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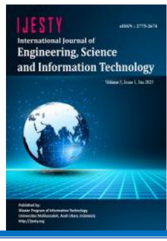

Predicting Electricity Consumption in Aceh Province Using the Markov Chain Monte Carlo Method

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Abstract

Electricity is essential to nearly every aspect of modern life, from industrial sectors to household needs. In Aceh Province, the demand for electricity has consistently increased along with economic growth, urbanization, and population expansion. Various studies indicate that rising electricity consumption is closely linked to economic growth and industrialization. This study uses the Markov Chain Monte Carlo (MCMC) method with the Metropolis-Hastings algorithm to predict electricity consumption in Aceh Province. The research addresses the significant increase in electricity consumption driven by economic growth and urbanization in the region. Electricity consumption data from January 2018 to December 2022 was utilized as the basis for modeling. The results indicate a 32.4% increase in electricity consumption over the past five years. The predictive model achieved high accuracy with a Mean Absolute Percentage Error (MAPE) of 2.41%, demonstrating its reliability in forecasting future electricity needs. Projections through 2030 show a continuous increase, reaching 482 GWh by the end of the period. These findings are expected to support decision-making in sustainable energy planning and providing adequate electricity infrastructure in Aceh. This study highlights the effectiveness of the Me-tropolis-Hastings algorithm in handling complex data with high variability, providing valuable insights for long-term energy planning.

***Keywords**: Electricity Consumption Prediction, Markov Chain Monte Carlo, Metropolis-Hastings, Energy Planning, Aceh.*

1. Introduction

Electricity is essential to nearly every aspect of modern life, from industrial sectors to household needs. In Aceh Province, the demand for electricity has consistently increased along with economic growth, urbanization, and population expansion. Various studies indicate that rising electricity consumption is closely linked to economic growth and industrialization, often showing a region's growth and economic advancement [1], [2].

As electricity demand increases, the challenges for electricity providers and the government also intensify. Without proper planning and management, this demand surge could lead to a gap between electricity availability and consumption. This imbalance could slow economic growth and affect social stability, particularly in developing areas like Aceh. International studies highlight that energy consumption prediction models are essential in supporting sustainable planning. For instance, Zhou et al. [3], in reviewing various energy prediction techniques, mention that regression models, neural networks, and machine learning can provide more accurate estimates of energy needs [3].

Several studies have been conducted to project electricity needs in Indonesia. Ekananta et al. [4] used the Average-Based Fuzzy Time Series method to predict electricity consumption in Indonesia, demonstrating improved accuracy in handling complex data. At the national level, Harisandy [5] applied Vector Auto Regression (VAR) and Autoregressive Integrated Moving Average (ARIMA) models to forecast household electricity consumption, finding that ARIMA provides more accurate prediction results. This research offers valuable insights for Indonesia, which has varied energy consumption characteristics [5].

In Aceh, Purnama et al. [6] projected electricity consumption in Aceh Tamiang through 2030, revealing an increase of 63.7% since 2013. Meanwhile, Nugraha et al. [7] employed the Adaptive Neuro-Fuzzy Inference System (ANFIS) to project electricity consumption in Aceh until 2028, which has been helpful in developing long-term strategies. Globally, Zhang et al. [8] explored the use of Support Vector

Regression (SVR) optimized by the Dragonfly algorithm to forecast electricity demand in China, showing that machine learning-based approaches are highly effective in managing dynamic and varied consumption patterns [8].

Additionally, Wang et al. [9] highlighted the application of artificial intelligence in forecasting electricity consumption more efficiently, underscoring the importance of adaptive and flexible predictive methods. These studies demonstrate that the variation in consumption patterns and data uncertainty requires advanced predictive approaches to improve accuracy.

Previous studies have shown that ARIMA and Triple Exponential Smoothing (TES) models have been effectively used in various sectors for time series data forecasting. These models can handle consumption pattern instability in multiple contexts, from predicting news popularity in West Sumatra to forecasting highly volatile cryptocurrency prices [10], [11]. However, ARIMA has limitations in handling high uncertainty and complex variability data. This necessitates a more adaptive predictive model capable of managing uncertainty, such as the Monte Carlo Markov Chain (MCMC) method, which can handle high uncertainty and variability in electricity consumption data.

This study aims to predict electricity consumption in Aceh Province using the Monte Carlo Markov Chain (MCMC) approach for the upcoming months (2023 to 2030). MCMC was chosen for its superior ability to handle data variability and uncertainty, which aligns with electricity consumption's dynamic and fluctuating nature. The prediction results are expected to support effective decision-making in sustainable energy planning in Aceh, helping the government and energy providers balance electricity supply and demand.

1. Literature Review

2.1. Previous Research

The Markov Chain Monte Carlo (MCMC) method has demonstrated its versatility in various scientific applications, mainly through the Metropolis-Hastings (MH) algorithm. In 2020, Yan et al. applied this algorithm to predict energy consumption behaviors in office environments. By leveraging Internet of Things (IoT) data, their model effectively identified complex energy usage patterns and provided accurate parameter estimates. This approach proved robust in handling uncertainty, outperforming traditional methods like Maximum Likelihood Estimation, especially in modeling unpredictable behaviors such as air conditioners and other electronic devices [12].

