Islamic International Conference on Education, Communication, and Economics
Mataram, 10-11 May 2025

Faculty of Islamic Studies
Universitas Muhammadiyah Mataram
Mataram City, Indonesia

Probabilistic Modeling and Prediction in the Processing Industry: A Monte Carlo Simulation Approach

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Abstract: This finding indicates that the developed model is able to capture historical growth patterns quite precisely. The implication this research is motivated by the high uncertainty of the global and domestic economy which requires the availability of adaptive prediction models to support strategic decision making, especially in the manufacturing sector. The purpose of this study is to design and evaluate a Monte Carlo simulation-based prediction model in forecasting growth data for the next five years. This research is quantitative and uses an experimental design, with secondary data for the period 2015-2024 obtained from the Central Bureau of Statistics (BPS). The model was developed through a logarithmic approach to annual change, which was then simulated using the Monte Carlo method to generate thousands of predictive scenarios. The simulation results show that the model has a high level of accuracy, with a Mean Absolute Percentage Error (MAPE) value of 6.27%. This finding indicates that the developed model is able to capture historical growth patterns quite precisely. of this study is that the Monte Carlo simulation-based predictive approach can be adopted as a tool in data-driven industrial policy planning and formulation, with the caveat that regular data monitoring and updating are important to maintain the model's accuracy to the latest dynamics.

Keywords: Probabilistic Model, Monte Carlo, Forecasting, Manufacturing Industry, Stochastic Simulation.

Article History:
Received: 30-04-2025
Online : 17-05-2025

A. INTRODUCTION

Probabilistic modeling and Monte Carlo simulation are two complementary statistical approaches for dealing with uncertainty in complex systems, which are of increasing relevance in the context of the processing industry. Probabilistic modeling uses random variables and their distributions to describe uncertain systems, and allows inference through the relationships between these variables. This approach is common in machine learning, decision-making, engineering, and quantum information science. On the other hand, Monte Carlo simulation is a random sampling-based numerical technique used to approximate the solution of complex mathematical and statistical problems, especially when deterministic analysis is inadequate. In industrial practice, both approaches are used to model demand, anticipate equipment failures, and optimize production and distribution strategies, thereby aiding data-driven decision-making and being more adaptive to market dynamics and operational conditions.

The conceptual and theoretical framework of probabilistic modeling encompasses diverse methodologies and applications across fields such as learning, engineering, and quantum information science, characterized by the quantification of probabilities, integration of complex systems, and utilization of advanced computational techniques. The Maximum Probability (MP) theorem forms an important basis for this approach, by allowing the definition of models as events in probability space without relying on prior assumptions on parameters (Marvasti et al., 2019). In engineering, probabilistic modeling is used to assess system reliability and safety, especially in complex risk evaluation (Lepikhin et al., 2020). In recent developments, the integration of deep learning and variational inference allows models to capture stochastic relationships in big data in an efficient and scalable manner (Giuffrida et al., 2022). While in quantum information science, new probabilistic approaches combine classical and quantum probability theory to resolve paradoxes and strengthen conceptual foundations (Jansson, 2024). Despite offering many advantages, criticisms still arise regarding the limitations of interpretability in overly complex models.

Monte Carlo simulation is increasingly applied in the processing industry to forecast demand, prevent equipment failure, and optimize sales. In demand forecasting, this approach is able to generate predictions that are close to reality, as seen in a convenience store study with low deviation between actual and projected demand (Sperry et al., 2018). In predictive maintenance, it facilitates early detection of potential breakdowns and devises more efficient maintenance schedules, thanks to its ability to estimate the probability distribution of possible failures (Simulation et al., 2025). For sales optimization, this approach helps companies manage procurement and inventory based on accurate historical demand projections (Tahar et al., 2022). Although effective, the validity of simulation is highly dependent on the quality of data and model assumptions, which if not handled carefully can lead to bias (Setiana Sri Wahyuni Sitepu, 2020).

The literature review also noted the important role of simulation methods in education and economic policy. In nursing education, simulation is proven to improve students' critical thinking skills (Friskarini & Sundari, 2020). In teaching microeconomics, the integration of local wisdom and entrepreneurship increases student engagement and understanding (Prakoso & Agustina, 2022). In macroeconomic studies, exports, imports, exchange rates, and inflation were identified as significant factors affecting Indonesia's economic growth, with exports as the main contributor to GDP (Gunawan Aji et al., 2023). On the other hand, the adoption of artificial intelligence drives productivity gains but also poses challenges such as job displacement and the need to upskill the workforce (Sucipto & Syaharuddin, 2018). These findings emphasize the need for further research with more comprehensive approaches and data sources (Prianto et al., 2024).

