LGJDX Journal Of Liaoning Technical University
ISSN No: 1008-0562 Natural Science Edition

FORECASTING INFLATION VOLATILITY IN SOUTH SULAWESI USING GJR-GARCH AND GENETIC ALGORITHM

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Abstract- This study aims to forecast inflation volatility in South Sulawesi Province using the GJR-GARCH model optimized by a Genetic Algorithm (GA). The GJR-GARCH model is employed to capture asymmetric effects in inflation volatility, while the GA is used to optimize parameter estimation and achieve globally optimal solutions. The results show that the GJR-GARCH model optimized with GA produces lower Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) compared to the standard GJR-GARCH model, indicating superior predictive performance. These findings suggest that integrating GJR-GARCH with GA enhances forecasting accuracy and provides a promising approach for modeling economic time series with nonlinear and heteroskedastic characteristics, which can support policymakers in monitoring and managing inflation risks.

Keywords- Inflation, Volatility, GJR-GARCH, Genetic Algorithm, Forecasting.

I. Introduction

Investment is an economic activity undertaken by individuals or groups to allocate funds with the aim of increasing wealth or capital. In Indonesia, the capital market has experienced significant growth in line with the rising public interest in becoming investors. This trend is driven by needs that go beyond basic necessities and the expectation of improved future welfare through investment returns. As an alternative to real investment, the capital market offers a variety of instruments, with stocks being among the most favored by investors [1].

Shareholders, whether from corporate or government sectors, often take into account certain macroeconomic variables when assessing stock value. Some of the key macroeconomic variables in this context include the inflation rate, interest rate, exchange rate, and money supply. These variables play a significant role in influencing stock market performance, both in developed and developing countries. Among these variables, inflation is often considered a primary factor due to its widespread impact on the overall economy, including the stock market [2].

Having been identified as one of the main macroeconomic variables affecting stock market performance, inflation has become a central focus in various studies conducted in both developing countries like Indonesia and advanced economies. Inflation exerts a broad impact, one of which is its associated social costs. In general, inflation can negatively affect a country by reducing consumers' purchasing power in the domestic economy. This negative effect extends to the stock market in the form of unexpected price fluctuations, which increase uncertainty regarding expected stock returns [3].

According to [3], inflation refers to a general rise in the prices of goods and services that are essential to the public, or a decline in the purchasing power of a country's currency. When inflation increases uncontrollably, the value of money tends to decrease. A high rate of inflation should be given serious attention due to its potential economic consequences, such as creating instability, slowing economic growth, and increasing unemployment [4].

In Indonesia, inflation is a persistent issue at both national and regional levels. In South Sulawesi, historical data show fluctuating inflation rates from 2007 to 2023, influenced by factors such as commodity prices, logistics costs, exchange rates, and interest rates. These fluctuations reflect inflation volatility, a critical aspect in understanding risk and uncertainty in economic forecasting.

In this context, understanding the behavior of inflation rates becomes crucial. As a key macroeconomics indicator, which represents a financial time series commonly used to evaluate economic stability and support the formulation of monetary and fiscal policies [5]. However, in analyzing financial time series data such as inflation, a common issue encountered is heteroskedasticity, where the conditional variance is not constant over time. This violates the assumption of homoskedasticity often relied upon in classical econometric models.

According to [6], revealed that conditional variance has a significant role in the volatility clustering phenomenon, where small price changes are usually followed by other small changes, while large price changes tend to be followed by subsequent large changes . The main challenge in analyzing this phenomenon is heteroskedasticity, a condition where the standard error is not constant over time, reflecting fluctuating volatility and forming clustering patterns [5]. To address this issue, the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model is applied to capture time-varying volatility, resulting in more accurate risk estimation and forecasting of inflation dynamics.

However, the GARCH model is characterized by the fact that the volatility response to a shock is symmetric, whether the shock is positive (good news) or negative (bad news). The asymmetric reaction in the volatility process to unexpected shocks is a key characteristic in financial time series. This phenomenon, known as the leverage effect, suggests that the conditional variance of inflation rates is often more affected by negative news than positive news [7]. The GARCH model cannot handle this asymmetry effect effectively. Therefore, to overcome the presence of leverage effect in stock return data, the GJR-GARCH (Glosten Jagannathan Runkle-GARCH) model is used, which is a variation of the GARCH model that can capture the asymmetry effect in volatility following positive and negative shocks.

