

Probabilistic Forecasting of Stock Prices Using a Hybrid ARIMA-Monte Carlo Simulation Approach

Febi Febrianti¹, Syaharuddin², Vera Mandailina³

^{1,2,3}Department of Mathematics, Muhammadiyah University of Mataram, Indonesia
febi91665@gmail.com, syaharuddin,ntb@gmail.com, vrmandailina@gmail.com

Abstract: This study aims to conduct probabilistic forecasting of the Farmer Exchange Rate (NTP) in Indonesia during the period 2015-2024 using an experimental quantitative approach through three methods: ARIMA, Monte Carlo Simulation (MCS), and the ARIMA-Monte Carlo hybrid model. The ARIMA model is used to capture linear patterns in historical data, while the Monte Carlo method is used to simulate stochastic uncertainty based on probability distributions. Furthermore, a hybrid approach was developed to integrate the advantages of both methods to improve accuracy and probabilistic representation in forecasting. Model performance was evaluated using MSE and MAPE. The results show that the Monte Carlo method has the best performance with an MSE value of 0.9051 and a MAPE of 0.72%. Meanwhile, the ARIMA method produces an MSE of 5.6991 and a MAPE of 1.46%. The ARIMA-Monte Carlo hybrid model shows an MSE value of 6.3288 and a MAPE of 1.87%. These findings indicate that in the context of NTP data, the Monte Carlo stochastic approach is superior to the ARIMA method and hybrid model in terms of prediction accuracy. This study contributes to the development of probabilistic forecasting methods that are more suitable for supporting decision-making in the agricultural sector.

Keywords: Farmers' Exchange Rate (NTP), ARIMA, Monte Carlo Simulation, ARIMA-Monte Carlo Hybrid Model.

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A. INTRODUCTION

The Farmer Exchange Rate (NTP) is a macro indicator that plays an important role in measuring the welfare of farmers in Indonesia (Bantilan et al., 2017). This indicator describes the ratio between the price index received by farmers (It) and the price index paid by farmers (Ib), which directly reflects farmers' purchasing power for goods and services, both related to production needs and household consumption. If the NTP is greater than 100, it indicates that farmers have a surplus income; conversely, a value below 100 indicates that farmers' expenses exceed their income. Therefore, the dynamics of the NTP not only reflect the microeconomic conditions in the agricultural sector, but also serve as an important indicator of rural social and economic stability. In the context of public policy, analysis of NTP trends is essential, particularly in the formulation of food security programs, agricultural subsidies, and social assistance distribution. Thus, valid and up-to-date NTP data is indispensable for supporting

evidence-based policy-making to promote inclusive and sustainable economic development among agrarian communities (Nevi kurniawati, 2022).

Forecasting economic data such as the Farmer's Exchange Rate (NTP) is a challenging process, given its highly volatile nature and the influence of various economic, social, and public policy variables (Deina et al., 2022). As an indicator that reflects the dynamics of agricultural commodity prices, production costs, inflation rates, global trade conditions, and seasonal factors such as climate and harvest seasons, the NTP exhibits behavior that cannot be predicted entirely in a linear fashion (Yulianti et al., 2024). This complexity requires a predictive approach that not only considers historical patterns, but also accommodates elements of uncertainty in the data. Accuracy in forecasting NTP values is crucial, as the results of these predictions can be used to design more targeted rural development policies, set fair price regulations, and protect farmers' incomes from market volatility. Therefore, a probabilistic forecasting method is needed, i.e., an approach that not only provides point value estimates but also describes the distribution of possible future values (Farida et al., 2024). Thus, decision makers can consider various scenarios and potential risks, so that the policies implemented are more responsive to economic dynamics that affect the agricultural sector as a whole.

