Forecasting of electrical energy consumption using Autoregressive Integrated Moving Average (Case Study: ULP Meulaboh Kota)

Putri Gunandra Siregar[1], Ilham Sahputra[2]*, Fidyatun Nisa[3]
1,2,3) Prodi Sistem Informasi, Fakultas Teknik, Universitas Malikussaleh, Indonesia

**Corresponding Author: ilham.sahputra@unimal.ac.id*

ABSTRACT

Forecasting electricity consumption is one of the solutions that can be implemented by the ULP Meulaboh Kota to ensure the availability of sufficient electricity supply. With the continuous increase in electricity demand, the ULP faces challenges in predicting and managing electricity consumption. Uncertainty in consumption patterns can lead to imbalances between supply and demand, potentially causing various issues such as power outages, high operational costs, and customer dissatisfaction. Therefore, accurate forecasting is essential to support effective decision-making and planning. This study aims to forecast electricity consumption across five different sectors: residential, social, business, industrial, and public, using the ARIMA (Autoregressive Integrated Moving Average) method. The forecasting process involves data collection, stationarity testing using the Augmented Dickey-Fuller (ADF) test, and differencing when necessary to achieve stationarity. The ARIMA model is identified through ACF and PACF plot analysis, estimated, and tested before being used for forecasting. The results indicate that the ARIMA method provides highly accurate forecasts for all sectors, as reflected by the low Mean Absolute Percentage Error (MAPE) values. The residential sector has a MAPE of 4.3957%, the social sector 4.3757%, the business sector 3.1125%, the industrial sector 7.9937%, and the public sector 4.3646%. Overall, the forecasting error produced by the ARIMA model remains below 8%, with an average MAPE of 4.8483% across all sectors.

Keywords: Forecasting, Electricity Consumption, ARIMA, Augmented Dickey-Fuller, MAPE.

ABSTRAK
Peramalan konsumsi energi listrik merupakan salah satu solusi yang dapat dilakukan oleh pihak ULP Meulaboh Kota untuk memastikan ketersediaan pasokan energi listrik tercukupi. Meningkatnya permintaan energi listrik yang terus berlanjut, pihak ULP menghadapi tantangan dalam memprediksi dan mengelola konsumsi energi listrik. Ketidakpastian dalam pola konsumsi energi listrik dapat menyebabkan ketidakseimbangan antara pasokan dan permintaan, yang akhirnya dapat mengakibatkan berbagai masalah seperti pemadaman listrik, biaya operasional yang tinggi, dan ketidakpuasan pelanggan. Sehingga, peramalan yang akurat sangat penting untuk mendukung pengambilan Keputusan dan perencanaan yang efektif. Penelitian ini bertujuan untuk meramalkan konsumsi energi listrik terhadap lima sektor yang berbeda, yaitu: sektor rumah tangga, sosial, bisnis, industri dan publik menggunakan metode ARIMA (Autoregressive Integrated Moving Average). Proses peramalan melibatkan pengumpulan data, uji stasioneritas menggunakan uji Augmented Dickey-Fuller (ADF), dan differencing jika diperlukan untuk membuat data stasioner. Model ARIMA diidentifikasi melalui analisis plot ACF dan PACF, diestimasi, dan diuji sebelum digunakan untuk peramalan. Hasil penelitian menunjukkan bahwa metode ARIMA dapat memberikan peramalan dengan sangat baik untuk semua sektor, hal ini dapat dilihat dari nilai MAPE (Mean Absolute Percentage Error) yang rendah untuk peramalan pada setiap sektor. Sektor rumah tangga dengan nilai MAPE sebesar 4.3957%, sektor sosial dengan nilai MAPE sebesar 4.3757%, sektor bisnis dengan nilai MAPE sebesar 3.1125%, sektor industri dengan nilai MAPE sebesar 7.9937%, dan untuk sektor publik dengan nilai MAPE sebesar 4.3646%. Secara umum eror yang dihasilkan oleh ARIMA berada dibawah 8% dengan rata-rata untuk semua sektor adalah sebesar 4.8483.

Kata Kunci: Peramalan, Konsumsi Energi Listrik, ARIMA, Augmented Dickey-Fuller, MAPE.

