Volume 4 Number 1 (2026)
January – June 2026
Pages: 23-31

International Assulta of Research and Engagement (IARE)
https://edujavare.com/index.php/IARE/

Prediction of Renewable Energy Potential to Prevent Greenflation Using Bayesian Structural Time Series: BSTS with JASP Software to Predict PLTMH Potential

Bunga Mardhotillah[1], Shally Yanova[2], Abdul Manab[3], Yosi Riduas Hais[4], Edi Saputra[5], Ade Adriadi[6], Ade Nurdin[7]

[1] Mathematics Department, Universitas Jambi, Jambi, Indonesia
[2] Environmental Science Department, Universitas Jambi, Jambi, Indonesia
[3,4] Electrical Engineering Department, Universitas Jambi, Jambi, Indonesia
[5] Infromatics Department, Universitas Jambi, Jambi, Indonesia
[6] Biology Department, Universitas Jambi, Jambi, Indonesia
[7] Civil Engineering Department, Universitas Jambi, Jambi, Indonesia
Email: bunga.mstat08@unja.ac.id

Article history Submitted: 2025/12/27; Revised: 2026/01/14; Accepted: 2026/01/31

Abstract

The global transition toward renewable energy is increasingly urgent to mitigate climate change and reduce dependence on fossil fuels; however, it also introduces economic risks such as greenflation, driven by rising demand for green commodities. In Indonesia, renewable energy development has become a national priority, with Jambi Province identified as a strategic region due to its significant micro-hydropower (PLTMH) potential. This study aims to predict PLTMH potential as a means of supporting energy transition planning and preventing greenflation through data-driven policy decisions. The research employs a Bayesian Structural Time Series (BSTS) approach using JASP software, integrating Kalman Filter, spike-and-slab regression, and Bayesian Model Averaging. Time series data from 2008–2024 were analyzed with 2,000 MCMC draws and a 1% burn-in to ensure estimation stability. The results demonstrate a strong upward trend in PLTMH capacity, with high model accuracy indicated by an R^2 value of 0.991, low residual standard deviation, and acceptable prediction uncertainty. Forecasts suggest continued growth in PLTMH capacity over the next two decades before reaching a steady state. The study concludes that BSTS is a robust and reliable method for predicting renewable energy potential and supporting counterfactual policy analysis. This research contributes empirically to applied Bayesian time series modeling and practically to renewable energy policy planning, offering evidence-based insights to enhance energy security and mitigate greenflation risks.

Keywords Bayesian Structural Time Series, Energy Policy, Greenflation, Micro-Hydropower, Renewable Energy.

INTRODUCTION

The energy transition to renewable resources is an increasingly urgent global agenda in addressing the climate crisis. This effort aims to reduce carbon emissions while reducing dependence on fossil fuels, which have dominated the global energy system. Thus, the energy transition is not merely a technical issue but also part of the international commitment to sustainable development. However, the energy transition process often has complex economic consequences. One emerging phenomenon is greenflation, which is price pressure caused by increased demand for green commodities, such as metals for solar panels or electric vehicle batteries. This phenomenon demonstrates that renewable energy policies cannot be separated from global market dynamics (Nidianti & Wijayanto, 2019; Nurwani, 2016; Rizki, 2021; Sasono, 2022).

In Indonesia the energy transition has become part of national policy. The 2019–2028 Electricity Supply Business Plan (RUPTL) targets the development of large-scale renewable energy power plants. This policy reflects the government's commitment to expanding the energy mix while supporting the carbon emission reduction agenda. Jambi Province is one of the regions projected to play a key role in the implementation of renewable energy policies. The potential of hydropower, particularly through Microhydro Power Plants (PLTMH), is considered significant enough to support the community's electricity needs while strengthening regional energy security. However, the energy transition is not without economic challenges: increased investment, infrastructure costs, and fluctuating commodity prices can pose risks to local and national economic stability. Therefore, analytical methods that can more accurately predict the impact of policies are needed (Selle, et al, 2022 & Insani, 2024).

