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Data Adjustment for ARIMA Method to Investigate the Impact of Pandemic on Electricity Consumption Prediction in Indonesia

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Abstract – *Indonesia's rapid population growth and industrial expansion have significantly increased electricity consumption over the past decades. However, the COVID-19 pandemic has had a profound impact on the energy sector, causing a sharp decline in electricity demand. This disruption not only altered electricity consumption patterns but also forced a downward revision of the national electricity consumption target by approximately 10% compared to the government's initial projection. Understanding these shifts is crucial for ensuring sustainable energy planning and policy development. This study aims to analyze the impact of the pandemic on electricity consumption and forecast electricity demand in Indonesia from 2021 to 2045 using the Autoregressive Integrated Moving Average (ARIMA) method. Two forecasting scenarios are examined: one incorporating data from 2020 and another excluding it. The results indicate that excluding the 2020 data yields a more realistic projection, estimating electricity consumption to reach 610,807.8 GWh by 2045. The predictive performance of the ARIMA model is validated with statistical metrics, achieving an RMSE of 2,807.25, MAE of 1,481.25, and MAPE of 5.47%, with an overall accuracy of approximately 94.53%. These findings demonstrate that the ARIMA method is a robust and reliable tool for long-term electricity demand forecasting in Indonesia. The insights gained from this study provide valuable guidance for policymakers and energy planners in designing resilient and adaptive strategies to accommodate future electricity demand while considering the impacts of unprecedented disruptions such as pandemics.*

Keywords – *Electricity Consumption Forecasting ; ARIMA Model ; COVID-19 Impact ; Energy Planning ; Renewable Energy Transition.*

I. Introduction

As the population and industrialization have grown, energy has emerged as one of the most crucial elements. According to Indonesia's Central Bureau of Statistics, the country's population grew by 1.25 percent between 2010 and 2020, reaching 270.20 million people [1]. This triggers an increase in energy consumption needs across various sectors, including industry and domestic needs. Various efforts are being made by the government to achieve energy equity, such as developing electricity infrastructure and expanding the electricity network to remote areas to minimize the energy access gap in Indonesia. In addition, electricity subsidies are provided for low-income communities and efforts are being made to accelerate the transition to clean energy domestically towards Net Zero Emission 2060 [2, 3].

Numerous attempts are still being made to increase the precision and effectiveness of forecasting methods for power consumption statistics that use the ARIMA method. According to S. Sharma and S. Kumar Mishra, ARIMA has a low error rate and is useful for forecasting short-term electricity demand for residential and commercial sectors [4]. However, Aurna et al. compared ARIMA with the Holt-Winters method, which is superior in handling seasonal patterns and long-term trends [5]. In addition, Izudin et al. proposed a hybrid ARIMA-ANN model, which combines the ability of ARIMA to handle linear data and ANN for non-linear data, resulting in more accurate predictions [6]. Ditago et al. revealed that the ARIMAX model is superior for social, business, and industrial groups, while the transfer function model is more accurate for household and public groups [7]. Mahia et al. proposed an ARIMA model with various sets of parameters to estimate electricity consumption. According to the experimental data, ARIMA (1,1,1) is a good tool for forecasting power consumption since it offers high pre-

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cision and reliable predictions [8]. Important insights from these articles provide more effective solutions in addressing the complex challenges of energy forecasting and yield more accurate results by considering other factors.

