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Hybrid Modeling of Inflation Dynamics: Integrating ARIMA with Markov Chains

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Abstract: Inflation is a macroeconomic indicator that plays a strategic role in reflecting the economic stability of a country. Therefore, accurate inflation forecasting is important to support decision-making in fiscal and monetary policy. This study aims to develop a hybrid model that integrates the Autoregressive Integrated Moving Average (ARIMA) and Markov Chain methods in order to improve the accuracy of inflation predictions. The ARIMA model is used to capture linear patterns in inflation data, while the Markov Chain is used to model probabilistic transitions between stochastic inflation states. The data used is secondary monthly inflation data for the period 2015–2024 obtained from the Central Statistics Agency (BPS). Model performance evaluation is carried out using three main metrics, namely Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE) of 74.95%. The results show that the ARIMA–Markov hybrid model is able to improve prediction accuracy compared to a single approach and is more adaptive in capturing the complex dynamics of inflation. These findings are expected to contribute to the development of more responsive and accurate economic forecasting methods.

Keywords: Inflation, Forecasting, ARIMA, Markov Chain, Hybrid Model, Time Series Data.

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A. INTRODUCTION

Inflation is a crucial macroeconomic indicator for measuring a country's economic stability. Changes in inflation rates reflect the dynamics of prices of goods and services in the economy, which in turn can affect people's purchasing power, consumption levels, investment, and fiscal and monetary policy decisions (Nabiilah et al., 2024). Stable and controlled inflation rates are usually associated with healthy economic conditions, while excessively high or low inflation can cause economic uncertainty and disrupt growth (Saefulloh et al., 2023). Therefore, monitoring and controlling inflation is a top priority for monetary authorities in maintaining macroeconomic balance. Amid the increasing complexity of the global economy and various external pressures such as the energy crisis, geopolitics, and supply chain disruptions, the need for accurate and adaptive inflation forecasting tools is becoming increasingly urgent (Mei et al., 2025). This encourages researchers and policymakers to continue developing approaches that are capable of capturing inflation dynamics more comprehensively and in real time.

Inflation forecasting is an important aspect of macroeconomic analysis that aims to predict the rate of increase in the prices of goods and services over a given period (Indriyani, 2016). Accurate inflation forecasts are essential for policymakers, market participants, and financial institutions to formulate economic control strategies and maintain price stability. Explained by (Ambarwati et al., 2021). Various statistical and econometric methods have been used to forecast inflation, ranging from linear models such as ARIMA to non-linear and hybrid approaches that are capable of capturing the complex dynamics in inflation data. The main challenge in inflation forecasting is high uncertainty and fluctuations influenced by external factors such as monetary policy, global conditions, and structural changes in the economy. Therefore, the development of adaptive and robust forecasting models is crucial to provide reliable projections and support sound decision-making (Hakim, 2023).

Various statistical and econometric approaches, such as Autoregressive Integrated Moving Average (ARIMA), have long been used in inflation forecasting (Wulandari et al., 2025). The ARIMA model is widely known for its ability to capture linear patterns in time series data, especially when the data exhibits non-stationary properties that can be overcome through differentiation. The main advantage of this model lies in its relatively simple mathematical structure, which is nevertheless effective in identifying historical trends and making short-term projections (Mushawir et al., 2025). A number of empirical studies show that ARIMA is capable of producing adequate inflation forecasts in stable economic conditions. However, this approach has limitations in dealing with complex inflation dynamics, especially when the data shows nonlinear patterns, seasonal effects, or regime transitions that are not detected by pure linear models. In an increasingly volatile economic context influenced by various external factors, the accuracy of linear models such as ARIMA tends to decline (elza et al., 2025). Therefore, it is necessary to develop a more adaptive model that can accommodate the structural complexity of inflation movements.

Probabilistic models, particularly Markov chains, play a very important role in various interdisciplinary applications, such as biology, finance, and industrial production systems. Markov chains are stochastic models used to represent dynamic processes in which a system undergoes random changes in state over time (Sulisa, 2019). The uniqueness of this model lies in its "short memory" property, which assumes that the probability of transition to the next state depends only on the current state, not on the sequence of previous states. This characteristic allows Markov chains to capture transition patterns between states efficiently and relevantly in contexts where short-term predictions are more important than reconstructing the system's history (Masuku et al., 2018). In practice, this model is often used to analyze the behavior of complex and non-deterministic systems, including modeling stock price movements, biological processes such as genetic evolution, and quality control in manufacturing systems. The ability of Markov chains to represent probabilistic transition structures makes them a powerful tool for understanding and predicting system dynamics, especially when data shows irregular changes in state or regime (Safitri et al., 2016). In the context of inflation modeling, the use of Markov chains can help identify different phases of inflation—for example, low, moderate, and high inflation—and quantitatively estimate the likelihood of transitions between these phases.