In the same year, Hariadi et al. utilized MCMC to forecast stock prices, combining Bayesian inference with the parallel computing capabilities of Apache Spark. This enabled faster and more efficient simulations, allowing investors to make more accurate data-driven decisions in shorter timeframes [13]. A year later, Dukunde et al. expanded the application of Metropolis-Hastings to the field of epidemiology by predicting the prevalence of type 2 diabetes in Rwanda. Their study revealed a significant increase in prevalence, from 2.8% in 2015 to over 22% by 2025. These findings underscored the urgent need for improved public health interventions, such as promoting physical activity and raising awareness about healthy lifestyles. The model projected historical data and provided valuable insights for policymakers in designing effective disease prevention strategies [14].

The potential of the Metropolis-Hastings algorithm has been further extended to environmental and hydrological fields. Wang and Nishi developed a stochastic model to simulate the distribution of polychlorinated biphenyls (PCBs) in marine ecosystems. Combining macroscopic and microscopic models, this algorithm successfully simulated the dynamics of marine pollution and bioaccumulation in the food chain, with results aligning well with empirical data. This study demonstrated the model's utility for more effective environmental risk monitoring and assessment [15]. Meanwhile, Fan et al. introduced the Particle Copula Metropolis-Hastings (PCMH) method in hydrology to enhance the accuracy of river flow predictions and uncertainty quantification. Compared to methods like Particle Filter and Particle MCMC, PCMH showed superior performance in tackling large data scenarios and complex uncertainties [16].

These diverse applications underscore the strengths of the Metropolis-Hastings algorithm as a powerful tool for addressing predictive challenges across multiple domains. This algorithm provides reliable solutions for generating more accurate and informative predictions, from analyzing human behavior in energy consumption and forecasting volatile stock prices to quantifying environmental and health risks. This highlights the critical role of MCMC in modern scientific research, where data-driven decision-making has become essential.

2.2. Electrical Energy Consumption

Relationship Between Energy and Economy Energy consumption, especially electricity, is closely related to economic growth. According to the International Energy Agency [1], increased energy consumption usually follows economic growth and industrialization, which requires energy to support activities in the industrial, transportation, and other sectors that accelerate the economic development of a region. Factors Determining Electrical Energy Consumption The main factors affecting electricity consumption include population growth and urbanization, increasing population and urbanization, and increasing the need for electricity to meet infrastructure and public service needs. Industrialization: Industrial activities require large amounts of energy for production and operational processes. For example, studies in China show that rapid industrialization has driven a significant increase in electricity consumption [8]. Weather and Seasonal Factors: In countries with extreme climates, electricity needs can increase in summer for cooling and winter for heating [17]. Energy Consumption as an Indicator of Welfare Electricity consumption is also considered a welfare indicator. OECD [2] states that increasing access to and consumption of electricity per capita is often associated with better living standards and higher quality of life, especially in developing countries. The Importance of Energy Efficiency and Sustainable Planning Energy efficiency and good planning are essential to reduce the environmental impact of increasing energy consumption. The International Renewable Energy Agency [18] highlights that energy efficiency in electricity use can help reduce energy demand and carbon emissions and support sustainable economic growth.

2.3. Time Series Models in Electricity Consumption

Time series models analyze historical data collected periodically, such as daily, monthly, or annual electricity consumption. In the context of energy consumption, time patterns often reflect long-term trends, seasonal patterns, or daily winters. These patterns help predict future energy consumption, essential in energy supply planning [19]. In a specific time analysis, it is necessary to determine whether the data is stationary or non-stationary. Stationary data has a constant mean and variance over time, while non-stationary data shows significant trend or seasonal pattern changes. Electricity consumption data is usually non-stationary because it is influenced by external factors such as population growth and economic changes [20]. Markov Chain Monte Carlo (MCMC) methods can be used in time series analysis to overcome the intimidation and high variability in the data. MCMC works by generating samples from the underlying probability distribution of the data, even when the distribution is complex or not explicitly known. With this capability, MCMC can predict energy consumption patterns by considering non-stationary time series data, providing more accurate and reliable projections [21].

2.4. Markov Chain Monte Carlo (MCMC)

Markov Chain Monte Carlo (MCMC) is a simulation method that combines the concepts of Markov Chain and Monte Carlo to estimate complex probability distributions. MCMC is used to calculate a target distribution's mean value, probability, or other parameters, especially when the distribution is difficult or impossible to calculate analytically [22]. Markov Chain is a stochastic process in which the probability of an event depends only on the current state, without considering how the state was reached. This process has several main components: State Space, Transition Probability, and Steady State. Markov Chain allows for highly efficient exploration of state space in simulation, which is very useful in modeling complex systems [23]. Monte Carlo is a random sample-based simulation method for calculating estimates of probability distributions. This method is used when the target distribution does not have an explicit form or when analytical integration is impossible. The advantage of Monte Carlo is its flexibility in handling high data dimensions and distribution complexity [24]. In general, there are two algorithms in MCMC, such as Metropolis-Hastings and Gibbs Sampling, used to generate samples from the target distribution by building a Markov chain with a steady state distribution according to the target distribution. This process allows us to estimate the parameter distribution even in models with many variables and uncertainties [21].