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1. INTRODUCTION

Electricity is a form of energy generated by the movement of electrons through conductors such as wires or electrical circuits [1]. It can be produced through the transformation of energy from other sources and, conversely, can also be converted into other forms of energi [2]. Due to rapid technological advancement and population growth, the demand for electricity continues to rise [3]. The use and availability of electricity are crucial for supporting various economic, social, and everyday activities [4]. As demand increases, addressing energy sustainability, climate change, and energy efficiency becomes even more critical.

The Meulaboh City Customer Service Unit (ULP) is one of the electricity service providers in the Meulaboh area and is currently facing challenges in predicting and managing the rising electricity consumption. Unstable energy consumption patterns can lead to an imbalance between electricity supply and demand [5], which in turn can result in power outages, high operational costs, and customer dissatisfaction [6].

The distribution network plays a vital role in delivering power from the generating stations to end users in the electricity supply process [7]. Electricity distribution is categorized into five main sectors: residential, social, commercial, industrial, and public [8]. Therefore, both technically and economically, reliable electricity supply and distribution are essential [9].

One approach to addressing this issue is by forecasting electricity consumption. Accurate and consistent forecasting is crucial for understanding long-term prediction techniques [10]. With electricity consumption forecasts, ULP Meulaboh City can plan its energy supply more effectively, optimize operations, and improve customer service. The ARIMA (Autoregressive Integrated Moving Average) method is one approach that generates forecasts based on patterns and trends in historical data [11]. The goal of ARIMA is to establish a strong statistical relationship between the forecasted variable and its historical values, enabling the model to make accurate predictions [12]. This method is particularly suitable for time series data with statistical dependencies [13].

The ARIMA model is denoted by three parameters: ARIMA(p,d,q), where (p) represents the number of autoregressive (AR) terms, (d) the degree of differencing to make the data stationary, and (q) the number of moving average (MA) terms [14] One of the key advantages of ARIMA is its high accuracy, making it suitable for fast, precise forecasting that relies solely on historical data [15].

In several case studies, ARIMA has proven effective in forecasting future events. However, this technique has not yet been applied at ULP Meulaboh City. To provide a more accurate picture of electricity consumption patterns and support better energy management decisions, this study applies the ARIMA method to forecast electricity consumption at ULP Meulaboh City.

The studies have compared ARIMA with other forecasting methods across various domains. For example, one study [16] compared ARIMA and LSTM for forecasting stock closing prices. By analyzing six categories of stocks, the researchers found that ARIMA outperformed LSTM in terms of average RMSE, MAPE, and prediction time—achieving values of 198.62, 1.79%, and 26.50 seconds, respectively. Meanwhile, another study [13] investigated the use of ARIMA and Support Vector Regression (SVR) to predict the stock prices of PT. Astra International Tbk. They developed a system combining technical analysis with ARIMA and SVR, implemented using Python and the TA-Lib library. The results indicated that SVR slightly outperformed ARIMA, with a 0.013941 advantage in both weekly and three-month prediction schemes, suggesting that SVR can be considered a viable tool for investor decision-making. Furthermore, a different study [17] applied ARIMA and ANFIS to analyze rainfall data, revealing that ANFIS performed better for nonlinear time series data, whereas ARIMA was more suited for linear patterns. In this case, ARIMA’s predictions showed a poor fit with actual daily and nonlinear data, with a correlation of 14.037 and an RMSE of 24.92%. In contrast, ANFIS achieved a correlation of 6.9811 and an RMSE of 87.29%, demonstrating higher accuracy.

To ensure optimal supply planning and operational efficiency, accurate forecasting of electricity consumption is essential. This study uses five years of historical data from various sectors—residential, social, commercial, industrial, and public. The research aims not only to develop an accurate forecasting model but also to assist energy managers in making better decisions regarding energy distribution and allocation. Ultimately, it is hoped that this study will contribute to more efficient and sustainable energy management in the future.