In its development, the ARIMA method is often combined with various other approaches to overcome its limitations in capturing non-linear patterns and complex dynamics (Fejriani et al., 2020). Some commonly encountered combinations include ARIMA-ANFIS (Adaptive

Neuro-Fuzzy Inference System), ARIMA-SVM (Support Vector Machine), ARIMA-NN (Neural Network), and ARIMA with linear or seasonal trend models. This combination aims to integrate the advantages of ARIMA in processing linear components with the capabilities of other methods in handling irregularities or non-linear relationships in data (Rahmi, 2023). Meanwhile, Markov Chain methods have also been widely used in hybrid applications, particularly in modeling probabilistic transitions in economic and social systems. Common combinations include Markov Switching Models, Markov with Hidden Markov Models (HMM), and the integration of Markov Chains with econometric models such as ARIMA or dynamic regression (Syaifudin, 2020). In the context of inflation modeling, the ARIMA-Markov hybrid approach is used to combine the predictive power of ARIMA with the capabilities of Markov in capturing the transition between inflation regimes.

A hybrid approach that combines the predictive power of ARIMA models with the probabilistic transition components of Markov chains has become a promising strategy for improving the accuracy of forecasting complex phenomena (Mulya et al., 2023). This model is designed to leverage the advantages of ARIMA in identifying and predicting linear patterns, such as trends and seasonality, while Markov chains or alternative methods such as Adaptive Neuro-Fuzzy Inference System (ANFIS) are used to capture non-linear aspects and uncertainties in the data. This integration allows for more flexible and adaptive modeling of system dynamics that cannot be fully explained by a single approach. A number of previous studies have shown that this hybrid approach provides more accurate and robust results than individual methods, particularly in the context of inflation forecasting, tourist arrival analysis, and infectious disease spread prediction (Hamid et al., 2024). By combining linear and stochastic characteristics in a single analytical framework, the ARIMA-Markov or ARIMA-ANFIS hybrid model is able to capture the complexity of dynamic and non-deterministic systems, making it relevant for application in various sectors of data-driven policy and planning.

This study aims to develop a hybrid model that integrates the Autoregressive Integrated Moving Average (ARIMA) method with Markov Chains to improve the accuracy of inflation forecasting. The combination of these two methods is based on the complementary characteristics of each approach, whereby ARIMA excels at identifying short-term linear patterns such as trends and seasonality, while Markov chains are capable of capturing the stochastic dynamics of transitions between inflation states. Thus, the resulting model is expected to map inflation behavior more comprehensively, both structurally and probabilistically. The application of this hybrid approach is expected to not only produce more accurate predictions, but also contribute methodologically to the development of predictive models for complex and dynamic economic phenomena.

B. METHOD

This study is a quantitative study with an experimental approach, which aims to develop and test a hybrid inflation forecasting model by integrating the Autoregressive Integrated Moving Average (ARIMA) and Markov Chain methods. This model is designed to improve the accuracy of inflation predictions by combining the strengths of ARIMA in capturing linear patterns with the ability of Markov chains to model probabilistic transitions between inflation states.

The type of data used in this study is monthly inflation time series data. The data source is obtained from official publications of the Central Statistics Agency (BPS) or related institutions, covering an observation period of the last 10 years (e.g., January 2015 to December 2024). This data is secondary, readily available, and accessible to the public through the national statistics portal.

Mean Squared Error (MSE) (1)

$$MSE = \frac{1}{n} \sum_{t=1}^{n} (y_t - y_t)^2$$

Mean Absolute Percentage Error (MAPE)