Although various efforts have been made by the government in this matter, several factors also affect the electricity sector. A case in point is the COVID-19 pandemic of 2019. The government of Indonesia is still working to prevent the COVID-19 virus from spreading further. Large-Scale Social Restrictions (PSBB) have been implemented by the central government as a result. This policy has impacted various sectors. In the energy sector, the PSBB policy caused a decrease in electricity consumption due to restrictions on office, business, commercial, and manufacturing activities. A 9.7% decrease in electricity consumption resulted in a loss of 27.16 trillion in PLN's revenue [9]. Furthermore, as a result, the 2025 renewable energy mix objective has been changed from 23% to 17% - 19% [10]. Thus, the COVID-19 pandemic caused the energy planning that had been made difficult to achieve. Therefore, a re-analysis and re-forecasting of energy supply targets and planning are needed to produce more accurate energy forecasts. In this study, adjustments were made to the data value decline through the ARIMA forecasting method [11]. In forecasting using time series data that is relatively dynamic due to the pandemic conditions, the ARIMA method requires special treatment so that this method can predict future electricity needs more accurately and logically.

This research is beneficial for improving the accuracy of electricity predictions, thereby helping electricity providers plan energy distribution more efficiently and avoid excess or shortage of electricity supply. With accurate predictions, energy management becomes more optimal, thereby reducing operational costs and preventing energy waste. The findings of this study can also be consulted when making decisions about the construction of electrical infrastructure for both short-term and long-term demands. This research also contributes to the development of science, particularly in the application of time series forecasting methods in the energy sector.

The structure of this research consists of four different sections to present the research results effectively. First, the problem underlying this research is explained. This is followed by a detailed discussion of the materials and methodologies used to predict electricity consumption in Indonesia. Next, the third section explains the technical aspects and discusses in detail the analysis of the prediction results from the specially treated ARIMA method, supported by data adjustments. Finally, the conclusion section summarizes the findings of this research and provides a detailed overview to identify potential future research.

II. Research Methods

i. Utilized Data

The dataset was obtained from historical data collected from the Ministry of Energy and Mineral Resources (ESDM) reports from 1975 to 2020 and has been cross-checked with various sources [12, 13]. The increase in electricity consumption has been evident from the initial year data, which recorded a total of 2,803.6 GWh, reaching its peak in 2019 at 245,518.2 GWh [14]. However, due to the pandemic conditions, there was a decrease of around two thousand GWh in the last year. This issue will be further investigated as it is key to predicting electricity consumption in Indonesia using the ARIMA method.

ii. Modeling through ARIMA

Traditional statistical models such as ARIMA, exponential smoothing, and moving averages can be used to model time series data [15]. Since future values are compressed into a linear function of historical data, these models are considered linear. Over the past few decades, researchers have placed a strong emphasis on linear models due to their simplicity and ease of implementation. An ARIMA model, also referred to as an ARIMA (p, d, q) model, consists of three components: p, the number of autoregressive terms; d, the number of differences; and q, the number of moving average terms [16, 17]. The following is the pseudocode 1 of the ARIMA method.

One of the most widely used forecasting techniques is the Box-Jenkins method, also known as the ARIMA model, which was first introduced in 1976 [18, 19]. ARIMA combines moving average and autoregressive models, assuming that a variable's future value is a linear function of several historical observations and random errors. The mathematical formula is expressed in Equation (1) [6]:

$$\begin{aligned} y_t = \theta_0 + \phi_1 y_{t-1} + \cdots + \phi_p y_{t-p} + \varepsilon_t \\ - \theta_1 \varepsilon_{t-1} - \cdots - \theta_q \varepsilon_{t-q} \end{aligned} \tag{1}$$

Equation (1) represents an ARIMA model, where y_t denotes the actual value at time t, and y_{t-i} represents the value of the series at the i-th previous period. The term ϕ_i is the i-th autoregressive coefficient, while ε_t denotes the random error (white noise) at time t, and ε_{t-i} refers to the previous error term at the i-th lag. The