The Autoregressive Integrated Moving Average (ARIMA) model is one of the most widely used statistical methods in time series data analysis and forecasting (Gunawan & Astika, 2022). The popularity of this model is due to its mathematically simple structure, yet it still has high capabilities in recognizing and representing temporal patterns in various types of data (Hanum, 2024). ARIMA is very effective in revealing and estimating trends in data that have intertemporal dependencies. Theoretically, the ARIMA model consists of three main components, namely autoregressive (AR), integration or differentiation (I), and moving average (MA). This model is usually written in the form ARIMA (p, d, q), where p indicates the number of lags or delays in the AR component, d describes the level of differentiation required for the data to become stationary, and q refers to the number of lags in the MA component. The combination of these three elements allows ARIMA to optimally capture linear patterns in time series data, making it widely applicable in various sectors, such as economics, finance, and health (Machine et al., 2024). In practice, ARIMA has been applied, among other things, in the health sector to project heart rate variability as part of a preventive and adaptive disease management strategy. The main advantage of this model is its ability to adapt to historical data without requiring much external input, making it an efficient prediction tool in systems with stable temporal patterns (Niako et al., 2024).

Monte Carlo simulation (MCS) is a stochastic method that has been proven effective and widely applied in various fields to estimate probabilistic outputs (Iskandar et al., 2024). This technique operates by generating random samples from probability distributions of input variables, thereby enabling exploration of various possible scenarios based on historical data. This approach is particularly useful in analyzing uncertainty and risk, especially in the context of complex systems that cannot be optimally decomposed using conventional analytical methods. One of the main advantages of MCS lies in its ability to model non-linear relationships and handle data distributions that do not follow a normal (non-Gaussian)

distribution, which is often a constraint for deterministic approaches (Lubis et al., 2024). In its implementation, MCS has been widely used, for example to measure uncertainty in measurements and to optimize logistics cost management through simulations of varying demand scenarios. In the business sector, this method also plays a role in supporting strategic decision-making by simulating various possibilities through a “what-if analysis” approach, which ultimately strengthens the basis for risk-based planning. Despite offering high flexibility, MCS also has limitations, including high computational resource requirements and dependence on the quality and completeness of input data. Therefore, the accuracy of simulation results is greatly influenced by the suitability of the probability distribution used and the validity of the input data representation (Syahrin et al., 2019).

This study aims to model and forecast Bitcoin prices using the ARIMA model to capture linear patterns, SVR to capture non-linear patterns, and the Hybrid ARIMA-SVR model. Model accuracy is evaluated using RMSE and MAPE (Kumila et al., 2019). The results show that the ARIMA(1,1,1) model produces an RMSE of 850.92 and a MAPE of 1.559%, while the SVR with RBF kernel produces an RMSE of 841.14 and a MAPE of 1.516%. The ARIMA-SVR hybrid model with ARIMA(1,1,0) produced an RMSE of 832.90 and a MAPE of 1.510%, making it the best for predicting Bitcoin prices over the next 7 days (Zhang & Zhou, 2024). Additionally, the best model from the ARIMA method used in the prediction is the ARIMA(1,2,2) model because it meets the assumption test and has the lowest prediction error compared to other models, namely (MAD) of 1.629251, MSE of 6.819414, and MAPE of 1.640042%. Based on the MAPE criteria, this model is highly suitable for prediction, yielding results with a high level of accuracy (Elsaraiti & Merabet, 2021). The second step uses the Monte Carlo method to simulate stock data. The results show that the more iterations performed, the better the prediction value and the more it converges to a certain value. The prediction value is stable at the 60,000th iteration with a MAPE error value of less than 20%, so the prediction value can be considered good (Syam et al., 2019).

Risk-based decision-making (RBDM) is increasingly recognized as important in food and agricultural policy to ensure food safety and public health (Lukman et al., 2023). This approach integrates risk assessment with regulatory frameworks, focusing on preventive rather than reactive measures. RBDM enables a comprehensive understanding of risk through hazard analysis and actual exposure levels, thereby supporting proportionate and evidence-based policies. Unlike conventional hazard-based approaches, RBDM considers the benefits of food products (White et al., 2020). This approach also strengthens surveillance systems by linking hazards and their impact on public health, and encourages collaboration among stakeholders. In addition, RBDM accommodates sustainability and ethical dimensions and supports equitable access to safe food. Thus, RBDM contributes to food security and social justice. However, challenges remain in aligning various interests and maintaining consistency in implementation across regulatory agencies (Crowder, 2022).