The parameter estimation process of the GARCH model is very complex and nonlinear. Therefore, genetic algorithm-based parameter estimation is used to obtain the optimal solution [8]. Genetic algorithm (GA) is an optimization, machine learning method inspired by the theory of genetic evolution, seeking the best solution by mimicking the process of natural selection and reproduction [9]. The essence of GA is to find the best solution by exploring many areas of the parameter space, then selecting the one with the greatest probability [8]. This is particularly important in GARCH models, where the parameter space can be very complex.

Inflation volatility forecasting is crucial for economic planning and policy-making, especially in regions like South Sulawesi, where economic dynamics can be complex. The GJR-GARCH model, an extension of the GARCH model, is particularly effective in capturing asymmetric volatility, making it suitable for inflation data where positive and negative shocks may have differing impacts. The GJR-GARCH parameters are usually estimated using the MLE method, which can potentially result in bias. Genetic algorithm, as a global optimization method, offers a potential solution to overcome this problem [9].

This study aims to test whether the GJR-GARCH model estimated using genetic algorithms can provide better volatility forecasting results compared to traditional models in the context of inflation data. Thus, this research is expected to contribute to the development of more accurate inflation volatility models and provide useful insights for policymakers in formulating effective strategies for inflation-related risk and ensure economic stability.

II. METHODOLOGY

The data used in this study are secondary data that can be accessed on the BPS South Sulawesi websites. The data taken in the form of monthly data on South Sulawesi Inflation during the period January 2007 to December 2023.

1. Time Series

A time series is a sequence of observed values collected over a certain period, generally at equal intervals [10]. Time series are often associated with the forecasting of specific characteristics for future periods. Forecasting is a technique used to estimate future values by considering both past and present data [11].

2. Autoregressive Integrated Moving Average

The ARIMA model is a non-stationary time series model with order p refers to AR order, order d to differencing, and order q to MA order.. The form of the ARIMA model equation is contained in the following equation:

$$\phi_p(B)Z_t = \theta_q(B)\varepsilon_t$$
$$(1 - \phi_1 B - \cdots - \phi_p B^p Z_t = (1 - \theta_1 B - \cdots - \theta_q(B)\varepsilon_t$$
$$Z_t = \phi_1 Z_{t-1} + \cdots + \phi_p Z_{t-p} + \alpha_t - \theta_1 \varepsilon_{t-1} - \cdots - \theta_q \qquad (1)$$

because $Z_t = Y_t - \mu$ equation (1) can be written as follows

$$Y_t - \mu = \phi_1(Y_{t-1} - \mu) + \cdots + \phi_p\left(Y_{t-p} - \mu\right) + \varepsilon_t - \theta_1\varepsilon_{t-1} - \cdots - \theta_p\varepsilon_{t-q}$$
$$Y_t = \phi_0 + \phi_1 Y_{t-1} \ldots + \phi_p Y_{t-p} + \varepsilon_t - \theta_1\varepsilon_{t-1} - \cdots - \theta_p\varepsilon_{t-q} \qquad (2)$$

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ISSN No: 1008-0562 Natural Science Edition

With (B) being the AR(p) operator and $\theta_q(B)$ being the MA(q) operator . This model is used for *time series* data that has been differentd or already stationary in the average, d is the number of *differencing* processes performed. Suppose the order$q = 0$, the ARIMA model (p, d, q) formed is also known as the *Autoregressive Integrated* or ARI model (p, d) . If the order is$p = 0$, the model is *Integrated Moving Average* or IMA (d, q) . If the order is$p = q = 0$ with *differencing*$d = 1$, the ARIMA model (0,1,0) is called a *random walk* model [12].

3. GARCH (Generalized Autoregressive Conditional Heteroskedasticity) Model

The ARCH (Autoregressive Conditional Heteroskedasticity) model was first introduced by Engle (1982) to handle the case of heteroscedasticity in time series data, especially in data that has high volatility (9). The ARCH model is used to volatility model with the assumption that the current conditional variance (σ^2) is influenced by the variance in the previous period. The ARCH model was developed by Bocllerslev into Generalized Autoregressive Conditional Heteroskedasticity (GARCH) [7].