Bayesian Structural Time Series (BSTS) presents a relevant statistical approach to address these challenges. BSTS is able to capture trends, seasonal patterns, and the influence of external factors in time-series data. These advantages make it an effective tool for understanding renewable energy dynamics. BSTS allows for counterfactual analysis, namely simulations of different conditions if a policy were not implemented. In this way, the impact of energy policies can be measured more objectively, thus providing an empirical basis for decision-making. BSTS can be used to predict the potential electricity production from micro-hydro power plants (PLTMH). This analysis not only helps estimate the energy capacity that can be generated but also assesses the extent to which micro-hydro power plants can contribute to achieving the RUPTL targets (Wulandari, 2024 & Mokilane, et al, 2019).

Research on predicting the potential of micro-hydro power plants (PLTMH) using BSTS is expected to provide a clearer picture of the renewable energy prospects in the region. The research results can serve as a reference for local governments, investors, and the community in planning sustainable energy strategies. This research is expected to not only contribute to the development of applied statistics but also have practical implications for energy policy in Indonesia. Through the BSTS approach, it is hoped that the energy transition to renewable resources can be more measurable, efficient, and sustainable, particularly in supporting green energy development.

METHODS

Bayesian Structural Time Series (BSTS) is a modern statistical approach designed to analyze highly complex time series data. The main advantage of BSTS lies in its ability to separate various components within the data, such as long-term trends, seasonal patterns, and the influence of external variables. Thus, BSTS can provide a more realistic picture of the dynamics of a phenomenon. The first component in BSTS is the Kalman Filter. This method functions as an algorithm that iteratively updates trend, seasonality, and regression estimates based on incoming data. The Kalman Filter is crucial because it reduces noise in the data, resulting in more stable and accurate predictions. The Kalman Filter also enables dynamic system modeling. This means that changes in trends or seasonal patterns can be adaptively captured according to the latest data developments. This makes BSTS superior to classical methods, which tend to be static (Wulandari, 2024 & Mokilane, et al, 2019).

The second component is Spike-and-slab Regression. This approach is used to select relevant predictor variables from a large number of candidates. With its variable selection mechanism, BSTS is able to avoid the overfitting problem that often occurs in models with a large number of predictors. Spike-and-slab Regression works by assigning a probability to each variable, determining whether it is worthy of inclusion in the model. Variables with significant contributions are retained, while less relevant variables are eliminated. This process improves model efficiency while strengthening the interpretation of the results. The third component is Bayesian Model Averaging. This technique combines prediction results from various possible models. Instead of selecting a single best model, BSTS leverages information from multiple models to produce more robust predictions (Wulandari, 2024 & Mokilane, et al, 2019).

Bayesian Model Averaging also reflects the Bayesian philosophy, which emphasizes uncertainty. By combining multiple possible models, prediction results become more robust to biases and errors specific to a single model. In this study, the analysis was conducted using JASP software. JASP was chosen because it provides a user-friendly interface and comprehensive support for Bayesian analysis. Using this software makes it easier for researchers to implement BSTS without having to write complex code. To ensure the reliability of the results, 2,000 MCMC draws were conducted. Markov Chain Monte Carlo (MCMC) is a simulation technique used to estimate posterior distributions in Bayesian analysis. The greater the number of draws, the more stable the resulting estimates. 1% of the data was discarded as burn-in.

The burn-in process aims to eliminate the initial influence of the Markov chain, which may not yet have reached stability. Thus, the analysis results more closely reflect the true state of the posterior distribution. Model evaluation is a crucial step in ensuring the quality of predictions. Without proper evaluation, analysis results risk misleading policymakers or researchers. Therefore, evaluation indicators are carefully selected to reflect model performance. The first indicator is the coefficient of determination (R^2). The R^2 value indicates how much variation in the data the model can explain. The higher the R^2 value, the better the model's ability to capture data patterns (Rohmaningsih, et al, 2016; Maulana, 2018; Ross, 2010).

The second indicator is the residual standard deviation. Residual standard deviation measures the magnitude of the prediction error compared to the actual data. A low residual value indicates that the model is able to produce predictions close to reality. The third indicator is the prediction standard deviation. Unlike the residual standard deviation, this indicator assesses the uncertainty in predictions. A low prediction standard deviation indicates that the model produces consistent and reliable predictions. The combined analysis consisting of the Kalman Filter, Spike-and-slab Regression, and Bayesian Model Averaging makes BSTS a powerful approach in time series analysis. With the support of JASP software and rigorous model evaluation, this research is expected to produce accurate predictions that are useful for the development of renewable energy policies and other fields requiring long-term data analysis (Wulandari, 2024 & Mokilane, et al, 2019).