This study will use the Metropolis-Hastings algorithm to predict electricity consumption. The Metropolis-Hastings (MH) algorithm is an iterative method that generates samples from the target distribution π(x). This algorithm works by proposing new samples based on the proposal distribution q(x^' |x), then accepting or rejecting the samples based on specific criteria

The steps of the Metropolis-Hastings algorithm, according to Turkman et al. [25] are as follows:

1. Initialization. Choose an initial value of $u^{(0)}$.
2. Proposal. Propose a sample $\tilde{u}$ from the proposal distribution $q\left(\tilde{u}|u^{(t)}\right)$.
3. Calculate the acceptance ratio: $R\left(u^{(t)},\tilde{u}\right)=\frac{\rho(\tilde{u})q\left(u^{(t)}|\tilde{u}\right)}{\rho\left(u^{(t)}\right)q\left(\tilde{u}|u^{(t)}\right)}$, where $\rho(u)$ is the target distribution, i.e., the probability distribution we want to sample, $q\left(\tilde{u}|u^{(t)}\right)$ Is the proposal distribution, which is used to generate candidate samples of $\tilde{u}$. This distribution describes the probability of generating u ̃ when in a position. $u^{(t)}$, $q\left(u^{(t)}|\tilde{u}\right)$ Is the proposal distribution for reversing the transition from $\tilde{u}$ to $u^{(t)}$
4. Acceptance Probability. Define the acceptance probability α as $\alpha=\min\left(1,R\left(u^{(t)},\tilde{u}\right)\right)$, this probability ensures that new samples are accepted according to the target distribution, even though the proposal distribution is asymmetric.
5. Update Sample. Update the value of $u^{(t+1)}$ based on the following rule: $u^{(t+1)}=\begin{cases}\tilde{u}, if\ \alpha\geq U(0,1)\\ u^{(t)}, otherwise\end{cases}$, where $U(0,1)$ is a random number from a uniform distribution on the interval $(0,1)$.
6. Iteration. Repeat steps 2–5 until the desired number of iterations is reached.

2.5. Bayesian Inference

Bayesian Inference is a statistical method that updates beliefs about model parameters based on observed data. It is founded on Bayes' Theorem, which connects the posterior probability, prior probability, and likelihood [21].

Bayes' Theorem [21] is expressed as:

$$P(\theta|data)=\frac{P(data|\theta).P(\theta)}{P(data)} \quad (1)$$

Where P(θ|data) is the posterior distribution, the probability of parameter θ after considering the observed data, p (data|θ) is a likelihood, the probability of the observed data given parameter θ, P(θ) is prior distribution, the initial belief about the parameter θ before observing the data, and P(data) is evidence or marginal likelihood, the probability of the observed data, used for normalization (scaling constant).

2.6. Accuracy Evaluation

Calculate prediction accuracy by using metrics like Mean Absolute Percentage Error (MAPE) to assess the model's performance in forecasting data [26]

$$MAPE=\frac{1}{n}\sum_{n}^{t=1}\left|\frac{Y(t)-\hat{Y}(t)}{Y(t)}\right|\times 100\% \quad ;Y(t)\neq 0 \quad (2)$$

Where $Y(t)$ is the actual value at time t, $\hat{Y}(t)$ is the forecasted value at time t, n is the total number of observations in Table 1.

Table 1. The Significance of MAPE

Prediction Accuracy	MAPE Value
Excellent Accuracy	MAPE < 10%
Good Accuracy	10% ≤ MAPE < 20%

Reasonable Accuracy	20% ≤ MAPE < 50%
Poor Accuracy	MAPE ≥ 50%

3. Research Method

3.1. The Research Flowchart

The research flowchart for this research involves several key steps in Figure 1.

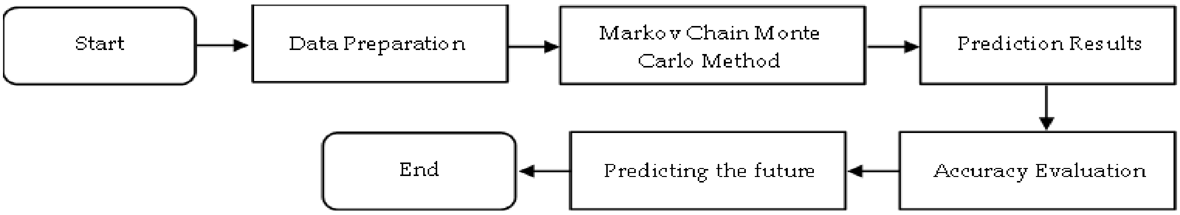

Fig 1. Research flowchart

3.2. The System Scheme of the Markov Chain Monte Carlo Method

The process carried out after data collection involves data analysis and processing using the R Studio application. The system scheme of the Markov Chain Monte Carlo method for predicting electricity consumption in Aceh province is as follows in Figure 2.