The GARCH model expands on the ARCH model by including the lag of the conditional variance itself, in addition to lags of the squared residuals. GARCH models make it possible to capture long-term dependencies in the variability of time series data. In the GARCH model, the residual variance is not only related to the residual variance in the previous period, but also with the squared residuals of the past period. The GARCH (*p,q*) model is as shown in the following equation:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^{\,2} + \cdots + \alpha_p \varepsilon_{t-p}^{\,2} + \beta_1 \sigma_{t-1}^2 + \cdots + \beta_q \sigma_{t-q}^2 \tag{3}$$

Where , $\alpha_1 \varepsilon_{t-1}^{\,2}$ is the ARCH component at time $t-1$, β_1 is the constant in the GARCH component, $\alpha_p \varepsilon_{t-p}^{\,2}$ is the ARCH component, and $\beta_q \sigma_{t-q}^2$ is the GARCH component.

If data has different response characteristics to a shock (positive shock or negative shock) then GARCH cannot be used. This aspect is important in a financial context where volatility is often higher after negative shocks. The solution is to use the *asymmetric* GARCH method. The asymmetry *effect* or often called the *leverage effect* is a phenomenon where volatility tends to increase more after a negative shock (price decrease or depreciation) than after a positive shock (price increase or appreciation). In *return* data, if the error value is less than zero, the estimated *return* will be greater than the original *return* value. This is a bad condition that is often called a negative surprise (*bad news*). Conversely, when the error is greater than zero, it means that the original *return* value will be greater than the estimated *return* value, resulting in a profit, which is often called a positive surprise (*good news*) [13].

4. Glosten Jagannathan Runkle- Generalized Autoregressive Conditional Heteroscedasticity (GJR-GARCH) Model

The GJR-GARCH model was introduced by Glosten, Jagannathan and Runkle in 1993, is an extension of the GARCH model that allows for an asymmetric volatility response to the value of the residuals, known as the *leverage effect* [14]. In general, the GJR-GARCH (*p,q*) model can be defined as follows.

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} ((\alpha_i + \gamma_i d_{t-i})\varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \, \sigma_{t-j}^2 \tag{4}$$

with

$$d_{t-i} = \begin{cases} 1 \; if \; \varepsilon_{t-i} < 0 \\ 0 \; if \; \varepsilon_{t-i} \geq 0 \end{cases}$$

where σ_t^2 is variance of the *error* at the time *t*, α_0 is a constant, α_i and β_j are the parameters of the GJR-GARCH model, model, while γ_i is a parameter that measures the asymmetry in the GJR-GARCH model. d_{t-i} is a *dummy* variable at time $t -$, *p* is the ARCH order and *q* is the GARCH order [15].

5. Genetic Algorithm

Genetic algorithm was introduced by John Holland in 1975. This optimization technique is inspired by the theory of natural evolution by mimicking the process of natural selection and reproduction. The essence of the genetic algorithm is to encode or encode an optimization function into an *array* containing characters to represent chromosomes, then perform processing or manipulation operations by genetic operators, then select based on *fitness* value, with the target of finding an optimal solution based on the problem being sought [16]. This algorithm is inspired by the genetic system of living things, which includes production, *crossover*, and mutation operators by applying the principle of natural selection, where the surviving individual is the strongest individual [8].

The objective function in estimating GARCH parameters with GA is to get the minimum *Root Mean Square Error* (RMSE) value, namely

$$RMSE = \sqrt{\frac{1}{N-n}\sum_{t=n+1}^{N}(\varepsilon_t^2 - \sigma_t^2)^2} \tag{5}$$

Therefore, the *fitness* function used to evaluate each chromosome is

$$Fitness = \frac{1}{RMSE} \tag{6}$$

with ε_t the residuals of observations at time *t*, the *conditional variance* forecast value σ_t^2 , *N* is all observations (*in-sample* and *out-sample*), and *n* is *in-sample* observations [17].

At each generation, the algorithm explores many areas in the parameter space and selects the one with the greatest probability. GA is able to evaluate a number of points in the parameter space simultaneously so that it will converge to a globally optimal solution [5].