2. RESEARCH METHOD

This study consists of several stages, namely: data collection, model identification, parameter estimation and testing, stationarity testing, and forecasting. The forecasting technique used is the ARIMA (Autoregressive Integrated Moving Average) method. ARIMA is classified into three types: Autoregressive (AR), Moving Average (MA), and a mixed model called Autoregressive Moving Average (ARMA). The research utilizes Jupyter Notebook software to assist in the process of forecasting electricity consumption.

The AR model equation is as follows:

$$Z_t = \emptyset_1 Z_{t-1} + \emptyset_2 Z_{t-2} + \ldots + \emptyset_p Z_{t-p} + \alpha_t \tag{1}$$

Where:
- Z_t is the actual value at time t
- $\phi_1, \phi_2, \ldots, \phi_p$ are the autoregressive coefficients
- p is the order of the AR model
- α_t is white noise (random error term with mean zero and constant variance)

The MA model equation is as follows:

$$Z_t = \alpha_t - \theta_1 \alpha_{t-1} - \theta_2 \alpha_{t-2} - \ldots - \theta_q \alpha_{t-q} \tag{2}$$

Where:
- $\theta_1, \theta_2, \ldots, \theta_q$ are the moving average coefficients
- q is the order of the MA model
- α_t is the random error at time t

The ARMA model equation is as follows:

$$Z_t = \emptyset_1 Z_{t-1} + \ldots + \emptyset_p Z_{t-p} + \alpha_t - \theta_1 \alpha_{t-1} - \ldots - \theta_q \alpha_{t-q} \tag{3}$$

The ARIMA model equation is as follows:

$$\emptyset_p(B)(1-B)^d Z_t = \theta_q(B)\alpha_t \tag{4}$$

Where:
- B is the backshift operator, such that $BZ_t = Z_{t-1}$
- d is the degree of differencing needed to make the series stationary
- $\phi_p(B)$ is the AR polynomial in terms of the backshift operator
- $\theta_q(B)$ is the MA polynomial
- α_t is the white noise error term

2.1. Data Collecting

This study uses secondary data obtained from the Meulaboh City ULP. The data consists of 300 historical records of electricity consumption over a five-year period, divided into five different sectors. Data collection spans from January 2019 to December 2023.

2.2. Stationary Test

In this study, the stationarity test was conducted by examining the p-value from the Augmented Dickey-Fuller (ADF) test. If the p-value is less than 0.05, the data is considered stationary. However, if the p-value is greater than 0.05, the data is non-stationary and differencing must be applied. Additionally, the stationarity test is used to determine the value of the parameter (d). If the data is stationary, then (d) = 0. If the data is non-stationary, then (d) equals the number of times differencing is applied. The differencing formula is as follows:

$$\text{diff} = Y_{actual\ data} - Y_{actual\ data-actual\ data\ before} \tag{5}$$

2.3. Model Identification

The identification of models in the five sectors was carried out by observing the lags that exceed the significance threshold (cut-off) on the autocorrelation (ACF) and partial autocorrelation (PACF) plot.

2.2. Estimation and Parameter Testing

After determining the values of p, d, and q and building a preliminary ARIMA(p,d,q) model, the next step is to estimate the parameters of the autoregressive (AR) and moving average (MA) components. These results will then be used to produce the final forecasting model.

2.2. Forecating

Forecasting can be carried out for a certain period after identifying the best model.

3. RESULTS AND DISCUSSION

3.1. Dataset

The dataset consists of historical monthly electricity consumption data obtained from ULP Meulaboh Kota. A total of 300 records were collected, divided into five sectors, covering the period from January 2019 to December 2023. The following is the dataset for each sector:

1. Household Sector

Table 1. Household Sector Dataset

No	Bulan	Dataset
1	Januari 2019	4815.841
2	Februari 2019	4249.512
...	...	...
59	November 2023	5355.871
60	Desember 2023	5697.709

2. Social Sector

Table 1. Social Sector Dataset

No	Bulan	Dataset
1	Januari 2019	471.128
2	Februari 2019	450.215
...	...	...
59	November 2023	710.439
60	Desember 2023	701.568

3. Bussiness Sector

Table 1. Bussiness Sector Dataset

No	Bulan	Dataset
1	Januari 2019	1598.309
2	Februari 2019	1459.105
...	...	...
59	November 2023	2024.553
60	Desember 2023	2132.373