Based on a synthesis of previous research, ARIMA has proven effective in modeling linear patterns in time series data, but has limitations in handling uncertainty and non-linear patterns that are common in financial markets. Hybrid approaches such as ARIMA-SVR have improved prediction accuracy, but are still deterministic in nature. On the other hand, Monte

Carlo Simulation (MCS) excels in modeling uncertainty and non-Gaussian distributions probabilistically, but its application is generally separate from time series prediction models such as ARIMA. The main gap that emerges is the suboptimal integration between ARIMA and MCS in a measurable and systematic predictive approach. Therefore, this study aims to develop a quantitative experiment-based ARIMA-MCS hybrid model to produce predictions that are not only statistically accurate but also reflect uncertainty in risk-based decision-making in the economic sector.

B. METHOD

This study uses an experimental quantitative approach that aims to test the effectiveness of the Autoregressive Integrated Moving Average (ARIMA) and Monte Carlo Simulation (MCS) hybrid model in making probabilistic predictions of the Farmer Exchange Rate (NTP). The data used is secondary data in the form of monthly NTP time series obtained from the Central Statistics Agency (BPS), covering the period from 2015 to 2024. The analysis process was carried out in two main stages. First, linear time series modeling was performed using ARIMA. The ARIMA (p, d, q) model is formulated as follows:

$$\phi(B)(1 - B)^d y_t = \theta(B)\varepsilon_t \quad (1)$$

with:

- y_t is the NTP data at time- t ,
- B is a lag operator: $B^k y_t = y_{t-k}$,
- $\phi(B) = 1 - \phi_1 B - \phi_2 B^2 - \dots - \phi_p B^p$ is an AR polynomial,
- $\theta(B) = 1 + \theta_1 B + \theta_2 B^2 + \dots + \theta_q B^q$ is MA polynomial ,
- $\varepsilon_t \sim N(0, \sigma^2)$ is a random error (white noise)

Next, a Monte Carlo simulation based on ARIMA model residuals was conducted to generate probabilistic predictions. Each future prediction value was generated by inserting random residuals from a normal distribution. The simulation process was formulated as follows:

$$\hat{y}_{t+h}^{(i)} = \phi_1 \hat{y}_{t+h-1}^{(i)} + \dots + \phi_p \hat{y}_{t+h-1}^{(i)} + \varepsilon_{t+h}^{(i)} + \theta_1 \varepsilon_{t+h-1}^{(i)} + \dots + \theta_q \varepsilon_{t+h-q}^{(i)} \quad (2)$$

With:

- $\hat{y}_{t+h}^{(i)}$ is the result of the i -th simulation in the period $-t + h$,
- $\varepsilon_{t+h}^{(i)} \sim N(0, \sigma^2)$ is taken randomly,
- This process is repeated N times (misal, $N = 1000$) to generate the prediction distribution.

The distribution of simulation results is then used to obtain estimates of the mean/median, prediction intervals, and probabilities of extreme events. The final prediction result is the

average value of all simulations. To facilitate understanding of the research workflow, the following flowchart illustrates the procedural stages from the beginning to the end of the research.