6. Best Model Selection Criteria

The best model selection criteria are used to evaluate the accuracy of the *time* series model. The best model selection can be done by using the values of the information criterion of the model information. Akaike introduced a method used to determine the best model using information criteria known as Akaike information criterion (AIC) [18]. AIC is defined as follows:

$$AIC = -2\log L + 2k \tag{7}$$

where L denotes the likelihood function, k denotes the number of parameters, and n denotes the number of data. The model with the smallest AIC values is called the best model [19].

III. MAIN RESULT

The first step in the analysis is to identify data patterns to understand the characteristics and general description of the data under study. Descriptive statistical analysis was conducted to see the characteristics of monthly inflation data in South Soluwesi Preliminary analysis of inflation rate is presentable in Table 1.

Table1. Descriptive Statistics of Inflation Rate

Descriptive Statistics	Nilai
Minimum	-1.74
Maximum	3.89
Rata-rata	0.4075
Standard Deviation	0.6573
Skewness	1.3743
Kurtosis	5.2024

Based on Table 1, inflation ranges from –1.74 to 3.89, with an average of 0.6573, indicating generally positive inflation despite occasional deflation. The standard deviation of 1.3694 reflects considerable fluctuations. The positive skewness (1.3694) indicates that most values lie below the mean with occasional extreme increases, while the kurtosis of 5.1067 suggests a sharp peak and heavy tails, implying the presence of outliers and potential ARCH effects. This makes the GARCH model a suitable choice for further analysis.

One method to identify the pattern is by plotting the data, as shown in Figure 1, which illustrates the inflation rate.

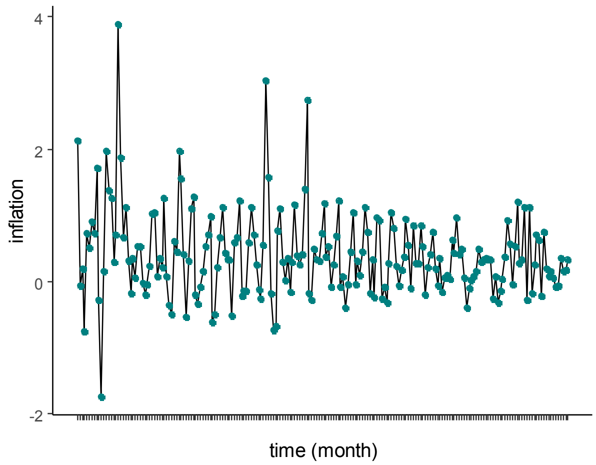

Figure 1 Plot of the inflation rate

Based on the graph in Figure 1, the time series appears stationary in its mean, as there is no noticeable change in the average over time. Stationarity refers to a condition where both the mean and variance of a time series remain constant. However, relying solely on visual inspection has limitations, as interpretations may vary between researchers. Therefore, a formal statistical test is required to support this conclusion. To confirm the stationarity, the Augmented Dickey-Fuller (ADF) test is conducted, with the results presented in Table 2

Table 2. Uji ADF

Lag	ADF	P-Value
0	-8,77	0,01
1	-8,01	0,01
2	-6,43	0,01
3	-4,58	0,01
4	-3,36	0,01

Based on Table 2, the p-values for lags 0 to 4 are 0.01, which is below the 0.05 significance level. This indica tes that the inflation data is stationary in its mean, so no additional differencing is required to achieve stationarity.

1. Identification of ARIMA (Autoregressive Integrated Moving Average) Model

The identification of the ARIMA model is carried out by examining the ACF and PACF patterns. From the inflation rate data, the best-fitting model is identified as ARIMA(2,0,2). The parameter estimation results for this model are presented in Table 3.

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Table 3. Parameter Estimation and Testing Results of ARIMA Model

Parameters	Parameters Estimation	Std. Error	*z value*	P-*value*
ϕ_1	0,9753	0,0145	$\mathbf{67.022}$	< 0.0001
ϕ_2	-0,9893	0,0115	$\mathbf{-85.714}$	< 0.0001
θ_1	-0,9514	0,0434	-21.880	< 0.0001
θ_2	0,9155	0,0386	$\mathbf{23.711}$	< 0.0001
μ	$\mathbf{0,4051}$	$\mathbf{0,00022}$	$\mathbf{4642.116}$	< 0.0001

The ARIMA (2,0,2) model equation for inflation rate is as follows:

$$\boldsymbol{Y_t = 0,4051 + 0,9753Y_{t-1} - 0,9893Y_{t-2} + 0,9514\varepsilon_{t-1} - 0,9155\varepsilon_{t-2} + \varepsilon_t}$$

To examine the presence of heteroscedasticity in the residuals of the averaging model, the lagrange multiplier (ARCH LM) test was conducted.