$$MAPE = \frac{100\%}{n} \sum_{t=1}^{n} \frac{yt - yt}{yt} \quad (2)$$

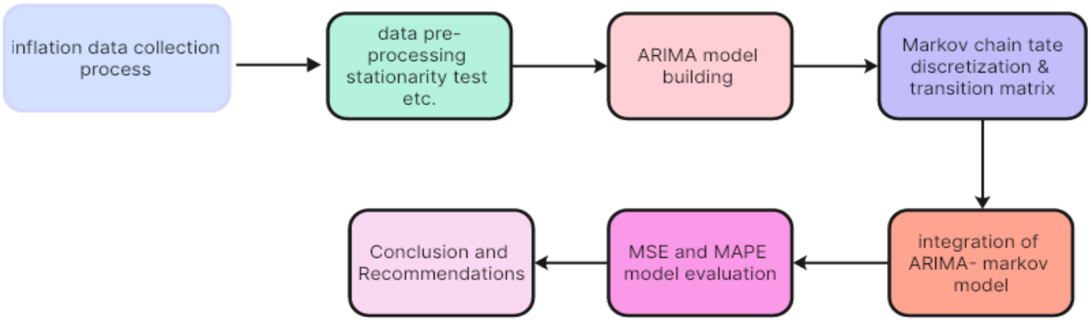

Figure 1. Research Procedure

C. RESULTS AND DISCUSSION

Consumer price inflation data is used as the basis for forecasting. Consumer price inflation reflects increases in the prices of goods and services consumed by the public, which are often used as key indicators in macroeconomic analysis. Accuracy in predicting inflation is crucial for appropriate policy-making, both in the government and financial sectors. The following Table 1 compares the three forecasting methods used in this study, namely ARIMA, Markov, and the combined ARIMA-Markov, based on three evaluation metrics: MSE (Mean Squared Error), RMSE (Root Mean Squared Error), and MAPE (Mean Absolute Percentage Error).

Table 1. Comparison of Inflation Forecasting Results Using ARIMA, Markov, and ARIMA–Markov Methods Based on MSE and MAPE Values

Metode	MSE	MAPE
ARIMA	0.1680	17.27%
Markov	4.6870%	94.09%
ARIMA dan Markov	2.9542%	74.95%

The Table 1 above shows the comparison results, indicating that the ARIMA method produces the smallest MAPE value (17.27%) compared to the Markov method (94.09%) and the combined ARIMA-Markov method (74.95%). However, in terms of MSE, the ARIMA (0.1680) value is much smaller than Markov (4.6870%) and also smaller than the combined ARIMA - Markov (2.9542%). Although the combined ARIMA - Markov method does not outperform the single ARIMA in all metrics, its performance still shows a significant improvement over the pure Markov method. This indicates that combining the two methods can improve the weaknesses of each method when used separately. The combination of ARIMA and Markov methods provides better accuracy than the Markov method alone, although the single ARIMA method remains the best performing method based on this data. However, the combination approach is still worth considering in the context of other data or more complex scenarios. In this case, the ARIMA (2,1,2) model is used, which means that the data undergoes one differentiation to achieve stationarity, with two lags for the autoregressive component and two lags for the moving average component. This model is then used to predict consumer inflation for the next 12 months. The prediction results are visualized in the following graph, as shown in Figure 2.