4. Industry Sector

Table 1. Industry Sector Dataset

No	Bulan	Dataset
1	Januari 2019	845.987
2	Februari 2019	817.894
...	...	...
59	November 2023	1076.934
60	Desember 2023	1024.218

5. Public Sector

Table 1. Household Sector Dataset

No	Bulan	Dataset
1	Januari 2019	626.59
2	Februari 2019	586.595
...	...	...
59	November 2023	639.809
60	Desember 2023	644.236

3.2. Estimation and Parameter Testing

The results of parameter estimation and testing conducted across five sectors are explained below:

1. Household Sector

   In the household sector, four candidate models were tested to determine the best one: models (2,0,2), (2,0,1), (1,0,2), and (1,0,1). Based on the parameter testing results, model (1,0,1) was identified as the best model for the household sector.

2. Social Sector

   In the social sector, five candidate models were tested: models (1,1,2), (1,1,1), (0,1,2), (1,1,0), and (0,1,1). Based on the results, model (0,1,1) was found to be the most suitable for the social sector.

3. Business Sector

   In the business sector, three candidate models were tested: models (1,1,1), (1,1,0), and (0,1,1). The testing revealed that model (0,1,1) was the best model for the business sector.

4. Industrial Sector

   In the industrial sector, four models were evaluated: models (3,1,2), (2,1,2), (2,1,1), and (1,1,1). The parameter testing indicated that model (2,1,1) was the most appropriate for the industrial sector.

5. Public Sector

   In the public sector, three models were tested: models (1,0,1), (1,0,0), and (0,0,1). The testing showed that model (0,0,1) was the best model for the public sector.

3.3. Forecasting

The results of forecasting electricity consumption for five sectors are presented as follows:

1. Household Sector

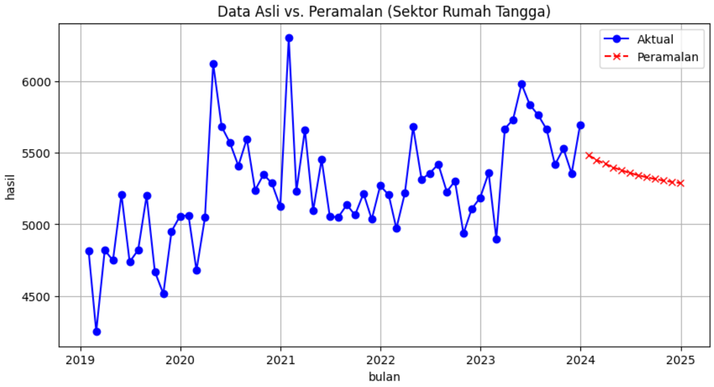


Figure 1. Forecast Plot for the Household Sector

Figure 1 shows the forecast plot of electricity consumption in the household sector, indicating a slight decline each month.

Table 6. Household Sector Forecast Results

Month	Result	Month	Result
1	5483.024796	7	5342.603483
2	5450.741529	8	5328.669397
3	5422.676793	9	5316.556111
4	5398.279341	10	5306.025697
5	5377.069961	11	5296.871316
6	5358.632060	12	5288.913159

Table 6 presents the forecasting results of household electricity consumption using the ARIMA (1,0,1) model for the next 12 months. After obtaining the forecast results, a percentage error test or MAPE (Mean Absolute Percentage Error) test was conducted to measure the accuracy of the model parameters. The resulting MAPE value was 4.3957%, indicating that the ARIMA (1,0,1) model provides a very accurate forecast.

2. Social Sector

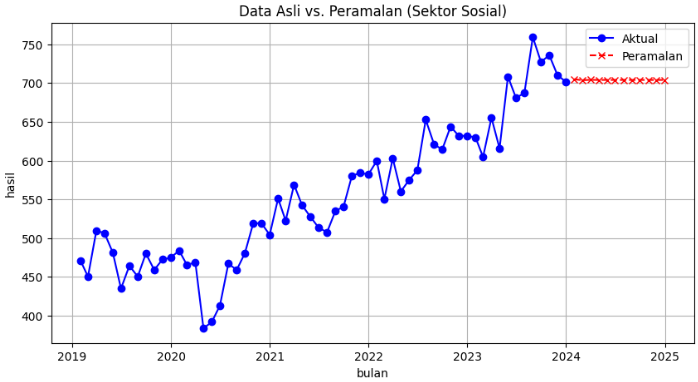


Figure 2. Forecast Plot for the Social Sector

Figure 2 shows the forecast plot of electricity consumption in the social sector, indicating a more stable trend at around the 700 to 710 level.