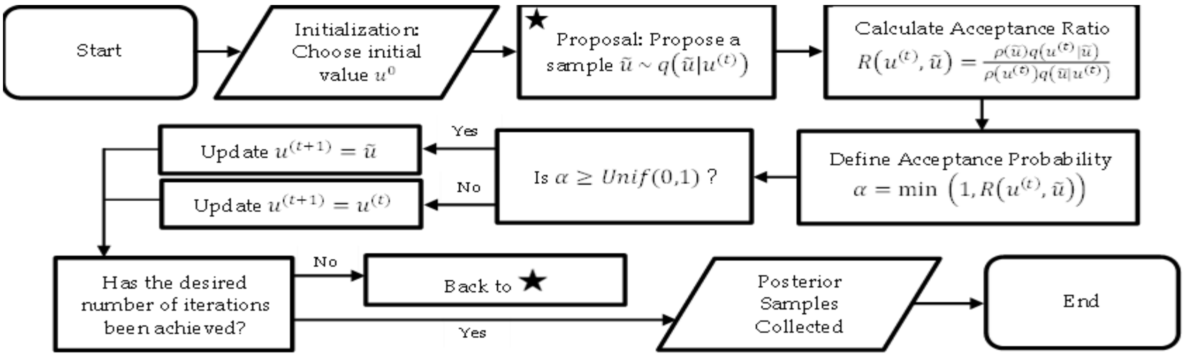

Fig 2. System scheme of the Markov Chain Monte Carlo method

4. Result and Discussion

This study implements the Metropolis-Hastings Algorithm to predict models of actual data. The system development in this study is based on R Studio software using the R programming language. The following are the steps of the analysis.

4.1. Data Analysis and Determination of a Suitable Model

By examining the graph in Figure 3, "Electricity Consumption of Aceh Province from January 2018 to December 2022," we can note an upward trend in electricity consumption from 2018 to 2022 and the possibility of seasonal patterns, such as increased consumption in certain months. Based on the above analysis, the appropriate model is a time series model that can capture the trend and possibly the seasonal components, a simple linear regression model in Table 2.

Table 2. Electricity consumption data (KWH) in Aceh Province for the period 2018 - 2022 (monthly)

Month/ Years	Total KWH	Month/ Years	Total KWH	Month/ Years	Total KWH	Month/ Years	Total KWH	Month/ Years	Total KWH
Jan 2018	203.589.362	Jan 2019	222.690.699	Jan 2020	239.097.474	Jan 2021	283.739.141	Jan 2022	252.643.513
Feb	193.315.100	Feb	205.737.083	Feb	224.714.451	Feb	236.223.021	Feb	235.801.520
Mar	218.138.334	Mar	235.790.615	Mar	244.161.249	Mar	209.827.249	Mar	256.855.792
Apr	216.667.245	Apr	232.927.295	Apr	262.372.897	Apr	246.041.129	Apr	272.486.855

May	224.525.573	May	248.827.597	May	252.108.245	May	298.736.020	May	265.483.320
Jun	218.130.610	Jun	231.953.629	Jun	252.444.359	Jun	264.817.443	Jun	272.560.682
Jul	222.739.187	Jul	240.359.071	Jul	252.916.028	Jul	251.673.583	Jul	271.937.571
Aug	222.282.160	Aug	240.602.261	Aug	263.633.215	Aug	257.269.699	Aug	271.828.917
Sep	214.382.436	Sep	234.370.371	Sep	248.191.166	Sep	251.003.973	Sep	271.193.256
Oct	216.932.141	Oct	229.294.156	Oct	253.299.482	Oct	263.317.444	Oct	256.595.952
Nov	217.823.202	Nov	226.906.042	Nov	247.329.852	Nov	254.341.476	Nov	256.979.175
Dec	219.187.023	Dec	232.042.802	Dec	197.730.766	Dec	257.475.964	Dec	269.647.552

Mathematically, we can consider a simple linear regression model:

$$y_t = \beta_0 + \beta_1 t + \epsilon_t \qquad (3)$$

where y_t is the electricity consumption at time t, β_0 is the intercept, β_1 is the trend coefficient, and ε_t is the error term assumed to be normally distributed with mean 0 and variance σ^2. We must define prior distributions for the model parameters β0 , β1 and σ2 in the Bayesian. Then, we will combine these priors with the data likelihood to obtain the posterior distribution. We can use normal priors for the regression parameters:

$$\beta_0 \sim N(0, 10^{12}) \ , \quad \beta_1 \sim N(0, 10^6) \ , \quad \sigma^2 \qquad (4)$$

The likelihood for a linear regression model with standard errors is:

$$L(\beta_0, \beta_1, \sigma^2 | y) = \prod_{t=1}^{n} \frac{1}{\sqrt{2\pi\sigma^2}} exp\left(-\frac{(y_t - \beta_0 - \beta_1 t)^2}{2\sigma^2}\right) \qquad (5)$$

The posterior is proportional to the prior multiplied by the likelihood:

$$p(\beta_0, \beta_1, \sigma^2 | y) \infty\, p(\beta_0) \times p(\beta_1) \times p(\sigma^2) \times L(\beta_0, \beta_1, \sigma^2 | y) \qquad (6)$$

The following is a graph of electricity consumption in Aceh Province from January 2018 to December 2022 in Figure 3.