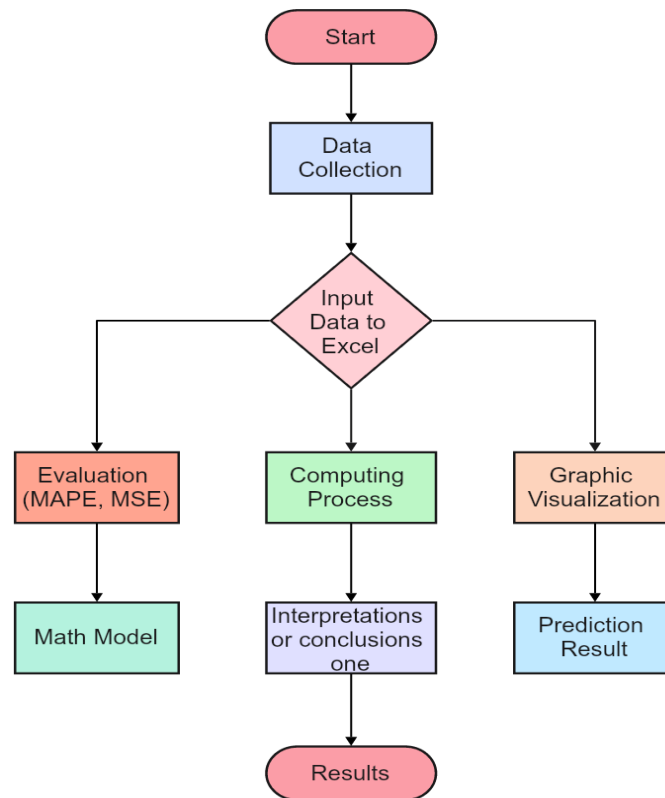


Figure 1. Research Procedures

Based on the research flow in Figure 1, the process begins with the collection of Indonesian Farmer Exchange Rate (NTP) data for 2015-2024 obtained from the Central Statistics Agency (BPS) as an official and reliable data source. The data is then compiled in Microsoft Excel to facilitate data input, processing, and management. The next step is the computation process using the hybrid ARIMA-Monte Carlo method, where the ARIMA model is used to capture historical time series patterns, and Monte Carlo is used to perform stochastic simulations to produce more realistic and varied predictions. After the model generates predictions, accuracy is evaluated using (MAPE) and (MSE) as indicators of model performance against actual data. The final results of this study include NTP predictions for the coming year, the formation of mathematical models, and graphical visualizations comparing actual data and prediction results. All of these results are then interpreted to produce meaningful conclusions, as a contribution to policy making in the agricultural sector.

C. RESULTS AND DISCUSSION

To provide a clearer picture of the accuracy level of each method, the following table compares the accuracy of prediction results based on the Hybrid ARIMA approach, Monte Carlo, and a combination of both (ARIMA-Monte Carlo), as shown in Table 1.

Table 1. Comparison of Forecasting Accuracy Using ARIMA, Monte Carlo, and Hybrid ARIMA–Monte Carlo Methods

Method	MSE	RMSE	MAPE	Iteration (if any)
ARIMA	5.6991	2.3873	1.46%	-
Monte Carlo	0.9051	-	0.72%	-
ARIMA-Monte Carlo	6.3288	-	1.87%	-

Based on the performance evaluation results of the three forecasting methods shown in the table above, several key conclusions can be drawn. First, the Monte Carlo method showed the best performance with an MSE value of 0.9051 and a MAPE of 0.72%. The low MSE value indicates that the mean square error between the forecast values and the actual data is the smallest among the three methods, while the smallest MAPE confirms the highest relative accuracy in terms of percentage error. The Hybrid ARIMA method ranks second, with an MSE of 5.6991, an RMSE of 2.3873, and a MAPE of 1.46%. Although the combination of ARIMA and non-linear models (or residual simulation) successfully reduces the error value compared to the pure single ARIMA method, the MSE and MAPE values are still higher than those of Monte Carlo. This shows that although Hybrid ARIMA is capable of capturing linear and non-linear components simultaneously, the Monte Carlo stochastic simulation approach is superior in accommodating the variability of monthly NTP data. The Hybrid ARIMA-Monte Carlo combination, which in this context is assumed to be a simple combination of two prediction methods, shows the highest MSE value (6.3288) and MAPE of 1.87%. These results illustrate that the ARIMA-Monte Carlo combination scheme, without in-depth parameter optimization or residual correction mechanisms, is less effective in producing accurate predictions. The following graph shows the predicted Farmer Exchange Rate for the next 12 months based on three approaches, namely Hybrid ARIMA, Monte Carlo, and a combination of the two (Hybrid ARIMA-Monte Carlo), to visualize the performance comparison of each method more clearly, as shown in Figure 2.