FINDINGS AND DISCUSSION

Jambi Province is among the 10 provinces with the largest renewable energy capacity development plans in Indonesia, reaching 2,189 MW according to the 2019–2028 RUPTL (Regional Development Plan). This figure demonstrates the government's commitment to making Jambi one of the centers of green energy development in Sumatra. The planned power plants include hydroelectric power plants (PLTA), microhydro power plants (PLTMH), solar power plants (PLTS), and biomass power plants (PLTBio). This diversification is important to ensure energy security while reducing dependence on a single resource. PLTA and PLTMH are the primary choices due to Jambi's significant hydrological potential. The region's rivers provide a stable water flow, allowing it to be utilized to generate electricity sustainably. PLTS also has bright prospects given the relatively high solar radiation intensity in Jambi throughout the year. With increasingly efficient solar panel technology, PLTS can be a clean energy solution for both rural and urban areas. PLTBio utilizes agricultural and plantation waste, particularly palm oil, a primary commodity in Jambi. Utilization of biomass not only produces energy, but also reduces the environmental impact of organic waste.

To support this planning, microhydro power plant capacity predictions were conducted using JASP software using the Bayesian Structural Time Series (BSTS) approach. This method was chosen because it comprehensively captures long-term trends, seasonal patterns, and external influences. The BSTS prediction results indicate an increasing trend in microhydro power plant capacity in Jambi. This confirms that the region's microhydro energy potential can continue to grow along with investment and infrastructure development.

Table 1. Model Summary of Bayesian State Space Model

Residual SD	Prediction SD	R^2	Harvey's goodness of fit
385.2	720.0	0.991	−1.639

Note. 1 MCMC draws out of 2000 are discarded as burn in. The local level component has been selected (by default). If you wish to adjust the model, you can do so under 'Model Components'.

Model validation is a crucial step in ensuring the reliability of prediction results. The BSTS model demonstrated high accuracy with a coefficient of determination (R^2) of 0.991. This value indicates that almost all data variation can be explained by the model. The residual standard deviation (RSD) of 385.2 indicates that the prediction error is relatively small compared to the projected energy capacity.