***Table 5**. LM Test*

Lag	P-*value weighted* LM ARCH
Lag [4]	$\mathbf{0}$
Lag [8]	$\mathbf{0}$
Lag [12]	$\mathbf{3.71 \times 10^{-07}}$
Lag [16]	$\mathbf{3.57 \times 10^{-03}}$
Lag [20]	$\mathbf{8.75 \times 10^{-01}}$
Lag [24]	$\mathbf{9.91 \times 10^{-01}}$

Based on Table 5, it can be seen that the p-values from lag 4 to lag 16 are smaller than the significance level of 0.05. This indicates the presence of an ARCH effect, i.e., heteroskedasticity in the residual variance (conditional variance), suggesting that the residual variance is not constant over time. In other words, there is volatility that cannot be captured by the ARIMA model, which assumes constant residual variance. Therefore, the residual variance is further modeled using the GARCH model.

2. GARCH Parameter Estimation

The GARCH model was estimated simultaneously with the previously identified ARIMA model. Model selection was based on the significance of the parameters and the lowest AIC value. The conditional variance was modeled using both the lag of the squared residuals (ARCH order) and the lag of the variance itself (GARCH order). Based on these criteria, the best model for the inflation rate is GARCH(2,2), with parameter estimates presented in Table 6.

Table 6. GARCH Model Estimation Parameter

Models	Parameters	Parameter Estimation	White noise	AIC
GARCH(1,1)	ω	0.0342	0.2316	1.8377
	α_1	0.1209		
	β_1	0.7818		
GARCH(1,2)	ω	0.0457	0.2611	1.8408
	α_1	0.1549		
	β_1	0.1799		
	β_2	0.5315		
GARCH(2,1)	ω	0.0457	0.2288	1.8401
	α_1	0.1660		
	α_2	0.0000		
	β_1	0.7090		

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Models	Parameters	Parameter Estimation	White noise	AIC
GARCH(2,2)	ω	0.0182	0.2611	1.8266
	α_1	0.3952		
	α_2	0.0000		
	β_1	0.0132		
	β_2	0.1448		

The best model of inflation rate is GARCH(2,2) with the following model equation:

$$\boldsymbol{\sigma_t^2 = 0.0182 + 0.3952\varepsilon_{t-1}^2 + 0.0000\varepsilon_{t-2}^2 + 0.0132\sigma_{t-1}^2 + 0.1448\sigma_{t-2}^2}$$

The GARCH model addresses the heteroscedasticity problem in the data; however, it cannot capture potential asymmetric effects on the inflation rate. Since not all time series exhibit such effects, a test is required to determine their presence. If asymmetry is detected, an asymmetric GARCH model will be applied. In the cross-correlation plot of the inflation data, significant peaks outside the confidence interval indicate possible asymmetry in the volatility process.

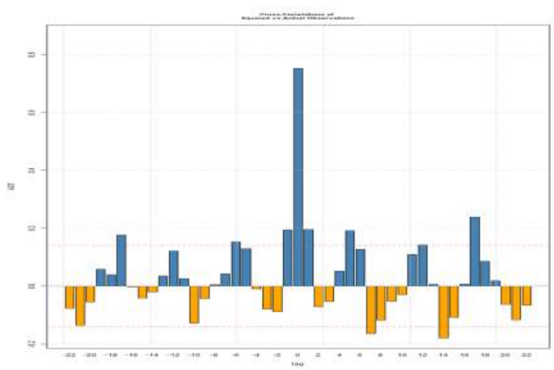

Figure 2. Cross Correlation Plot of Inflation Rate

Based on Figure 2, it appears that there are bars that exceed the significant limit, which means that there is asymmetry in volatility inflation data. Therefore, modeling is done with asymmetric GARCH, namely GJR-GARCH.