Algorithm 1 ARIMA Forecasting Method

Initialization:
Import required libraries: numpy, pandas, statsmodels, matplotlib
Load dataset
Convert Date to datetime and set as index
Exploratory Data Analysis & Stationarity Check:
Plot original production data
Compute and plot rolling mean and standard deviation (12-month window)
Perform seasonal decomposition and plot components
Apply Augmented Dickey-Fuller (ADF) test on original data
if p-value ≤ 0.05 **then**
    Data is stationary $\rightarrow$ Proceed
else
    Apply differencing
end if
Data Transformation (Differencing):
Compute First-order differencing (First_diff) and perform ADF test
Compute Second-order differencing (Second_diff) and perform ADF test
Compute Seasonal differencing (lag=12) and perform ADF test
Determine ARIMA Parameters (p, d, q):
Plot Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF)
Identify values for p, d, q and seasonal parameters (P, D, Q, s)
Model Training & Forecasting:
Define and train SARIMA model (p, d, q) $\times$ (P, D, Q, s)
Print model summary and evaluate residuals
Plot residuals and Kernel Density Estimate (KDE)
Output Predictions:
Generate in-sample predictions and plot actual vs predicted
Extend timeline and forecast future values
Save results

parameter θ_i indicates the i-th moving average coefficient. Here, p is the number of lags for the dependent variable, and q is the number of lags for the error term.

Equation (1) represents a significant case within the ARIMA model family. When $q = 0$, the equation reduces to an autoregressive (AR) model of order p, while when $p = 0$, it simplifies into a moving average (MA) model of order q.

The Box-Jenkins principle consists of three iterative processes: model identification, parameter estimation, and diagnostic testing [20, 21]. A key criterion for determining an appropriate model is that a time series must possess theoretical autocorrelation properties if it is derived from the ARIMA process. By comparing empirical and theoretical autocorrelation patterns, we can identify one or more potential models for the given time series. To determine the order of the ARIMA model, Box and Jenkins suggested using the autocorrelation function (ACF) and the partial autocorrelation function (PACF) as fundamental tools [22].

Data transformation is typically required in the identification step to ensure a stationary time series, which is a prerequisite for applying the ARIMA model. A stationary time series maintains consistent statistical properties, such as its mean and autocorrelation structure, over time. Before using the ARIMA model, power transformations and differencing are often applied to the data to eliminate trends and stabilize variance.

After identifying the model, estimating its parameters becomes straightforward. These parameters are determined to minimize overall errors. The final step involves diagnostic testing to evaluate the model's suitability. In this phase, residual plots and diagnostic statistics are analyzed to verify the validity of the error assumptions. If the model is found to be inadequate, additional parameters must be estimated, and the model must be re-evaluated. Through diagnostic checks, an improved model can be formulated.

The Box-Jenkins approach is an iterative process that requires multiple refinements until errors are minimized and a high degree of model accuracy is achieved. Consequently, this model is widely applicable for forecasting various variables. However, researchers emphasize that parameter estimation requires a large number of observations. As a result, applying the ARIMA model has certain limitations. Nevertheless, once applied correctly, the ARIMA model provides highly accurate forecasts, making it a reliable tool for time series prediction.

iii. Measurement of Reliability and Error

The parameter for assessing the reliability of most forecasting methods is calculating the percentage error. The smaller the error, the greater the level of confidence in the prediction results. Here are some error metrics to measure the performance of the ARIMA method. Y_i is the actual value for the i-th element in the formula below, while X_i is the anticipated value. Using the ground truth dataset, the regression approach predicts element X_i for the corresponding element Y_i.

iv. *Root Mean Square Error (RMSE)*

RMSE is the square root of the mean squared error (MSE), as the name implies [23]. Taking the root does not affect the relative ranking of the model, but it produces metrics with the same unit as Y, which easily represent the typical error or "standard" error for normally distributed errors. Through the square root, there is a monotonic relationship between MSE and RMSE. Models based on RMSE will be in the same order as regression models based on MSE. This metric is widely used to evaluate model accuracy, especially in fields such as statistics, engineering, and data science. The model's performance is revealed by RMSE, which calculates the average size of the error between projected values and data [24].

$$\mathrm{RMSE} = \sqrt{\frac{1}{m}\sum_{i=1}^{m}(X_i - Y_i)^2} \tag{2}$$

where the best score is 0 and the worst score is $+\infty$.

v. *Mean Absolute Error (MAE)*

Compared to RMSE, MAE is thought to be simpler to understand since it evaluates the average magnitude of errors in a set of predictions directly, without taking into account their direction. On the other hand, RMSE can be influenced by variations in the distribution of errors and the number of errors. MAE can be divided into systematic and unsystematic components, which provide a more detailed understanding of the model's error characteristics [25]. Compared to a similar decomposition of RMSE, this decomposition includes bias error, proportionality error, and unsystematic error, which can provide greater information [26].