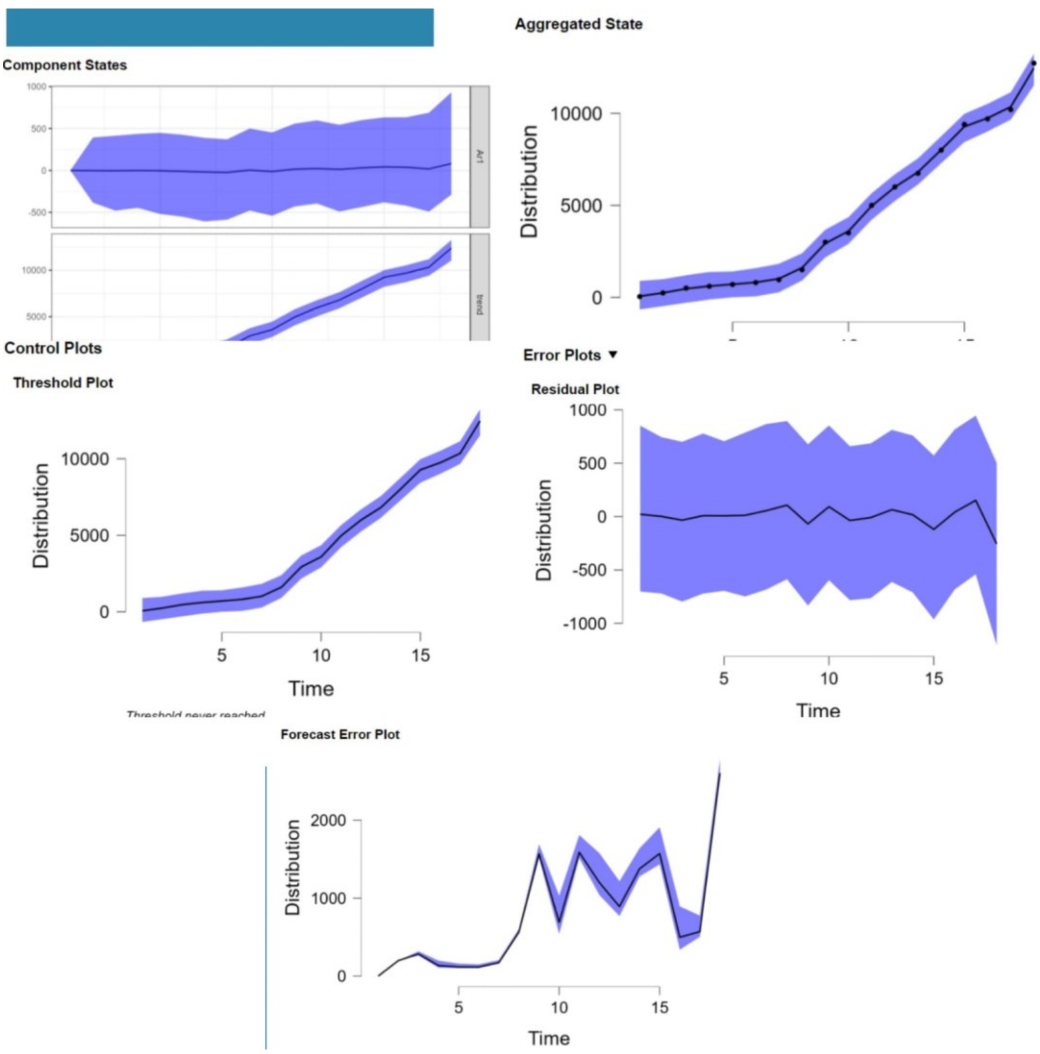

Figure 1. Bayesian Structural Time Series Plots

This strengthens confidence that the model is able to capture data patterns well. The prediction standard deviation (PSD) of 720 indicates the model's consistency in producing predictions. Despite the uncertainty, this value is still within reasonable limits for time series analysis with complex variables. Time Series Data for predict PLTMH potential start from 2008 - 2024 The results show that PLTMH capacity in Indonesia has experienced a significant upward trend from 2018 to 2028, and steady state in 2029 – 2038 as shown in Figure 2.

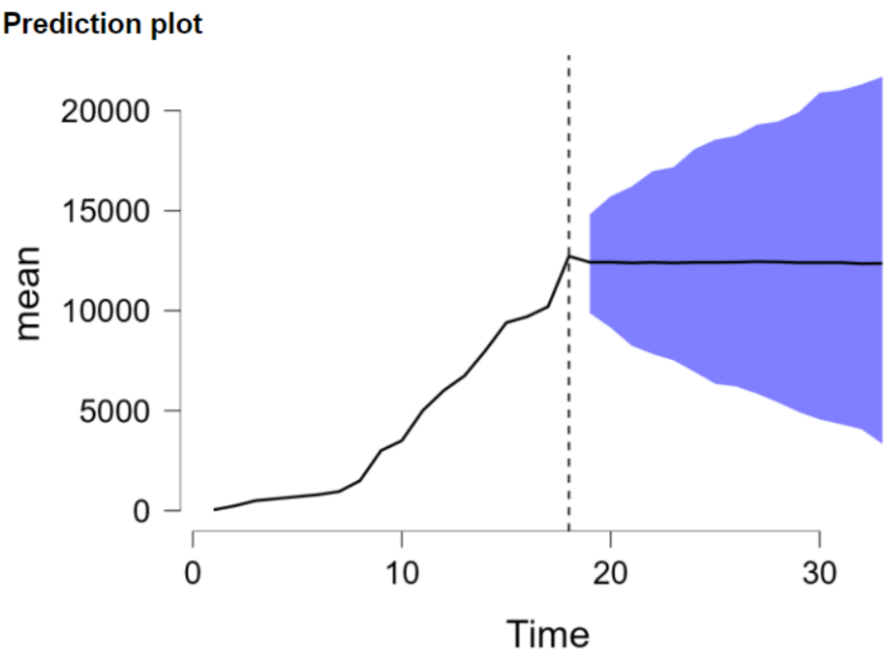

Figure 2. BSTS Prediction Plot for PLTMH Potentials

The research confirms that micro hydro power plants (PLTMH) have significant potential as a stable renewable energy source in Indonesia. The advantage of micro hydro power plants lies in their relatively small scale, making them easier to implement in remote areas. The increasing capacity trend indicates positive prospects for supporting the national energy transition. The prediction graph using the BSTS shows that the potential of micro hydro power plants will increase over the next 20 years and reach a steady state within the next 30 years.