Table 7. Forecast Results for the Social Sector

Month	Result	Month	Result
1	704.998881	7	704.045242
2	703.671979	8	704.040801
3	704.185162	9	704.042519
4	703.986687	10	704.041855
5	704.063448	11	704.042112

6	704.033760	12	704.042012

Table 7 presents the forecasting results of electricity consumption in the social sector using the ARIMA (1,1,0) model for the next 12 months. The obtained MAPE value is 4.3757%, indicating that the (1,1,0) parameters provide a very good forecasting performance.

3. Business Sector

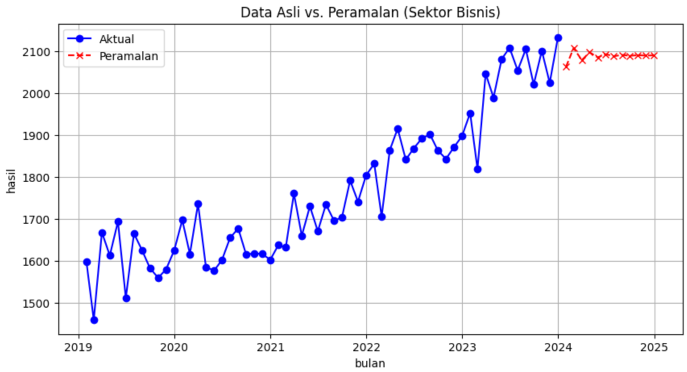


Figure 3. Forecast Plot for the Business Sector

Figure 3 shows the forecast plot of electricity consumption in the business sector, indicating an upward trend.

Table 8. Forecast Results for the Business Sector

Month	Result	Month	Result
1	2062.916751	7	2088.184818
2	2107.659568	8	2091.382206
3	2078.836824	9	2089.322490
4	2097.404063	10	2090.649332
5	2085.443288	11	2089.794598
6	2093.148264	12	2090.345287

4. Industrial Sector

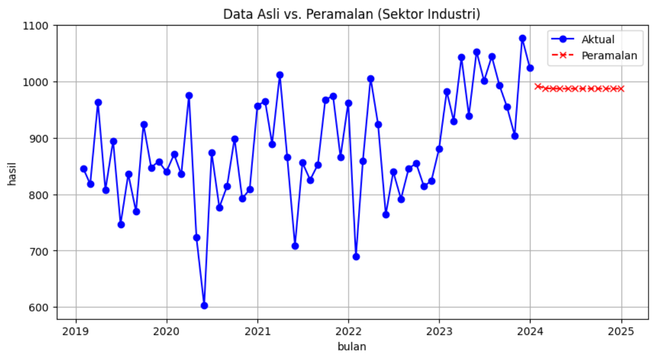


Figure 4. Forecast Plot for the Industrial Sector

Figure 4 shows the forecast plot of electricity consumption in the industrial sector, which indicates an upward trend. The forecast results for the years 2024 to 2025 show a relatively stable trend at a level of around 950 to 1000.

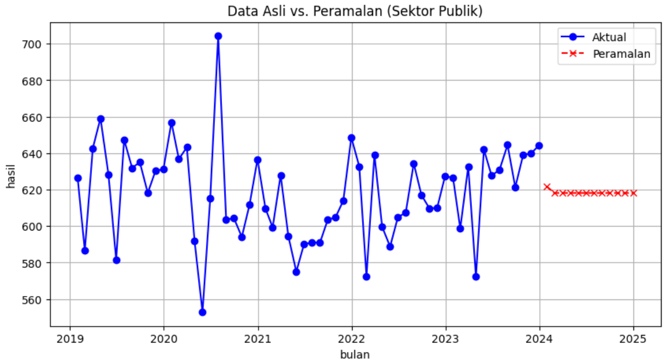
Table 8. Forecast Results for the Business Sector

Month	Result	Month	Result
1	991.937224	7	987.312718
2	988.217275	8	987.312618
3	987.456709	9	987.312601
4	987.337681	10	987.312598

5	987.316794	11	987.312597
6	987.313312	12	987.312597

Table 9 presents the forecasting results of electricity consumption in the industrial sector using the ARIMA (2,1,1) model for the next 12 months. The resulting MAPE value is 7.9937%, indicating that the ARIMA (2,1,1) model performs the forecasting very well.