3. GJR -GARCH Modeling

To modeling GJR-GARCH (p,q), the best model for inflation data is selected based on the lowest AIC values. Table 7 presents the results of the GJR-GARCH model parameter estimation for inflation data. The best GJR-GARCH model for inflation data based on the smallest AIC value is GJR-GARCH (2,1).

***Table** 7. Parameter Estimation Results of GJR-GARCH*

Parameter	(GJR-GARCH(2,1))	
	Coefficient	P-*value*
ω	0,0013	0,0000*
α_1	0,0094	0,0000*
α_2	0,0062	0,0000*
β_1	0,9401	0,0000*
γ_1	-0,1199	0,0000*

Based on the estimation results in Table 7, the coefficient γ_1 is statistically significant, indicating the presence of asymmetry in the inflation data. Since γ_1 is negative (–0.1199), negative shocks ($\varepsilon_t < 0$) have a different effect on volatility compared to positive shocks. This suggests an asymmetric volatility response, although

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ISSN No: 1008-0562 Natural Science Edition

the negative sign implies that negative shocks reduce volatility relative to positive shocks, which is less common compared to the typical leverage effect ($\gamma > 0$).

4. GJR-GARCH-GA Modeling

GJR-GARCH-GA estimation uses the best model, GJR-GARCH(2,1). The parameters of the GARCH(2,1) model, namely ω, $\alpha_1, \alpha_2, \gamma_1$, β_1 are optimized using *genetic algorithm* (GA) to obtain the global optimum estimation. The first step in estimation with GA is to form an initial chromosome consisting of six genes, namely ω, α_1, α_2, γ_1, β_1 as a solution to the algorithm. The illustration of the GJR-GARCH(2,1) chromosome shows in Table 8. The GJR-GARCH(2,1) model parameters (ω, α□, α□, γ□, β□) were estimated using a Genetic Algorithm (GA). The estimation process began with a randomly generated initial population of chromosomes, each representing a potential solution. The fitness function was defined as 1/RMSE, so that chromosomes with smaller RMSE values had higher fitness.

After calculating fitness values, the Roulette Wheel selection method was used to determine parent chromosomes for the next generation, where the probability of selection was proportional to fitness. Crossover was then applied using the single-point method with a probability of 0.8, while mutation was performed with a probability of 0.1 to maintain population diversity. Elitism was also introduced to ensure that the best chromosomes were preserved across generations.

The evolutionary process of selection, crossover, mutation, and elitism was repeated for 100 iterations until convergence was achieved. The final estimates of the GJR-GARCH(2,1) parameters obtained through GA optimization are presented in Table 10.

Table 10. Results of Inflation Parameter Estimation Using GA

Parameters	Estimation
ω	1.9710
α_1	0.1068
α_2	0.3318
γ_1	0.5372
β_1	0.2927

Systematically the equation of ARIMA(2,0,2), GJR-GARCH(2,1)-GA is

$$\boldsymbol{Y_t = 0.4051 + 0.9753 Y_{t-1} - 0.9893 Y_{t-2} + 0.9514 \varepsilon_{t-1} - 0.9155 \varepsilon_{t-2} + \varepsilon_t}$$

The conditional variance of the residual ε_t is modeled by

$$\boldsymbol{\sigma_t^2 = 1.9710 + 0.1068 \varepsilon_{t-1}^2 + 0.3318 \varepsilon_{t-2}^2 + 0.5372 d_{t-1} \varepsilon_{t-1}^2 + 0.2927 \sigma_{t-1}^2}$$

The GJR-GARCH(2,1) model indicates that inflation volatility is influenced by past shocks, with stronger effects from two periods earlier. The results also reveal an asymmetric effect, where negative shocks increase volatility more than positive shocks, and a persistence effect, although at a relatively low level.

5. **Forecasting Inflation Volatility**

Following the estimation of the ARIMA(2,0,2) – GJR-GARCH(2,1)-GA model, the forecasting evaluation was conducted. Table 11 reports the forecasted volatility values for the subsequent 12 periods.