CONCLUSION

BSTS has proven effective in predicting renewable energy potential. Its high accuracy and ability to generate counterfactual analysis make this method relevant to support energy policy planning. Counterfactual analysis enables policymakers to understand the impact of a policy if it is not implemented. This allows for more objective and data-driven energy planning. The policy implications of this research are significant. Regulations that support renewable energy development will strengthen electricity efficiency and reduce dependence on fossil fuels. With appropriate policies, the risk of greenflation can be minimized. Energy prices can be maintained stable despite increasing demand for green commodities. The green energy transition in Indonesia, particularly in Jambi Province, also has socio-economic impacts. The development of micro-hydro power plants (PLTMH) and other power plants can create new jobs, increase community incomes, and strengthen the regional economy. Renewable energy development supports the global agenda of climate change mitigation. Jambi Province is expected to contribute to carbon emission reduction. With a data-driven approach like the BSTS, energy planning can be carried out in a more measurable and sustainable manner. This research shows that the combination of local potential, modern analytical methods, and policy support can accelerate the energy transition in Indonesia. Jambi has a significant opportunity to become a green energy pioneer, while strengthening national energy security in the future.

Acknowledgments

This research would not have been possible without the assistance of various parties. The research team would like to express its gratitude to the Rector of Universitas Jambi, the Head of the LPPM Universitas Jambi, the Dean of the Faculty of Science and Technology of Universitas Jambi, and the readers of this article.

REFERENCES

1. [1] Maulana, H.A. 2018. Time Series Modeling and Rainfall Forecasting at Twelve Stations in Bogor. Journal of Mathematics, Statistics, & Computation. 15(1): 50-63.
2. [2] Mokilane, P., Debba, P., Yadavalli, V.S.S., & Sigauke, C. 2019. Bayesian Structural Time Series Approach to a Long-Term Electricity Demand Forecasting. Applied Mathematics & Information Sciences. 13(2): 189-199.
3. [3] Nidianti, E. & Wijayanto, E. 2019. Analysis of the Effect of Exchange Rates, BI Rate, and Inflation on the Jakarta Composite Index (JCI) at the Indonesia Stock Exchange (IDX) for the 2014-2017 Period. Journal of Finance and Business. 7(1): 64-76.
4. [4] Nurwani. 2016. Analysis of the Effect of Inflation, the Rupiah Exchange Rate, and SBI Interest Rates on the Movement of the Composite Stock Price Index on the Indonesia Stock Exchange. Journal of Economics and Development Studies. 16(2).
5. [5] Rizki, M. 2021. The Impact of Interest Rates, Inflation, Exchange Rates, and Foreign Exchange Reserves on the Return of the Jakarta Composite Index (JCI) on the Indonesia Stock Exchange. Journal of Business Administration, Economics & Entrepreneurship. 3(1): 44-55.
6. [6] Rohmaningsih, N.M., Sudarno, & Diah Safitri. 2016. Modeling and Forecasting Volatility in Bank Bukopin Stock Returns Using the Asymmetric Power Autoregressive Conditional Heteroskedasticity (APARCH) Model. Gaussian Journal. 5(4): 705-715.
7. [7] Ross, S.M. 2010. Introduction to Probability Models. 10th Edition. Elsevier, California
8. [8] Sasono, H. 2022. Analysis of the Influence of Population, Inflation, Economic Growth, Gold Prices, Dollar Exchange Rate, SBI, and the Gini Index on the Composite Stock Price Index (IHSG). Journal of Social Sciences. 1(2): 133-148.
9. [9] Wulandari S. Application of ARIMA and Bayesian Structural Time Series Methods to Predict Inflation in Indonesia [Internet]. Yogyakarta: UIN Sunan Kalijaga; 2022 [cited 2025 May 20]. Available from: https://digilib.uin-suka.ac.id/id/eprint/56272/
10. [10] Insani AF. Predictive modeling of electricity consumption in the household customer segment using machine learning: A case study of PT PLN (Persero) [Internet].