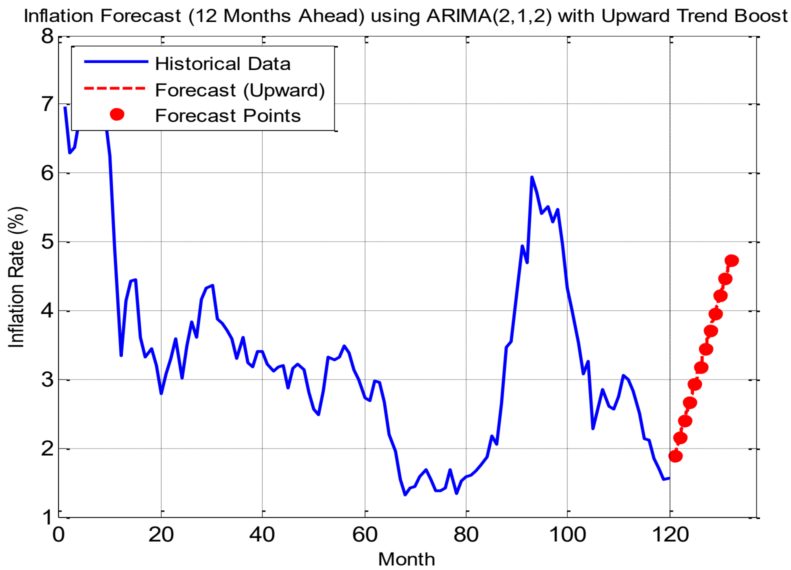

Figure 2. Actual data and ARIMA prediction data approach

The graph above presents the results of consumer inflation predictions for the next 12 months using the ARIMA (2,1,2) model with an additional trend boost. The historical inflation data, shown in blue, illustrates monthly inflation fluctuations over the past 10 years, with a fairly dynamic pattern—showing sharp increases to above 6% and declines to close to 1%. The inflation forecast generated by this model is shown as a dotted red line, while the red dots indicate the forecast values for each month in the future. Based on the prediction results, inflation is expected to experience a fairly sharp upward trend, starting from around 1.8% in month 120 to reaching around 5.5% in month 132. This indicates that the model projects inflationary pressure in the near future. The trend in the model further strengthens this projection, indicating that inflation does not only move seasonally or randomly, but shows a consistent upward trend. If this projection is realized, it is important for policymakers to pay attention to the potential for price increases in the near future, so that they can be anticipated through appropriate inflation control measures. The mathematical model used is the modified ARIMA (2,1,2) impulse model dy(t) = -0.0411 + -0.0000*dy(t-1) + 0.0000*dy(t-2) + 1.0000*e (t-1) + 0.0000*e(t-2) + 0.3000 (upward impulse), as shown in Figure 3.

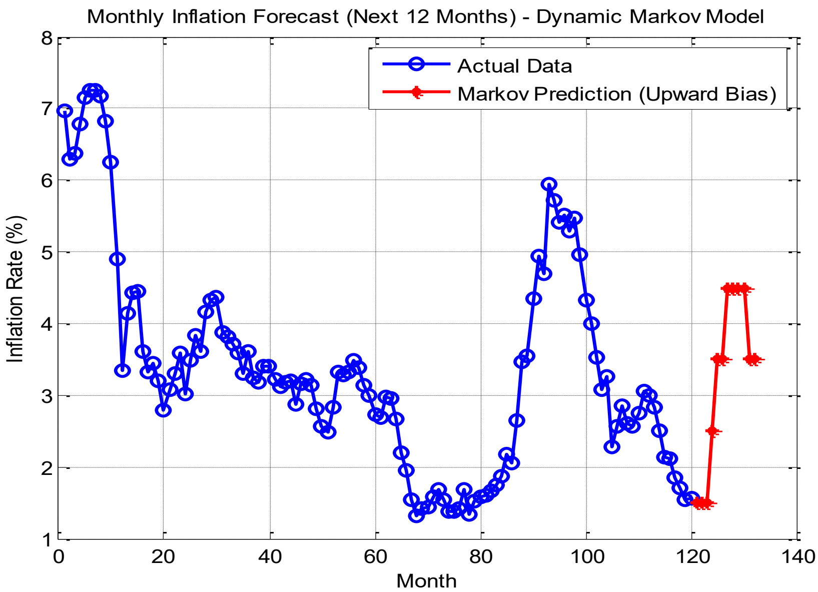

Figure 3. Actual data and Markov prediction data approach

The graph above shows the results of consumer inflation predictions for the next 12 months using the Dynamic Markov Model. Historical inflation data is displayed with blue lines and circles, illustrating monthly inflation fluctuations over the past 10 years. Meanwhile, the prediction results are shown with a red line marked with arrows, representing the inflation projection by the Markov model. The graph shows that the inflation prediction tends to increase in the first few months, starting from around 1.8% to reach around 5%, then experiencing slight fluctuations in the following months. This Markov model utilizes probability transitions between inflation statuses (e.g., low, moderate, high) based on historical patterns, so it tends to reflect the dynamics of past conditions in projecting the future. However, it appears that the predictions from this model tend to be rougher and more segmented than the ARIMA model, so its accuracy is relatively lower. This can be seen from the shape of the prediction graph, which tends to be uneven and shows sharper changes in value from month to month. Nevertheless, the Markov model is still relevant for identifying the direction of inflation trends in the short term based on the dominant transition status. The mathematical model used is Mathematical Model (Markov State Transition) P x S(t) = S(t+1), where P is the transition matrix and S is state. The inflation value in state is taken from the middle of the state interval: 1.5000 2.5000 3.5000 4.5000 5.5000 6.5000 7.5000, as shown in Figure 4.