If some of the erroneous data is represented by the outliers, MAE may be applied. Since the $L1$ norm smoothes out all errors from possible outliers, MAE actually does not penalize training outliers excessively, giving the model a broad and constrained performance metric. However, the model's performance will be poor if the test set also contains a large number of outliers [27].

$$\mathrm{MAE} = \frac{1}{m}\sum_{i=1}^{m}|X_i - Y_i| \tag{3}$$

where the best score is 0 and the worst score is $+\infty$.

vi. *Mean Absolute Percentage Error (MAPE)*

MAPE is a widely used metric for evaluating the accuracy of forecasts and regression models [28, 29]. This is valued for its scale-independence and ease of interpretation. Its use is recommended in tasks where it is more important to be sensitive to relative variation rather than absolute variation [30].

$$\mathrm{MAPE} = \frac{100\%}{m}\sum_{i=1}^{m}\frac{|Y_i - X_i|}{Y_i} \tag{4}$$

where the best score is 0 and the worst score is $+\infty$.

III. Results and Discussion

The first step in this study is collecting annual data from the ESDM reports. The load demand prediction utilizes the dataset *Indonesian Electricity Consumption* spanning from 1975 to 2020. The dataset consists of four categories: household electricity consumption, industry, business & general consumption, and total overall consumption. The dataset processed using the ARIMA method is visualized in Figure 1.

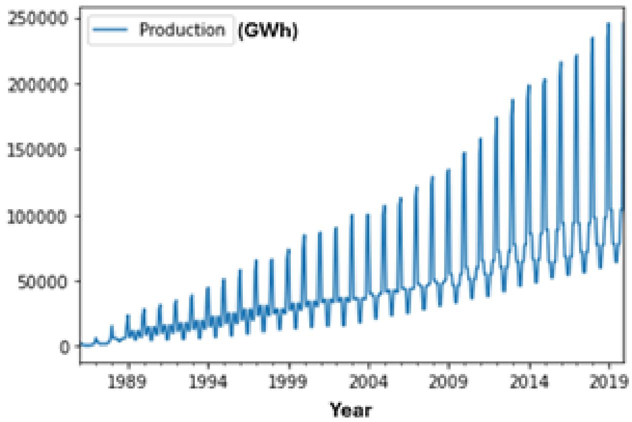

Figure 1: Plot of load dataset (1975-2020).

As seen in Figure 2, the dataset exhibits seasonal patterns where certain months tend to show an increase. To confirm the trend, a 12-period Simple Moving Average (SMA) is applied. Additionally, the Standard Deviation (STD) is plotted to assess the variance. The standard deviation does not vary significantly, indicating minimal variance in the data.

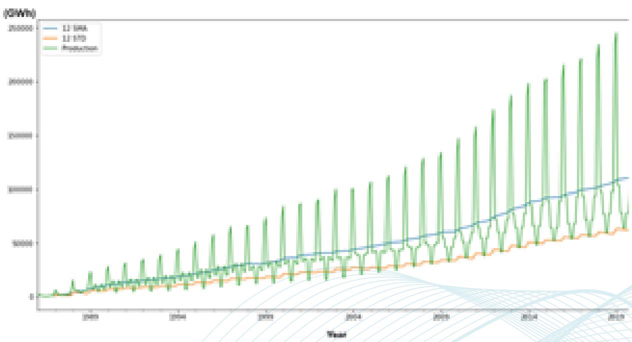

Figure 2: Standard Deviation, Simple Moving Average, and Trend of load data.