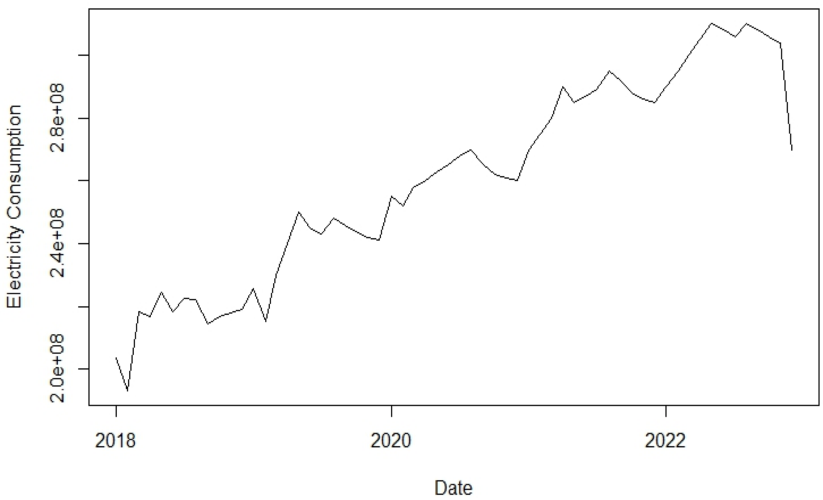

Fig 3. Electricity Consumption of Aceh Province from January 2018 to December 2022

4.2. Prediction Model and Accuracy Evaluation

Predictions are made by inputting parameter estimates into the regression model:

$$\hat{y}_t = \hat{\beta}_0 + \hat{\beta}_1 t \ , \quad t = 1,2,3, \dots ,60 \qquad (7)$$

The prediction model data is obtained in Table 3, and a comparison graph of the prediction model data and actual data is shown in Figure 6.

Table 3. Prediction model data result

Month/ Years	y_t	$\hat{y}_t$	Month/ Years	y_t	$\hat{y}_t$	Month/ Years	y_t	$\hat{y}_t$
Jan	203.589.362	208.263.454	Sep	234.370.371	243.711.072	May	298.736.020	279.158.690

2018								
Feb	193.315.100	210.035.835	Oct	229.294.156	245.483.453	Jun	264.817.443	280.931.071
Mar	218.138.334	211.808.216	Nov	226.906.042	247.255.834	Jul	251.673.583	282.703.452
Apr	216.667.245	213.580.597	Dec	232.042.802	249.028.215	Aug	257.269.699	284.475.833
May	224.525.573	215.352.977	Jan 2020	239.097.474	250.800.596	Sep	251.003.973	286.248.214
Jun	218.130.610	217.125.358	Feb	224.714.451	252.572.977	Oct	263.317.444	288.020.595
Jul	222.739.187	218.897.739	Mar	244.161.249	254.345.358	Nov	254.341.476	289.792.976
Aug	222.282.160	220.670.120	Apr	262.372.897	256.117.738	Dec	257.475.964	291.565.357
Sep	214.382.436	222.442.501	May	252.108.245	257.890.119	Jan 2022	252.643.513	293.337.738
Oct	216.932.141	224.214.882	Jun	252.444.359	259.662.500	Feb	235.801.520	295.110.118
Nov	217.823.202	225.987.263	Jul	252.916.028	261.434.881	Mar	256.855.792	296.882.499
Dec	219.187.023	227.759.644	Aug	263.633.215	263.207.262	Apr	272.486.855	298.654.880
Jan 2019	222.690.699	229.532.025	Sep	248.191.166	264.979.643	May	265.483.320	300.427.261
Feb	205.737.083	231.304.406	Oct	253.299.482	266.752.024	Jun	272.560.682	302.199.642
Mar	235.790.615	233.076.787	Nov	247.329.852	268.524.405	Jul	271.937.571	303.972.023
Apr	232.927.295	234.849.167	Dec	197.730.766	270.296.786	Aug	271.828.917	305.744.404
May	248.827.597	236.621.548	Jan 2021	283.739.141	272.069.167	Sep	271.193.256	307.516.785
Jun	231.953.629	238.393.929	Feb	236.223.021	273.841.548	Oct	256.595.952	309.289.166
Jul	240.359.071	240.166.310	Mar	209.827.249	275.613.928	Nov	256.979.175	311.061.547
Aug	240.602.261	241.938.691	Apr	246.041.129	277.386.309	Dec	269.647.552	312.833.928

The following are the results of comparing actual and predicted data in Figure 4.