5. Public Sector



Gambar 1. Plot Hasil Peramalan Sektor Publik

Figure 5 shows a plot of the forecasted electricity consumption in the public sector, which indicates an upward trend. The forecast results for the years 2024 to 2025 show stability at a relatively constant level, ranging from 620 to 640.

Table 10. Forecast Results for the Public Sector

Month	Result	Month	Result
1	621.732396	7	618.151611
2	618.151611	8	618.151611
3	618.151611	9	618.151611
4	618.151611	10	618.151611
5	618.151611	11	618.151611
6	618.151611	12	618.151611

Table 10 presents the forecast results of electricity consumption in the public sector using the ARIMA (0,0,1) model for the next 12 months. The obtained MAPE value is 4.3646%, indicating that the (0,0,1) model provides a very good forecasting performance.

4. CONCLUSION

Based on the research findings, the application of the ARIMA method has proven to be effective in forecasting electricity consumption across various sectors, including residential, social, commercial, industrial, and public sectors. The model's accuracy is demonstrated by an average MAPE value of 4.8484% across all sectors, which falls within the <10% range, indicating a high level of accuracy. With this level of precision, the forecasting model not only provides reliable predictions but also has the potential to support better decision-making in supply planning and energy distribution optimization. These results are expected to contribute to more efficient and sustainable energy management in the future.

REFERENCES

M. Sigala, A. Beer, L. Hodgson, and A. O'Connor, *Big Data for Measuring the Impact of Tourism*

Economic Development Programmes: A Process and Quality Criteria Framework for Using Big Data. 2019.

[1] Lambey, D. S., Amin, N., Pirade, Y. S., & Santoso, R. (2021). Analisis Konsumsi Energi Listrik Untuk Pencapaian Efisiensi Energi Di Kantor Dewan Perwakilan Rakyat Daerah Kabupaten Tojo Una-Una. Foristek, 11(2), 108–114. https://doi.org/10.54757/fs.v11i2.112

[2] Rifais, A. (2018). Prediksi Konsumsi Energi Listrik Menggunakan Metode Jaringan Syaraf Tiruan Recurrent di PLN APJ Salatiga. 1–83.

[3] Rajagukguk, A. S. F., Pakiding, M., & Rumbayan, M. (2015). Kajian Perencanaan Kebutuhan dan Pemenuhan Energi Listrik di Kota Manado. Jurnal Teknik Elektro Dan Komputer, 4(3), 1–11. https://ejournal.unsrat.ac.id/index.php/elekdankom/article/view/7972

[4] Setiawan, W. (2020). Ketersediaan Suplai Energi Listrik di Indonesia. https://www.goodnewsfromindonesia.id/2020/06/23/ketersediaan-suplai-energi-listrik-di-indonesia

[5] Syachreza Himawan, D., & Sudiarto, B. (2022). Upaya Konservasi Energi Listrik pada Universitas Indonesia Berdasarkan Metode Intensitas Konsumsi Energi. Edu Elektrika Journal, 11(2), 30–34.

[6] Kristiana, A., Wilandari, Y., Gaussian, A. P.-J., & 2015, undefined. (2015). Peramalan Beban Puncak Pemakaian Listrik Di Area Semarang Dengan Metode Hybrid Arima (Autoregressive Integrated Moving Average)-anfis (Adaptive Neuro. Ejournal3.Undip.Ac.IdA Kristiana, Y Wilandari, A PrahutamaJurnal Gaussian, 2015•ejournal3.Undip.Ac.Id, 4, 715–723. https://ejournal3.undip.ac.id/index.php/gaussian/article/view/10125

[7] Hasibuan, A., Afrizal, A., Fariadi, D., & Nisa, F. (2024). PERHITUNGAN SUSUT DENGAN MEMBANDINGKAN ANTARA PERHITUNGAN PT. PLN ULP LHOKSEUMAWE KOTA DENGAN PERHITUNGAN SOFTWARE ETAP SETELAH DILAKUKAN PERUBAHAN POLA OPERASI TAHUN 2023 Arnawan. 26(1), 1–10.