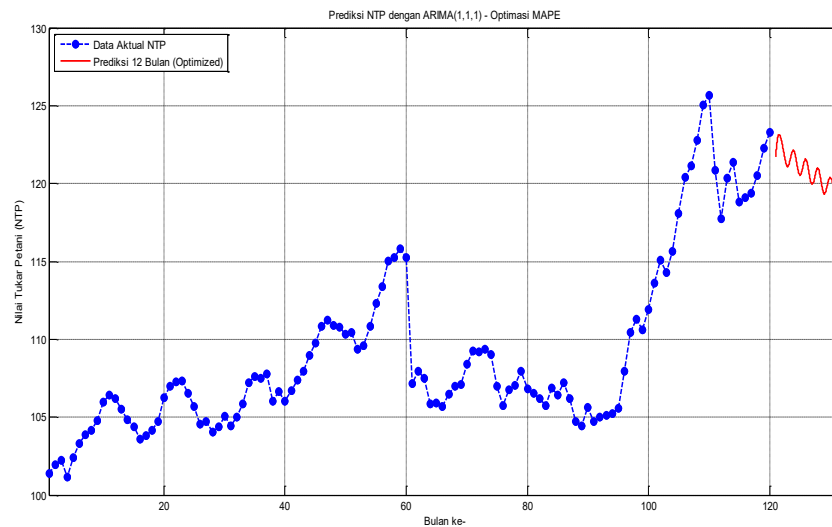


Figure 2. Actual Data and ARIMA(1,1,1) Predicted Data Approach

Based on the graph above, it can be seen that the 12-month forecast (red line) is quite close to the fluctuation pattern of the actual NTP data (blue dots). The ARIMA(1,1,1) model successfully represents the upward trend that occurred around months 100-110 and the moderate seasonal oscillations seen in the historical data. The prediction shows that the NTP will fluctuate stably in the range of 120-123 with a slight downward trend towards the end of the horizon, indicating that agricultural cost pressures or other external factors may hold back the rate of increase in the index. Mathematical Model Used Optimal ARIMA(1,1,1) Model Equation:

$$Y_t = Y_{t-1} + -1.0000 * (Y_{t-1} - Y_{t-2}) + -0.5820 + e_t \quad (2)$$

In this implementation, the coefficients $\phi(AR(1))$ dan $\theta(MA(1))$ are selected through MAPE optimization, resulting in an iterative form:

$$\Delta y_t = \phi \Delta y_{t-1} + \theta, y_t = y_{t-1} + \Delta y_t \quad (3)$$