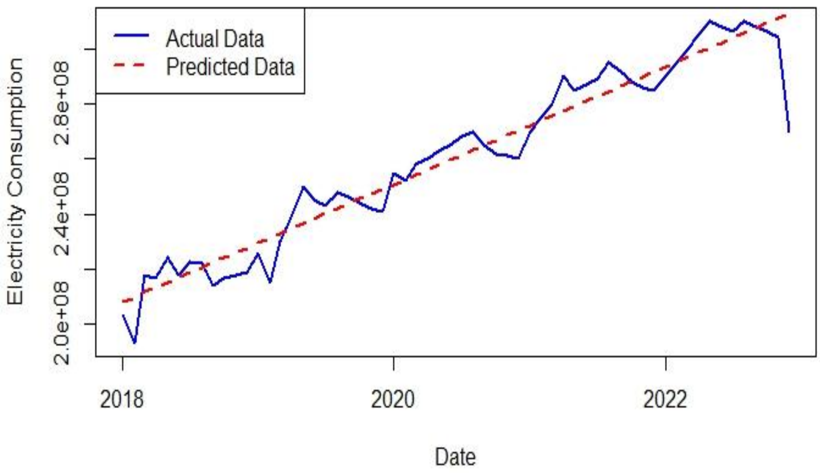

Fig 4. Comparison of Actual and Predicted Data

The accuracy of the forecasting method can be seen by calculating the MAPE value; the smaller the MAPE value, the smaller the percentage of forecasting error. In the electricity consumption data in Aceh Province for the period January 2018 to December 2022 using the Markov Chain Monte Carlo (Algorithm Metropolis-Hastings) method, the MAPE value shown in equation 11 is obtained as 2.4058%, which means that the average percentage of forecasting error is 2.4058%.

4.3. Predicting The Future

Based on the same concept as when creating historical prediction data, we create future prediction data for electricity consumption in Aceh province from January 2023 to December 2030 with a simple regression model designed with estimated parameters. $\hat{\beta}_0$ and $\hat{\beta}_1$ with the following code steps in Figure 5.

```
# Menentukan periode prediksi
future_dates <- seq(as.Date("2023-01-01"), as.Date("2030-12-01"), by = "month")
future_n <- length(future_dates)
total_n <- n + future_n

# Indeks waktu untuk data masa depan
t_future <- (n + 1):total_n

# Menggunakan parameter estimasi untuk prediksi
future_consumption_pred <- beta0_est + beta1_est * t_future

# Membuat tabel hasil prediksi
future_results <- data.frame(
  Date = future_dates,
  Predicted_Consumption = future_consumption_pred
)

# Menggabungkan data aktual dan prediksi masa depan
all_dates <- c(date, future_dates)
all_consumption <- c(consumption, rep(NA, future_n))
all_predictions <- c(consumption_pred, future_consumption_pred)
```

```
combined_results <- data.frame(
  Date = all_dates,
  Actual_Consumption = all_consumption,
  Predicted_Consumption = all_predictions
)

# Plot data aktual
plot(date, consumption, type = "l", col = "blue", lwd = 2,
     xlim = range(all_dates), ylim = range(c(all_consumption, all_predictions), na.rm = TRUE),
     xlab = "Tanggal", ylab = "Konsumsi Energi Listrik",
     main = "Prediksi Konsumsi Energi Listrik hingga Desember 2030")

# Tambahkan prediksi untuk periode historis
lines(date, consumption_pred, col = "red", lwd = 2, lty = 2)

# Tambahkan prediksi untuk periode mendatang
lines(future_dates, future_consumption_pred, col = "green", lwd = 2, lty = 3)

# Tambahkan legenda
legend("topleft", legend = c("Data Aktual", "Prediksi Historis", "Prediksi Masa Depan"),
       col = c("blue", "red", "green"), lwd = 2, lty = c(1, 2, 3))

  return go(f, seed, [])
}
```

Table 1. Comparison Methods

Fig 5. Code of future prediction data for electricity consumption in Aceh province for January 2023 to December 2030

From this R code, we obtain predicted data for Aceh province electricity consumption for January 2023 to December 2030, presented in Table 4 and Figure 6. The results of this prediction can be used to project future electricity needs, which are useful for energy planning and helping decision-making regarding electricity generation capacity, distribution, and future energy policies.

Table 4. Prediction data result for Aceh province electricity consumption for Jan 2023 to Dec 2030