[8] Prasasti, W. (2022). Peramalan Konsumsi Energi Listrik Dikabupaten Blora Pada Tahun 2022-2025 Menggunakan Metode Autoregressive Integrated …. Simetris, 16(2), 7–15. https://www.sttrcepu.ac.id/jurnal/index.php/simetris/article/view/247%0Ahttps://www.sttrcepu.ac.id/jurnal/index.php/simetris/article/download/247/157

[9] Bandri, S. (2019). Prediksi Perkembangan Kebutuhan Energi Listrik di Unit PLN Kayu Aro. Menara Ilmu, XIII(6), 187–205.

[10] Abdullah, D., Wandi, R., & Nasution, Z. (2021). Implementasi Metode Double Exponential Smoothing Untuk Peramalan Konsumsi Listrik Berdasarkan Pemakaian Kwh Di Pt. Pln (Persero) Ulp Natal. TECHSI - Jurnal Teknik Informatika, 13(1), 61. https://doi.org/10.29103/techsi.v13i1.3091

[11] Dona, A. R., & Sugiman. (2021). Peramalan Metode ARIMA Data Saham PT. Telekomunikasi Indonesia. PRISMA: Prosiding Seminar Nasional Matematika, 4, 611–620. https://journal.unnes.ac.id/sju/index.php/prisma/

[12] Ayuningtyas, S. J. (2019). PERAMALAN JUMLAH KASUS TUBERKULOSIS DI PROVINSI JAWA TIMUR DENGAN MENGGUNAKAN METODE HYBRID AUTOREGRESSIVE INTEGRATED MOVING AVERAGE – ADAPTIVE NAURO FUZZY INFERENCE SYSTEM (ARIMA – ANFIS) FORECASTING.

[13] Kurniawati, A., & Arima, A. (2021). Analisis Prediksi Harga Saham PT. Astra International Tbk Menggunakan Metode Autoregressive Integrated Moving Average (ARIMA) dan Support Vector Regression (SVR). Jurnal Ilmiah Komputasi, 20(3), 417–423. https://doi.org/10.32409/jikstik.20.3.2732

[14] Annasiyah, F., & Prastuti, M. (2023). Peramalan Konsumsi Energi Listrik untuk Sektor Industri di PT PLN (Persero) Area Gresik Menggunakan Metode Time Series Regression dan ARIMA. *Jurnal Sains Dan Seni ITS*, *12*(1). https://doi.org/10.12962/j23373520.v12i1.104264

[15] Prasasti, W. (2022). Peramalan Konsumsi Energi Listrik Dikabupaten Blora Pada Tahun 2022-2025 Menggunakan Metode Autoregressive Integrated .... Simetris, 16(2), 7–15. https://www.sttrcepu.ac.id/jurnal/index.php/simetris/article/view/247%0Ahttps://www.sttrcepu.ac.id/jurnal/index.php/simetris/article/download/247/157

[16] Milniadi, A. D., & Adiwijaya, N. O. (2023). Analisis Perbandingan Model Arima Dan Lstm Dalam Peramalan Harga Penutupan Saham (Studi Kasus : 6 Kriteria Kategori Saham Menurut Peter Lynch). SIBATIK JOURNAL: Jurnal Ilmiah Bidang Sosial, Ekonomi, Budaya, Teknologi, Dan Pendidikan, 2(6), 1683–1692. https://doi.org/10.54443/sibatik.v2i6.798

[17] Ayu Wulandari, R., & Gernowo, R. (2019). Metode Autoregressive Integrared Moving Average (ARIMA) dan Metode Adaptive Neuro Fuzzy Inference System (ANFIS) dalam Analisis Curah Hujan. Berkala Fisika, 22(1), 41–48.