The data is then transformed into a stationary form. To determine stationarity, the Augmented Dickey-

Fuller (ADF) test is employed. The null hypothesis of the Dickey-Fuller test states that the time series is non-stationary and contains a unit root, whereas the alternative hypothesis asserts stationarity. The residual values are plotted to analyze error distribution. As depicted in Figure 3, the errors are distributed around zero, indicating a good model fit.

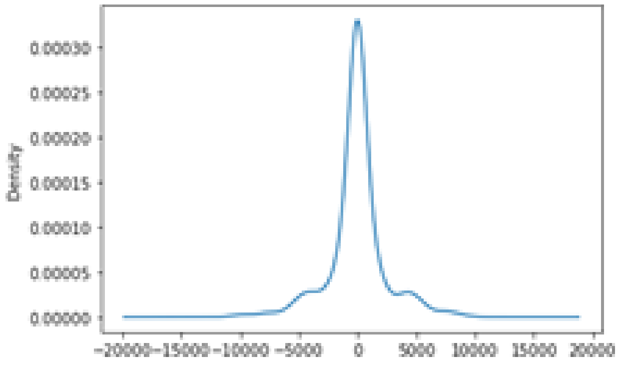

Figure 3: Error distribution of the dataset.

Model performance is evaluated through predictions. First, the model's capability to predict existing data is assessed before transitioning to future data forecasting. As shown in Figure 4, the model effectively predicts current data. For future predictions, additional periods with zero values can be appended to the dataset before applying the prediction model.

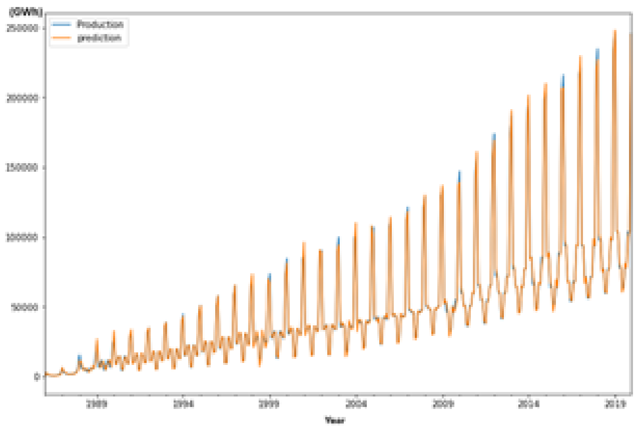

Figure 4: Validate actual data and predict future electrical energy consumption.

The trend from the forecast can be clearly observed for future values. In this paper, forecasting is conducted for 25 years leading up to Indonesia's 100th independence anniversary (2021-2045). The prediction results for electricity consumption using the ARIMA method yield an RMSE of 2807.25, an MAE of 1481.25, and an MAPE of 5.47%. This indicates that the ARIMA method has an average confidence level of approximately 94.53%. Thus, the forecasting results can be considered highly reliable [31].

However, if the data used is not adjusted, the predictions may become illogical. To address this, two scenarios are investigated, as illustrated in Figure 5 for Scenario 1 and Figure 6 for Scenario 2. In Scenario 1, historical data from the last year (2020) is included, leading to an unrealistic prediction where electricity consumption reaches a negative value of -39,484.52 GWh by 2045. In contrast, Scenario 2 excludes 2020 data, resulting in a much smoother and more logical growth in electricity consumption, reaching 610,807.8 GWh in 2045.

