and accurate forecasts that support not only daily operational planning of power plants but also investment and development planning in the electricity sector. Through automated model selection using *pmdarima* and AIC, the optimal ARIMA configuration was identified, balancing model complexity and forecasting accuracy. The final model achieved a MAPE of 1.91% and a RMSE of 38.123, demonstrating its robustness in capturing short-term load patterns and fluctuations. This study fills a critical research gap by providing a simple yet effective ARIMA-based model validated across different data spans, offering practical value for daily operational decision-making. The results highlight the capability of ARIMA-based forecasting to reduce deviations between projected and actual peak loads, thereby contributing to improved operational management, enhanced investment efficiency, and cost savings in energy management. Moreover, this research lays a methodological foundation for future advancements, including the integration of ARIMA with machine learning techniques and the application of longer historical datasets to further enhance forecasting accuracy. The findings are expected to provide valuable insights for refining RUPTL planning, supporting the development of smart grid systems, and strengthening strategic energy management at both regional and national levels.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C	:	**C**onceptualization	I	:	**I**nvestigation	Vi :	**Vi**sualization
M	:	**M**ethodology	R	:	**R**esources	Su :	**Su**pervision
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CONFLICT OF INTEREST STATEMENTS

The authors declare that there is no conflict of interest regarding the publication of this paper. All authors have reviewed and approved the final version of the manuscript and agree that there are no financial, personal, or professional relationships that could be construed as influencing the work reported in this paper.

INFORMED CONSENT

We confirm that informed consent was obtained from all individuals who participated in this study. All participants were informed about the objectives, procedures, potential risks, and benefits of the research, and provided written consent prior to inclusion. The authors affirm that participants' privacy and confidentiality were strictly maintained throughout the study.

ETHICAL APPROVAL

This study did not require ethical approval because it did not involve any direct intervention with human participants or the use of sensitive personal data. All procedures were conducted in accordance with applicable national regulations and institutional policies.

DATA AVAILABILITY

The authors declare that the data supporting the findings of this study are available within the article and its supplementary materials. No new data were created or specifically analyzed in this study. Additional information related to this research is available from the corresponding author upon reasonable request.

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