Month/ Years	$\hat{y}_t$	Month/ Years	$\hat{y}_t$	Month/ Years	$\hat{y}_t$	Month/ Years	$\hat{y}_t$
Jan 2023	314.606.308	Jan 2025	357.143.450	Jan 2027	399.680.592	Jan 2029	442.217.734
Feb	316.378.689	Feb	358.915.831	Feb	401.452.973	Feb	443.990.115
Mar	318.151.070	Mar	360.688.212	Mar	403.225.354	Mar	445.762.496
Apr	319.923.451	Apr	362.460.593	Apr	404.997.735	Apr	447.534.877
May	321.695.832	May	364.232.974	May	406.770.116	May	449.307.258
Jun	323.468.213	Jun	366.005.355	Jun	408.542.497	Jun	451.079.639
Jul	325.240.594	Jul	367.777.736	Jul	410.314.878	Jul	452.852.020
Aug	327.012.975	Aug	369.550.117	Aug	412.087.259	Aug	454.624.400
Sep	328.785.356	Sep	371.322.498	Sep	413.859.639	Sep	456.396.781
Oct	330.557.737	Oct	373.094.879	Oct	415.632.020	Oct	458.169.162
Nov	332.330.118	Nov	374.867.259	Nov	417.404.401	Nov	459.941.543
Dec	334.102.498	Dec	376.639.640	Dec	419.176.782	Dec	461.713.924
Jan 2024	335.874.879	Jan 2026	378.412.021	Jan 2028	420.949.163	Jan 2030	463.486.305
Feb	337.647.260	Feb	380.184.402	Feb	422.721.544	Feb	465.258.686
Mar	339.419.641	Mar	381.956.783	Mar	424.493.925	Mar	467.031.067
Apr	341.192.022	Apr	383.729.164	Apr	426.266.306	Apr	468.803.448
May	342.964.403	May	385.501.545	May	428.038.687	May	470.575.829
Jun	344.736.784	Jun	387.273.926	Jun	429.811.068	Jun	472.348.210
Jul	346.509.165	Jul	389.046.307	Jul	431.583.449	Jul	474.120.590
Aug	348.281.546	Aug	390.818.688	Aug	433.355.830	Aug	475.892.971
Sep	350.053.927	Sep	392.591.069	Sep	435.128.210	Sep	477.665.352
Oct	351.826.308	Oct	394.363.449	Oct	436.900.591	Oct	479.437.733
Nov	353.598.689	Nov	396.135.830	Nov	438.672.972	Nov	481.210.114
Dec	355.371.069	Dec	397.908.211	Dec	440.445.353	Dec	482.982.495

The following are the results of comparing actual data, historical predictions, and future prediction data in Figure 6.

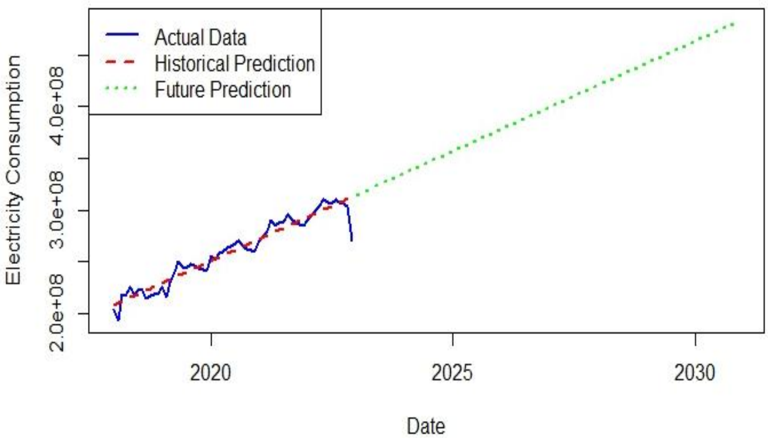

Fig 6. Comparison of actual data, historical predicted, and future prediction data

5. Conclusion

This study provides significant insights into applying the Metropolis-Hastings algorithm to predict electricity consumption in Aceh Province. The analysis highlights several key findings:

1. Increase in Electricity Consumption

The data analysis indicates a consistent upward trend in electricity consumption in Aceh Province from 2018 to 2022. Consumption in January 2018 was 203.589.362 kWh, rising to 269.647.552 kWh by December 2022, representing a total increase of 32,4% over five years.

2. Model Prediction Accuracy
   The prediction model, utilizing the Metropolis-Hastings algorithm, achieved a Mean Absolute Percentage Error (MAPE) of 2.41%, demonstrating high accuracy and reliability for future projections.
3. Future Electricity Consumption Projections
   The model forecasts continuous growth in electricity consumption, projecting 314.606.308 kWh for January 2023 and 482.982.495 kWh by December 2030, an overall increase of 53.5% over the eight years.
4. Model Alignment with Data Trends
   The prediction model successfully captures both seasonal and long-term trends. Peak electricity consumption occurs in May and December, likely due to seasonal temperature variations and increased economic activities.
5. Trace Plots and Parameter Convergence
   The trace plots for the parameters β_0', β_1' and ${\sigma^2}'$ Indicate strong convergence:
   - Parameter β_0': converged around a mean value of 206.491.073 with no significant upward or downward trends, indicating a stable chain.
   - Parameter β_1': Stabilized around 1.772.381, showing random fluctuations around this mean and confirming proper convergence.
   - Parameters ${\sigma^2}'$: Although it also converged, the values fluctuated into a broader range of $7{,}445 \times 10^{13}$ to $7{,}465 \times 10^{13}$. This range reflects the inherent variability in the model's error term but still supports the model's reliability.
6. Significance for Energy Planning
   The findings are critical for energy providers and policymakers, such as PT. PLN, to plan future electricity generation and distribution. With predicted consumption reaching 482 GWh by 2030, strategic actions are required to ensure a balanced and sustainable energy supply.
7. Effectiveness of the Metropolis-Hastings Algorithm
   The Metropolis-Hastings algorithm proved highly effective in handling complex data with high variability. Its robust convergence and parameter stability enhances its reliability in predicting dynamic systems like electricity consumption.
   These conclusions highlight the utility of MCMC methods, notably the Metropolis-Hastings algorithm, in providing accurate, data-driven insights for long-term energy planning.