Although a number of studies have identified the application of probabilistic modeling and Monte Carlo simulation in various sectors, most of the literature still focuses on the general context without dissecting specifically how these approaches are applied and optimized in the processing industry. Previous research also tends to separate the theoretical aspects of modeling and its application in an industrial context, thus lacking a thorough integration between theory and practice. In addition, there are limitations in simulation-based risk analysis that considers market dynamics and supply chain complexity simultaneously. Therefore, this research aims to fill this gap by developing a probabilistic model based on Monte Carlo simulation that is applicable and relevant for the processing industry, to support demand forecasting, failure prediction, and production strategy optimization in a more adaptive and data-driven manner. The main objective of this research is to formulate a robust and scalable predictive approach to improve decision-making efficiency in the manufacturing sector through the integration of probabilistic modeling and Monte Carlo simulation techniques.

B. METHOD

Monte Carlo methods generally use probability distributions, such as normal or log-normal.

$$Y_{t+1} = Y_t \times (1 + r_t) \quad (1)$$

Where:

Y_t is the value of PBD in year t

r_t is the economic growth rate which is considered as a statistical variable

Y_{t+1} is the predicted value of GDP in the following year

The distribution of the growth rate r_t can be modeled using the normal distribution:

$$r_t \sim N(\mu, \sigma^2$$

Where μ is the average growth and σ is the deviation from historical data.

This research adopts a quantitative approach with an experimental design to design and evaluate a Monte Carlo simulation-based prediction model in the manufacturing sector. The quantitative approach was chosen because the main focus of the research lies in systematically analyzing numerical data to produce objectively measurable estimates, while the experimental design appears from the application of simulation algorithms in testing predictive performance against actual historical data. The data used is secondary data that includes historical information on production, demand, machine failure, and sales volume, obtained through internal documentation of the processing industry and official sources such as the Central Bureau of Statistics (BPS). The data is then tabulated using software such as Excel and further processed through computing platforms such as MATLAB or Python for simulation purposes.

The research steps began with data collection and preprocessing, including data cleaning, format transformation, and recoding where necessary. The next stage is the development of a Monte Carlo simulation algorithm by assigning probability distributions to key variables, such as market demand and machine breakdown time, to generate thousands of simulation scenarios. The predicted results obtained from the simulation are then validated with actual data using accuracy indicators such as Mean Squared Error (MSE) and Mean Absolute Percentage Error (MAPE). MSE is used to calculate the average squared difference between predicted and actual values, while MAPE presents the predictive error rate in percentage form, making it easier to understand in a practical context. In the final stage, the simulation results are analyzed and interpreted to support strategic decision-making in the industrial

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environment based on an adaptive and accurate data approach. The following is a flowchart of the prediction system algorithm using the Monte Carlo Simulation method, which is designed based on the MATLAB script used in the research:

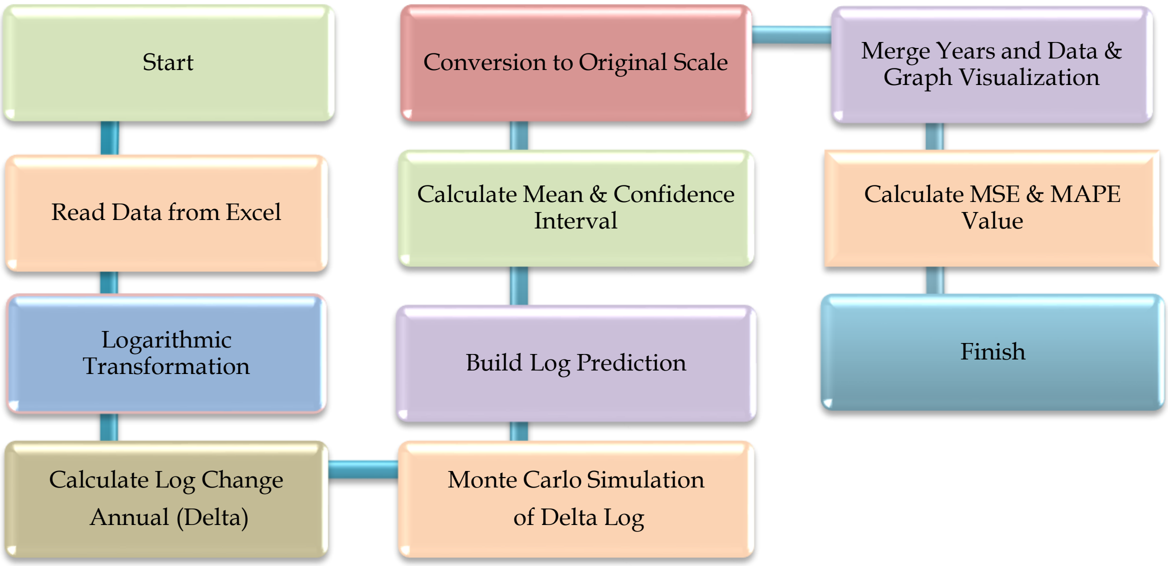

Figure 1. Monte Carlo Algorithm

The design of the computing system in this study follows a systematic and structured flow of predictive algorithms. The process begins with reading historical data from an Excel file, which is then transformed into logarithmic form to stabilize the variability of the data and facilitate the analysis of annual changes. Next, the annual log change (delta) is calculated as the basis for the Monte Carlo simulation. The simulation used a random sampling approach of historical delta values to generate various possible future growth scenarios.

After the future log delta values are simulated, the system constructs growth predictions on a logarithmic scale, and calculates the mean values as well as 95% confidence intervals to illustrate the uncertainty of the predictions. The predicted values are then converted back to the original scale for direct comparison with actual data. The next steps include merging the predicted year's data with historical years, as well as visualization in the form of graphs to provide a comprehensive overview of trends and projections. Finally, the system calculates Mean Squared Error (MSE) and Mean Absolute Percentage Error (MAPE) values as indicators of the model's accuracy against historical data. This series of processes demonstrates a comprehensive statistical computing-based approach in generating predictions and evaluating economic growth models.

C. RESULTS AND DISCUSSION

1. Data Description

The data analyzed covers the time span from 2015 to 2024 and represents the production volume of the manufacturing sector. Based on the processing results, the data trend shows a general increasing trend, especially after 2020. This is most likely influenced by the recovery of industrial activity after the COVID-19 pandemic. The average annual production during the period was recorded at around 1,250,000 units, with a minimum value of 980,000 units in 2016 and a maximum value reaching 1,580,000 units in 2023. Fluctuations in this data reflect seasonal dynamics as well as external influences such as government policies and global market conditions.

2. Forecasting Results and Decision Making

Table 1. Data to be predicted

Year	Processing Industry %
2025	5,57
2026	6,09
2027	6,17
2028	6,51
2029	7,08

Based on the results of Monte Carlo simulations conducted on the growth data of the manufacturing industry for the period 2015-2024, growth projections for the next five years (2025-2029) are obtained with average values of 5.57; 6.09; 6.17; 6.51; and 7.08 percent, respectively. This range of predictions indicates the potential for steady positive growth, although the 95% confidence interval shows high variability, with the lower bound reaching negative values and the upper bound surpassing 6,200 percent in the final year. This indicates considerable uncertainty in the industry's growth dynamics, which policy makers need to anticipate.

The evaluation of the model against historical data shows that the Mean Squared Error (MSE) reaches 1,568 and the Mean Absolute Percentage Error (MAPE) is at a very high rate of 297.69%. The large MAPE value indicates that the model tends to experience large deviations from the actual values in the historical data, which can be caused by outliers or extreme fluctuations in the data. Therefore, although the predictions show a positive direction, the government and industry should use these results as an indication of the general trend, not an exact value. Policies that can be implemented include risk mitigation strategies, such as production diversification, efficiency improvement, and regular monitoring of domestic and global economic indicators that may affect the manufacturing sector.