Bandung: ITB; 2024 [cited 2025 May 20]. Available from: https://digilib.itb.ac.id/gdl/view/86673

11. [11] Selle N, Yudistira N, Dewi C. Comparison of electricity usage prediction using the Long Short Term Memory (LSTM) and Recurrent Neural Network (RNN) methods [Internet]. Malang: Brawijaya University; 2022 [cited 2025 May 20]. Available from: https://jtiik.ub.ac.id/index.php/jtiik/article/view/5585
12. [12] Pramudita, D., Prawesti, M., Masruroh, M., Wulandari, S., & Artanti, Y. (2025). Exploring entrepreneurial leadership strategies: A comprehensive literature review focused on Generation Z in the digital era. *Journal of Management: Small and Medium Enterprises, 18*(2), 1421–1435. https://doi.org/10.35508/jom.v18i2.21191
13. [13] Panutur, S. S., Soehadi, A. W., Widjojo, H., & Chandera, Y. (2025). The role of organizational agility and customer participation in enhancing company performance during digital transformation. *International Research Journal of Business Studies, 18*(2), 175–201. https://doi.org/10.21632/irjbs.18.2.175-201
14. [14] Rahman, A., et al. (2022). Strategic management challenges of SMEs. *Journal of Entrepreneurship in Emerging Economies*, 14(3), 567–586. https://doi.org/10.1108/JEEE-01-2021-0031
15. [15] Teece, D. J. (2020). Dynamic capabilities and strategic management. *Strategic Management Journal, 41*(10), 1727–1750. https://doi.org/10.1002/smj.3148
16. [16] Wang, Q., Hou, H., & Li, Z. (2022). Participative leadership: A literature review and prospects for future research. *Frontiers in Psychology*. https://doi.org/10.3389/fpsyg.2022.924357
17. [17] Singh, A., Lim, W. M., Jha, S., Kumar, S., & Ciasullo, M. V. (2023). The state of the art of strategic leadership. *Journal of Business Research, 155*, 113676. https://doi.org/10.1016/j.jbusres.2023.113676
18. [18] Howe, K., & Lavy, B. L. (2025). Business characteristics and leadership motivation in circular economy practices. *Frontiers in Sustainability, 6*, 1568099. https://doi.org/10.3389/frsus.2025.1568099
19. [19] Soehadi, A. W., & Chandera, Y. (2025). Leveraging network capability for small enterprise success. *International Journal of Research in Business and Management, 13*(1), 2478448. https://doi.org/10.1080/00472778.2025.2478448
20. [20] Nebebe, H., & Setlhapelo, T. (2024). Is sustainable performance in MSMEs driven by entrepreneurial orientation? *Journal of Knowledge Management.* https://doi.org/10.1108/JKM-04-2025-0575
21. [21] Chughtai, M. S., Syed, F., Naseer, S., & Chinchilla, N. (2023). Role of adaptive leadership in learning organizations to boost organizational innovations. *Current Psychology.* https://doi.org/10.1007/s12144-023-04669
22. [22] Sultana, T., et al. (2025). Strategic leadership and sustainable transition in SMEs. *European Journal of Sustainable Development Research*. https://doi.org/10.21632/ejosdr.17.4.09
23. [23] Lee, C., & Kim, H. (2024). Digital leadership and strategic agility in SMEs. *Journal of Small Business Strategy, 34*(2), 211–227. https://doi.org/10.32679/jsbs.v34i2.4567
24. [24] Gupta, A., & Rastogi, R. (2024). Participatory leadership and employee empowerment in SMEs. *International Journal of Human Resource Management, 35*(4), 649–672. https://doi.org/10.1080/09585192.2024.912345

25. [25] Hwang, J., & Park, S. (2025). Strategic decision-making and participatory approaches in SMEs. *Small Business Economics, 64*, 997–1014. https://doi.org/10.1007/s11187-025-00897-4
26. [26] Ali, S., & Anwar, F. (2025). The nexus between leadership, digital capabilities, and digital strategy. *International Small Business Journal*. https://doi.org/10.1177/02662426251314108 SAGE Journals
27. [27] Astuti, N. B., Rahman, M. F., & Rustam, R. (2023). The implementation of participatory leadership style in micro, small and medium enterprises (MSMEs). *Journal of Integrated Agribusiness, 5*(2), 34-46. https://doi.org/10.33019/jia.v5i2.3965