References

[1] International Energy Agency (IEA), World Energy Outlook 2019. Paris: IEA Publications, 2019.
[2] OECD, OECD Economic Outlook 2020. OECD Publishing, 2020.
[3] Y. Zhou, et al., "A Review of Energy Prediction Techniques," Energy Reports, vol. 5, pp. 123-145, 2019.
[4] D. Ekananta, M. Santoso, and B. Pradana, "Average-Based Fuzzy Time Series for Predicting Electricity Consumption in Indonesia," Journal of Applied Energy Research, vol. 16, no. 3, pp. 201-211, 2018.
[5] A. Harisandy, "Forecasting Household Electricity Consumption in Indonesia using VAR and ARIMA Models," Indonesian Journal of Energy, vol. 7, no. 2, pp. 123-136, 2021.
[6] D. Purnama and E. Siregar, "Projection of Electricity Consumption in Aceh Tamiang until 2030," Energy Journal of Sumatra, vol. 6, no. 1, pp. 45-52, 2015.
[7] F. Nugraha and D. Purnama, "Predicting Electricity Consumption in Aceh using Adaptive Neuro-Fuzzy Inference System (ANFIS)," Journal of Regional Energy Studies, vol. 8, no. 2, pp. 151-162, 2020.
[8] Y. Zhang, T. Li, and W. Ma, "Support Vector Regression Optimized by Dragonfly Algorithm for Electricity Demand Forecasting in China," Energy Prediction Journal, vol. 11, no. 4, pp. 389-398, 2017.
[9] S. Wang, et al., "AI Applications in Energy Demand Forecasting," Renewable Energy Journal, vol. 35, pp. 56-70, 2021.
[10] A. Ansharulhaq, N. Nurdin, and Z. Yunizar, "News Popularity Prediction in West Sumatera Using Autoregressive Integrated Moving Average," International Journal of Engineering, Science and Information Technology, vol. 5, no. 1, pp. 19-27, 2025. doi:10.52088/ijesty.v5i1.623
[11] A. Prasetyo, N. Nurdin, and H. A. K. Aidilof, "Comparison of Triple Exponential Smoothing and ARIMA in Predicting Cryptocurrency Prices," International Journal of Engineering, Science and Information Technology, vol. 4, no. 4, pp. 63-71, 2024. doi:10.52088/ijesty.v4i4.577
[12] Q. Yan, et al., "Markov Chain Monte Carlo Based Energy Use Behaviors Prediction of Office Occupants," Algorithms, 2020.
[13] M. Hariadi, et al., "Prediction of Stock Prices Using Markov Chain Monte Carlo," CENIM 2020, 2020.
[14] A. Dukunde, et al., "Prediction of Prevalence of Type 2 Diabetes in Rwanda Using the Metropolis-Hastings Sampling," African Health Sciences, 2021.
[15] Z. Wang and Y. Nishi, "Stochastic Model for Simulating Levels of Polychlorinated Biphenyls in Small Tuna and Planktons Us-ing Metropolis-Hastings Algorithm," Ecotoxicology and Environmental Safety, 2022.
[16] Y. R. Fan, et al., "Towards Reliable Uncertainty Quantification for Hydrologic Predictions, Part I: Development of a Particle Copula Metropolis-Hastings Method," Journal of Hydrology, 2022.
[17] E. Yildirim, M. Yasar, and A. Aslan, "Energy Consumption and Economic Growth in the USA: Evidence from Renewable Energy," Renewable Energy Reviews, vol. 29, no. 4, pp. 2313-2321, 2019.
[18] International Renewable Energy Agency (IRENA), Renewable Energy in Developing Regions. IRENA Report, 2020.
[19] C. Chatfield, The Analysis of Time Series: An Introduction, 6th ed. Boca Raton, FL: Chapman and Hall/CRC, 2004.
[20] R. H. Shumway and D. S. Stoffer, Time Series Analysis and Its Applications: With R Examples, 4th ed. New York: Springer, 2017.

[21] A. Gelman, J. B. Carlin, H. S. Stern, D. B. Dunson, A. Vehtari, and D. B. Rubin, Bayesian Data Analysis, 3rd ed. Boca Raton, FL: CRC Press, 2014.
[22] S. Brooks, A. Gelman, G. Jones, and X. L. Meng, Handbook of Markov Chain Monte Carlo. Boca Raton, FL: CRC Press, 2011.
[23] J. S. Rosenthal, A First Look at Stochastic Processes. Singapore: World Scientific, 2019.
[24] C. P. Robert and G. Casella, Monte Carlo Statistical Methods, 2nd ed. New York: Springer, 2004.
[25] M. A. A. Turkman, C. D. Paulino, and P. Müller, Computational Bayesian Statistics: An Introduction. Cambridge, U.K.: Cambridge University Press, 2019.
[26] D. C. Montgomery, E. A. Peck, and G. G. Vining, Introduction to Linear Regression Analysis, 5th ed. New York, NY: Wiley, 2015.