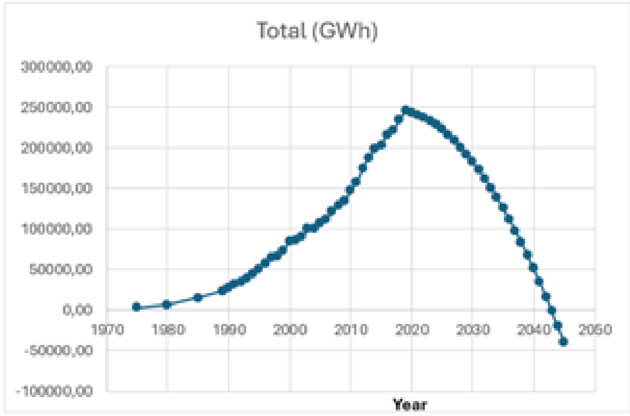

Figure 5: Scenario 1: Forecasting results through the ARIMA method (with 2020 data).

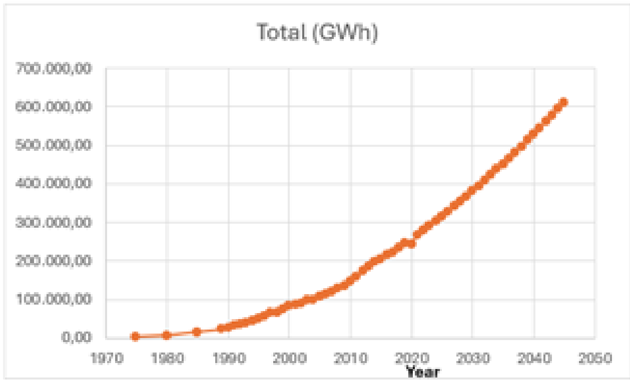

Figure 6: Scenario 2: Forecasting results through the ARIMA method (without 2020 data).

Examining the prediction results from both scenarios, Scenario 2 appears more reasonable as the energy consumption growth follows a well-regressed trend. Meanwhile, Scenario 1 suggests a decline in electricity consumption to negative values, which is unrealistic. Adjusting the input data for ARIMA-based forecasting is crucial, as the method heavily depends on the most recent data. The anomaly in the 2020 dataset, caused by the pandemic, highlights the need for data adjustments when applying machine learning in energy consumption forecasting.

In 2021, electricity consumption began recovering, reaching 257,634.25 GWh. A year later, it increased significantly to 273,761.48 GWh. If forecasting is restarted from 2022, it is recommended to replace the 2020 electricity consumption data with the average of 2019 and 2021 values. This approach enhances the prediction model by mitigating the impact of anomalous data. If the last year's data already exhibits an increasing trend, predictions can be conducted without requiring special data treatment.

By refining the input data, the ARIMA method yields more realistic electricity usage predictions. This discussion provides valuable insights for policymakers and energy planners regarding Indonesia's electricity landscape. Addressing unmet energy supply targets requires evaluating multiple approaches carefully. The ARIMA model serves as an efficient forecasting tool, guiding strategic power plant development towards Indonesia's independence centennial in 2045.

IV. Conclusion

Considering the pandemic's impact, the 2020 dataset is disregarded in this study, as its inclusion leads to inaccurate projections. Scenario 2 provides a more logical forecast, predicting a continuous increase in electricity consumption over the next 25 years. By 2045, Indonesia's electricity consumption is expected to reach 610,807.8 GWh, more than doubling from the present. Metric testing of the ARIMA model for power consumption prediction resulted in an RMSE of 2807.25, an MAE of 1481.25, and an MAPE of 5.47%. This suggests that the ARIMA approach, with data adjustments, achieves an average confidence level of approximately 94.53%. The ARIMA model successfully predicts future electricity consumption trends in this seasonal dataset with non-stationary characteristics. By applying appropriate transformations, stationarity is achieved, leading to highly accurate prediction results. **Future Work:** Considering advancements in energy-efficient technologies, future electricity consumption may decline, potentially resembling Scenario 1's trend. Thus, additional factors beyond historical data should be integrated into ARIMA-based forecasting. Incorporating hybrid forecasting models could further enhance prediction accuracy and relevance.

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