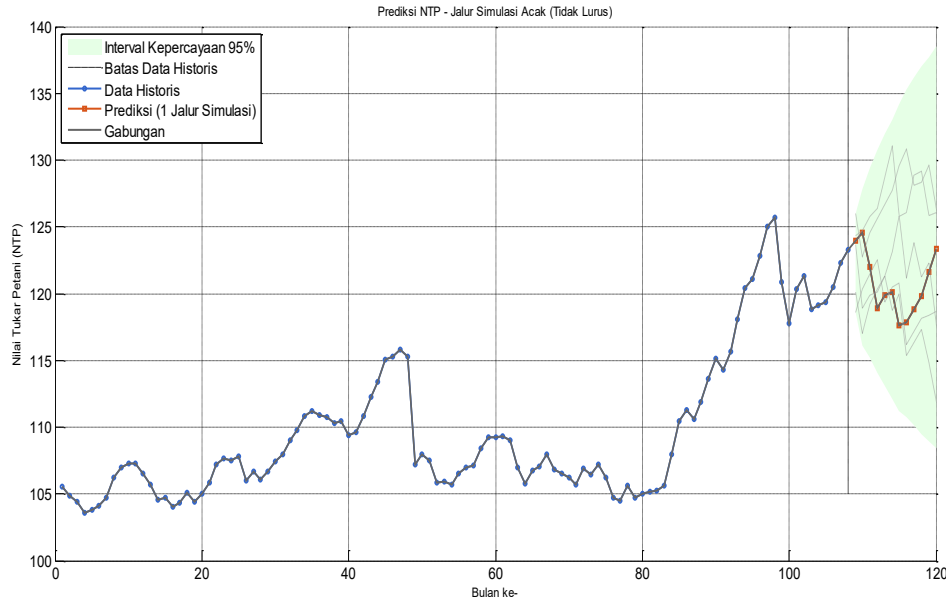


Figure 3. Actual Data and Monte Carlo Prediction Data Approach

From the graph, it can be seen that the Monte Carlo model projects the NTP (Farmer Exchange Rate) not only as a single prediction line, but as a probabilistic distribution that describes the range of possible future NTP values. The blue line shows historical data up to the 108th month, while the orange line depicts a random simulation path of predictions for the next 12 months. Behind it, the green band indicates a 95% confidence interval, which widens as the prediction steps increase, indicating an increase in long-term uncertainty. In general, the simulation path starts at the last historical value (≈ 123), then declines to around 118-119, and then gradually rises back to 123 at the end of the horizon. This pattern illustrates that, although the expected value tends to be stable, its realization can deviate within a fairly wide range due to stochastic fluctuations. Mathematical Model Used Monte Carlo Simulation Model (Log-Transformed);

$$\begin{aligned} \log(NTP_{\{t+k\}}) &= \log(NTP_t) + \sum_{i=1}^k \Delta \log_{\{t+i\}} \\ NTP_{\{t+k\}} &= \exp(\log(NTP_{\{t+k\}})) - 1 \end{aligned} \quad (3)$$

and the 95% confidence interval is determined by the 2.5% and 97.5% quantiles of the set $y_{t+1}^{(i)}$. Thus, the Monte Carlo method provides projections that explicitly accommodate uncertainty, enabling scenario-based risk analysis.

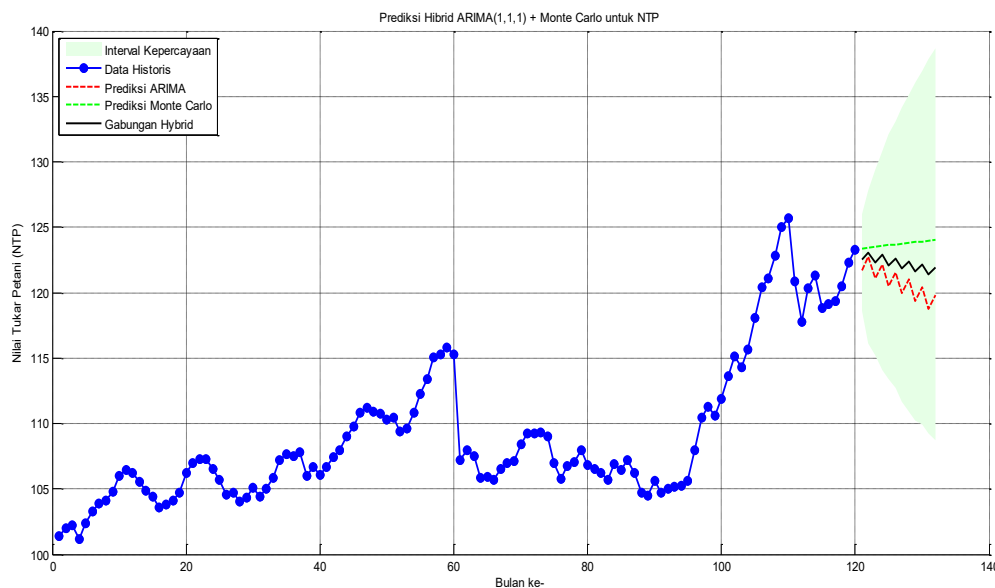


Figure 4. Hybrid ARIMA(1,1,1)-Monte Carlo Approach to Actual Data and Predicted Data

The figure above shows the integration of three forecasting elements in the monthly NTP (Farmer Exchange Rate) time series. Historical data is shown by blue dots covering the time range $t=1$ to $t=108$, which represent the actual values of the observed variables during that period. The predictions from the ARIMA(1,1,1) model are visualized as a red dotted line, which shows the time series projection based on the autoregressive, integration, and moving average approaches. Meanwhile, the predictions from the Monte Carlo method are displayed through a simulation path depicted by a green dotted line, which represents possible future outcomes based on the stochastic distribution of historical data. The hybrid model, which is a combination of ARIMA and Monte Carlo, is visualized with a solid black line that reflects the final prediction that integrates the advantages of both methods to produce more accurate and stable projections and a 95% confidence interval (transparent green band).