Table 11. Volatility Forecast

Periods	Actual	GJR-GARCH	GJR-GARCH-GA
T+1	-0.22	-0.9025	-0.8034
T+2	0.75	1.1699	1.2504
T+3	0.2	0.0979	0.1635
T+4	0.09	-0.2171	-0.1488
T+5	0.16	-0.1845	-0.1118
T+6	0.06	-0.3923	-0.3278
T+7	-0.08	-0.5824	-0.5285
T+8	-0.06	-0.4573	-0.3955
T+9	0.36	0.3754	0.4625
T+10	0.16	-0.1073	-0.0054
T+11	0.17	-0.1526	-0.0691
T+12	0.63	-0.9853	1.0314
RMSE		0.3787	0.3383
MAPE		3.1195	2.4043

Based on Table 11, the GJR-GARCH-GA model provides more accurate and stable volatility forecasts compared to the standard GJR-GARCH model in most of the 12 future periods. This is indicated by the The RMSE and MAPE values of the GJR-GARCH(2,1)-GA model are smaller than the GJR-GARCH(2,1) model without using genetic algorithm, so that estimation with the GJR-GARCH(2,1)-GA model produces better forecasts than without using GA. Therefore, it can be concluded that the GJR-GARCH-GA model demonstrates superior predictive performance on this dataset.

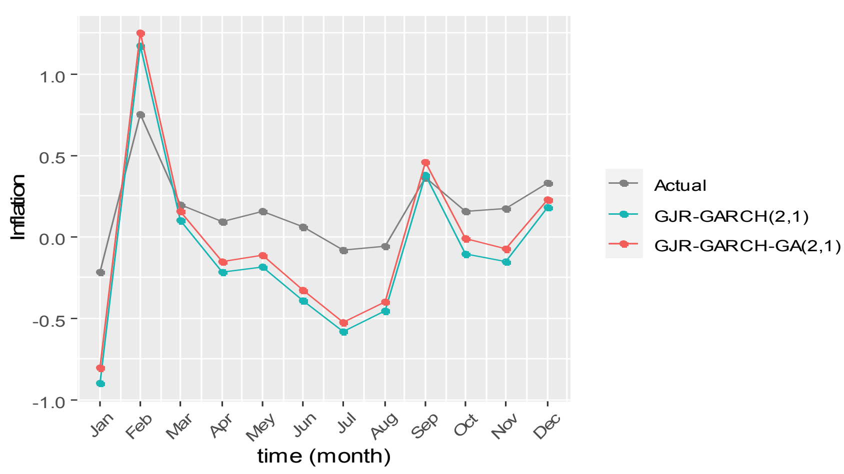

Figure 3. Plot of Model Comparison

Based on the plot, it can be concluded that the GJR-GARCH(2,1) model optimized using a genetic algorithm (GJR-GARCH-GA(2,1)) produces forecasts that are closer to the actual data compared to the standard GJR-GARCH(2,1) model. The GJR-GARCH-GA(2,1) line consistently tracks the actual values more closely throughout most months in 2023, which indicates improved forecasting accuracy.

LGJDX Journal Of Liaoning Technical University
ISSN No: 1008-0562 Natural Science Edition

CONCLUSION

In this study, the GJR-GARCH model combined with a Genetic Algorithm (GA) is applied to forecast inflation volatility in South Sulawesi. The dataset consists of daily observations from January 2007 to December 2023. The inflation rate exhibits fluctuating patterns with non-constant variance, as shown in Figure 1. Moreover, the data reveal the presence of asymmetry effects (leverage effects), which cannot be adequately captured by conventional GARCH models. To address this limitation, the GJR-GARCH model is employed, as it is specifically designed to model asymmetric volatility behavior. Considering the complexity of parameter estimation, the Genetic Algorithm (GA) is utilized to obtain more efficient estimates.

The forecasting results using the ARIMA(2,0,2)-GJR-GARCH(2,1) model, with parameters optimized by GA, show a lower RMSE compared to the standard GJR-GARCH model. This indicates that the hybrid GJR-GARCH-GA model provides improved accuracy in modeling and forecasting inflation volatility.

Furthermore, based on the monthly inflation chart for South Sulawesi, a notable spike occurred in February, when the actual inflation rate surged above 1.0, marking the highest point of the year. This sharp increase reflects strong inflationary pressures early in the year, primarily driven by rising prices of essential goods and energy, including fuel (BBM), rice, and air transportation fares, as also reported by Statistics Indonesia (BPS) during the same period.

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