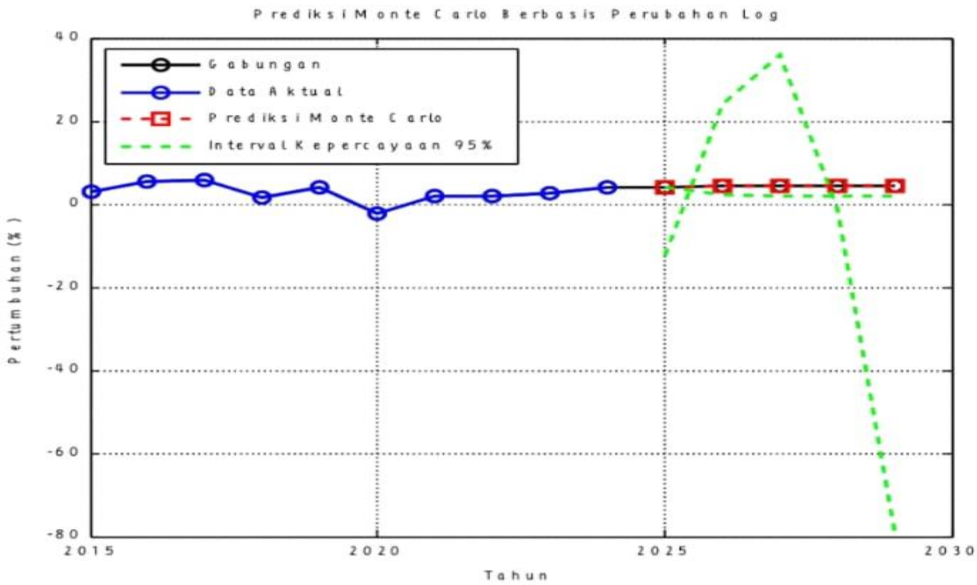

Figure 2. Prediction Chart for the Next 5 Years

Average Prediction for the next 5 years: 4.2090 + 0.0360i 4.2547 - 0.0165i 4.3498 - 0.2506i 4.3194 - 0.1555i 4.3103 - 0.0667i
Lower Limit: 3.9891 2.1734 2.0505 1.9324 1.8189
Upper Limit: -12.4106 - 0.0000i 24.0872 + 0.0000i 36.0948 + 0.0000i -1.1073 + 0.0000i -79.3989 - 0.0000i

Based on the graph of the forecasting results using logarithmic change-based Monte Carlo simulation, the predicted annual growth from 2025 to 2029 tends to stabilize at around 2%. The red line marked with a box represents the Monte Carlo average prediction result, which shows a moderate growth trend without significant spikes. The historical data visualized by the blue line shows a relatively stable trend from 2015 to 2024, although there are minor fluctuations at some points. The 95% confidence intervals, depicted by the dashed green lines, indicate a potentially high degree of uncertainty in the medium term, especially after 2026, where the intervals become very wide.

Table 2. Table of MSE and MAPE Values of Prediction Results

Variables	MSE	MAPE
Processing industry	0.2653	6.27%.

The quantitative results of the model evaluation show that the Mean Squared Error (MSE) value is 0.2653, and the Mean Absolute Percentage Error (MAPE) is 6.27%. The low MSE value indicates that the average squared error of the forecasting results is relatively small, while the MAPE below 10% indicates that the model has a good level of accuracy in forecasting historical growth data.

In general, these forecasting results indicate that economic growth or the analyzed variables will move in a relatively stable trajectory, with small but positive average growth. The uncertainty in the medium term reflected by the wide confidence intervals needs to be a concern, as there is a possibility of extreme scenarios that cannot be ignored, either in the form of very high growth or a drastic decline. Given the moderate and stable growth pattern, the right policy is to maintain sustainability and strengthen the foundation of the economy or related sectors. The government or policy makers are advised to implement anticipatory and adaptive strategies, such as building risk reserves, diversifying investments, and strengthening resilience to global uncertainty. In addition, given the potential for large fluctuations in the next few years, it is also important to improve monitoring systems and regular data updates, in order to recalibrate predictive models to remain accurate and responsive to the latest dynamics.

D. CONCLUSIONS AND SUGGESTIONS

Based on the results of the analysis of manufacturing production data from 2015 to 2024, it is known that this sector is experiencing a positive growth trend, especially after 2020. Economic recovery after the COVID-19 pandemic is a significant factor driving the increase in production volume. Growth predictions for the period 2025 to 2029 obtained through the Monte Carlo simulation method show relatively stable values with average annual growth ranging from 5.57% to 7.08%. However, the results of the model evaluation show a significant difference in accuracy. In the early stages, the very high Mean Absolute Percentage Error (MAPE) values indicated a large deviation of predictions from historical data, while the latest evaluation results showed a significant improvement in accuracy, with a MAPE of 6.27% and a Mean Squared Error (MSE) of 0.2653. This shows that the model has been improved and is more reliable as a predictive tool.

However, the wide confidence intervals in the medium- to long-term predictions indicate that there are uncertainties that need to be considered, especially after 2026. This uncertainty reflects the sensitivity of the industrial sector to external dynamics, such as policy changes, global market conditions, and geopolitical factors. Therefore, these forecasting results should not be used as an absolute benchmark, but rather as a strategic reference in policy formulation and long-term planning.

As an anticipatory measure, it is recommended that the government and industry players implement risk mitigation strategies, including through product diversification, strengthening domestic supply chains, improving production efficiency, and investing in digital transformation and industrial technology 4.0. In addition, it is important to regularly monitor and calibrate predictive models so that the forecasting results remain relevant to the latest dynamics. An adaptive, data-driven approach will be helpful in responding to changing conditions more quickly and appropriately. Thus, the sustainability of growth in the manufacturing sector can be maintained amidst growing global uncertainty.

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