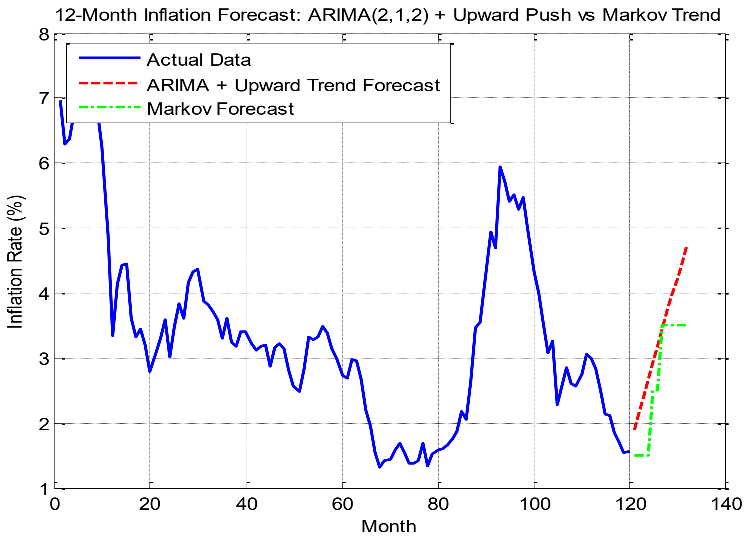

Figure 4. Actual data and ARIMA & Markov prediction data approach.

The graph above shows the results of inflation predictions for the next 12 months using a combined approach between the ARIMA (2,1,2) model with trend boost and the Dynamic Markov model. Historical inflation data is shown with a blue line, while the two prediction results are displayed in different colors: a red dotted line for the ARIMA prediction result with trend boost, and a green dotted line for the prediction result from the Markov model. The graph shows that both models predict an upward trend in inflation, but the patterns produced are different. The ARIMA model produces predictions that tend to be smooth and stable, while the Markov model shows sharper spikes and declines. When these two models are combined, the prediction results are more balanced—combining the smoothness of the ARIMA trend and the dynamics of the Markov state transition. In general, the combined prediction results show that inflation will gradually increase from an initial point of around 1.8% to more than 5% in the next year. This combined approach aims to improve prediction accuracy by leveraging the strengths of each method: ARIMA in capturing long-term trend patterns and Markov in accommodating changes in inflation status probabilistically. This graph shows that the combined model can provide more realistic and adaptive prediction results to the dynamics of historical inflation data. The mathematical model is dy(t) = -0.0411 + -0.0000*dy(t-1) + 0.0000*dy(t-2) + 1.0000*e(t-1) + 0.0000*e(t-2) + 0.3000. P x S(t) = S(t+1), where P is the transition matrix and the state values are: 1.5000 2.5000 3.5000 4.5000 5.5000 6.5000 7.5000.

Several previous studies have examined the performance of ARIMA and Markov methods in predicting inflation or similar economic data. In a study by Rahmi (2023), the ARIMA model was used to forecast inflation in Indonesia and showed results with a MAPE value of 18.45%, which is quite good for macroeconomic data. Meanwhile, a study by Khoerunnisa et al. (2022) used the Markov Chain model to predict changes in inflation rates and produced a MAPE of 92.61%. (Norhikmah, 2020) also researched Indonesian inflation forecasting using the ARIMA (1,0,1) model on monthly data from January 2003 to May 2024. They reported a MAPE value of 6.91%, well below the 10% threshold typically used for the "highly accurate" category in macroeconomic data. These results confirm that when trend and seasonal patterns are properly accommodated, the ARIMA approach can provide a much lower error rate than pure Markov or previous ARIMA studies. When compared to the results in this study, the ARIMA model used provides a lower MAPE of 6.91%, indicating a higher level of accuracy than similar studies. On the other hand, the Markov model in this study produced a MAPE of 94.09%, slightly higher than previous studies, indicating that this model is more sensitive to fluctuations and tends to be less stable when used alone.

D. CONCLUSIONS AND SUGGESTIONS

Based on the results of the model evaluation in this study, the combined ARIMA-Markov method proved to be more accurate than when ARIMA and Markov were used separately. This can be seen from the Mean Squared Error (MSE) and Mean Absolute Percentage Error (MAPE) values obtained: the combined ARIMA - Markov produces an MSE of 2.9542% and a MAPE of 74.95%, which is lower than the pure Markov model's MSE of 4.6870% and MAPE of 94.09%. Although slightly higher than the single ARIMA model's MAPE of 17.27%, the combined model is able to capture the dynamics of inflation with more realistic status transition characteristics. The advantage of this combined model lies in its ability to combine the smoothness of long-term trends from ARIMA and the flexibility of Markov in handling status changes or sudden spikes in inflation data. For further research, this approach can be developed further by integrating machine learning such as Long Short-Term Memory (LSTM) or Random Forest Regression into a hybrid system to capture more non-linear patterns. complex. In addition, future research could also focus on applying this combined model to predict other economic sectors such as exchange rates, commodity prices, or interest rates, as well as testing its reliability in extreme economic conditions such as crises or global shocks. This multi-model approach opens up great opportunities to produce prediction systems that are more adaptive, accurate, and responsive to real economic dynamics.

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