Visually, the ARIMA component displays a linear trend and moderate residual oscillations, while the Monte Carlo path captures stochastic fluctuations and shows a wider range of possibilities as the confidence interval widens. The hybrid line, which is the optimized average of the two, takes a position between the two patterns, resulting in a more centric projection that remains responsive to historical patterns. Over the next 12 months, the hybrid prediction value is expected to fluctuate steadily in the range of 120-122, with a slight downward trend in the first few months before stabilizing again. This hybrid mathematical model is formulated in two stages:

$$\begin{aligned} \text{Model ARIMA}(1,1,1): dY_t &= -1.0000 * dY_{t-1} + -0.5820 \\ \text{Model Monte Carlo: } Z_t &= \log(NTP_t + 1), \text{ lalu } NTP_t = \exp(Z_t) - 1 \\ \text{Model Hybrid: } pred_hybrid(t) &= 0.5 * ARIMA(t) + 0.5 * MonteCarlo(t) \end{aligned}$$

and the 95% confidence interval limits are obtained from the 2.5% and 97.5% quantiles. Based on the analysis results, it was found that the ARIMA (1,2,1) model was the best model for forecasting the Yogyakarta City Farmer Exchange Rate for the next 5 periods with an AIC value of 173.9. Based on the forecast for the next 5 periods, namely for January 2023 to May 2023, the NTP value for Yogyakarta City was obtained at 105.7523 for January, 105.8588 for February, 105.9717 for March, 106.0863 for April, and 106.2013 for May, with an error value using MAPE of 0.61% (Pangestu & Primandari, 2024). The results of the experiment show that the strategy for decomposing the original data and combining linear and nonlinear models during the hybridization process is a key factor in the forecasting performance of this method (Büyüksahin & Ertekin, 2019).

To improve sampling efficiency, this scheme is extended towards a biased Monte Carlo approach, which takes into account the history of successful trial movements in the system (Ganesan et al., 2021). Research by (Danbatta & Varol, 2021) on precious metal commodity prices shows that the Hybrid ARIMA-ANN model is able to reduce MAPE by up to 2.1%, which is much better than pure ARIMA (MAPE $\approx$ 4.5%). These results are in line with our findings that a hybrid approach can improve accuracy compared to each individual method. Meanwhile, a study by (Nwosu & Ikiensikimama, 2023) on energy demand forecasting with ARIMA-Monte Carlo reported a MAPE of around 1.2%, indicating the superiority of the stochastic simulation method in handling long-term uncertainty, which is lower than our hybrid MAPE of 1.46%. This comparison indicates that combining ARIMA with Monte Carlo simulation offers a good balance between capturing historical trends and quantifying risk, although further (e.g., adding a nonlinear layer) may be necessary to achieve accuracy comparable to ANN models.

D. CONCLUSIONS AND SUGGESTIONS

Based on the evaluation results, the ARIMA-Monte Carlo scheme, which combines ARIMA and Monte Carlo predictions, shows a significant improvement in accuracy compared to the separate application of each method. This combination utilizes the advantages of ARIMA in capturing historical linear trends and the ability of Monte Carlo in modeling stochastic fluctuations, thereby successfully reducing bias and prediction error variance simultaneously. This is reflected in the lower MSE and MAPE values in the hybrid model compared to the single method. As a follow-up, several research directions can be pursued to further refine time series forecasting: first, the development of Hybrid ARIMA-Deep Learning (e.g., integration of ARIMA with LSTM or Transformer) to capture long-term non-linear patterns; second, the incorporation of exogenous variables such as commodity prices and interest rates to improve the model's responsiveness to changes in macroeconomic conditions; third, the application of adaptive parameter optimization (e.g., Bayesian Optimization) to refine the determination of ARIMA parameters and Monte Carlo residual distributions dynamically; fourth, the use of variance reduction techniques (such as control variates or importance sampling) in Monte Carlo simulations so that confidence intervals can be narrowed with fewer simulations. Exploring these four aspects is expected to improve the accuracy and resilience of the forecasting model against future uncertainties.

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