Forecasting Monthly Insurance Policy Sales Using the Box-Jenkins ARIMA Framework

Nurhayati[1]*, Andi Fitriawati[2], Dian Resa Rahmawati[3]
[1]Department of Mathematics, Indonesia Defense University, Indonesia
[2,3]Department of Actuarial Science, Institut Teknologi Sumatera, Indonesia
Email korespondensi*: nurhayati09.nur@gmail.com

Abstrak

Peramalan penjualan polis asuransi yang akurat sangat penting untuk mendukung perencanaan strategis dan evaluasi kinerja dalam industri asuransi. Fluktuasi penjualan bulanan menimbulkan ketidakpastian yang dapat memengaruhi keputusan pemasaran dan pencapaian target operasional. Penelitian ini bertujuan untuk menentukan model AutoRegressive Integrated Moving Average (ARIMA) yang paling sesuai untuk meramalkan penjualan polis asuransi bulanan di PT Avrist Assurance KPA Lampung serta mengevaluasi kinerja peramalannya. Penelitian ini menerapkan kerangka Box–Jenkins yang meliputi tahap identifikasi model, estimasi parameter, dan pemeriksaan diagnostik menggunakan 55 observasi bulanan selama periode Januari 2021 hingga Juli 2025. Pemilihan model didasarkan pada signifikansi parameter, diagnostik residual, dan kesalahan peramalan in-sample. Hasil penelitian menunjukkan bahwa model ARIMA (3,1,0) memberikan hasil terbaik di antara model kandidat dengan nilai Mean Absolute Percentage Error (MAPE) in-sample sebesar 12,11%. Model terpilih selanjutnya digunakan untuk menghasilkan peramalan lima periode ke depan, yaitu Agustus hingga Desember 2025, sebagai dasar perencanaan jangka pendek. Hasil penelitian menunjukkan bahwa model ARIMA dapat digunakan untuk memodelkan dan menghasilkan peramalan jangka pendek penjualan polis asuransi di PT Avrist Assurance KPA Lampung.
Kata kunci: Penjualan polis asuransi; ARIMA; metode Box-Jenkins; peramalan deret waktu

Abstract

Accurate forecasting of insurance policy sales is essential for strategic planning and performance evaluation in the insurance industry. Fluctuations in monthly sales create uncertainty that may affect marketing decisions and the achievement of operational targets. This study aims to determine the most appropriate AutoRegressive Integrated Moving Average (ARIMA) model for forecasting monthly insurance policy sales at PT Avrist Assurance KPA Lampung and to evaluate its forecasting performance. The study applies the Box–Jenkins framework, including model identification, parameter estimation, and diagnostic checking, using 55 monthly observations covering January 2021 to July 2025. Model selection is based on statistical significance, residual diagnostics, and in-sample forecasting error. The results indicate that the ARIMA (3,1,0) model provides the best fit among the candidate models, with an in-sample Mean Absolute Percentage Error (MAPE) of 12.11%. The selected model is subsequently used to generate five-step-ahead forecasts for August to December 2025 as a basis for short-term planning. These findings demonstrate the applicability of the ARIMA framework for modeling and forecasting short-term insurance policy sales.
Keywords: *Insurance policy sales; ARIMA; Box–Jenkins method; Time series forecasting*

1. Introduction

Every societal activity, particularly those related to financial matters, is inherently exposed to risks that may result in economic losses, such as illness, accidents, or death. To mitigate such risks, individuals require risk-transfer mechanisms, one of which is insurance. According to Article 246 of the Indonesian Commercial Code (KUHD), insurance is a legally binding agreement between the insured and the insurer, whereby the insurer receives premiums and is obligated to provide compensation in the event of loss arising from uncertain circumstances [1]. Therefore, insurance plays a crucial role as a financial protection instrument against various

potential risks in the future. In addition to providing financial protection, insurance also functions as an investment vehicle that supports economic growth. Collected premiums are allocated to various financial instruments, including deposits, bonds, stocks, sukuk, and mutual funds [2].

The increasing demand for financial security and improved financial management has contributed to the continued development of the insurance industry in Indonesia. According to the 2022 Insurance Statistics published by the Financial Services Authority (OJK), as of December 2022 there were 147 active insurance companies with total assets amounting to IDR 1,113 trillion and gross premium income of IDR 34.57 trillion, representing a 4.3 percent increase from the previous year [3]. This condition reflects sustained industry growth and rising public interest in insurance products. Operationally, insurance companies primarily generate revenue through product sales, which are formalized in the form of policies. A policy serves as an official contract outlining the rights and obligations of both parties and acts as an indicator of sales performance [4]. However, policy sales tend to fluctuate and are inherently uncertain. Such instability creates challenges in marketing strategy formulation and managerial decision-making. Therefore, an accurate forecasting method is required to estimate future policy sales more reliably.

One of the widely used methods for time series forecasting is the AutoRegressive Integrated Moving Average (ARIMA) model, developed by Box, Jenkins, and Reinsel [5][6]. This method is flexible in handling non-stationary time series and is widely applied in short-term forecasting [7][8]. Previous studies have demonstrated the application of ARIMA in various forecasting contexts. [9] obtained an ARIMA (9,1,10) model for property sales forecasting, while [10] applied ARIMA (3,1,3) to short-term Bitcoin price forecasting. These studies demonstrate the applicability of ARIMA to different types of time series. However, the characteristics of property sales and financial price series differ from those of insurance policy sales, particularly in terms of their temporal dynamics. Because the data in this study consist of monthly observations, seasonality was examined using the monthly time-series pattern and autocorrelation structure, particularly at the seasonal lag of 12 months. No clear and consistent annual seasonal pattern was identified. Therefore, a non-seasonal ARIMA framework was retained. Nevertheless, the application of ARIMA to insurance policy sales at the branch-office level remains limited. Therefore, this study aims to forecast monthly insurance policy sales at PT Avrist Assurance KPA Lampung using the ARIMA framework and to evaluate the forecasting performance of the selected model.

Nevertheless, the application of ARIMA in forecasting insurance policy sales at the branch-office level remains limited. This limitation indicates a research gap that warrants further investigation. Therefore, this study aims to forecast insurance policy sales at PT Avrist Assurance KPA Lampung using the ARIMA method. The best model is selected based on the smallest Mean Absolute Percentage Error (MAPE) value, and the resulting forecasts are expected to support managerial decision-making and the formulation of effective sales strategies in the future.

2. Methodology

2.1 Insurance and Insurance Policy

Insurance originates from the Dutch terms assurantie and verzekering, referring to risk coverage or indemnification. In Indonesian regulation, insurance is formally governed by Law

No. 40 of 2014, Article 1 paragraph (1), which defines insurance as an agreement between an insurance company and a policyholder, whereby the policyholder pays a premium in exchange for compensation or benefits arising from uncertain events, including risks related to health, life, or property [11]. Insurance provides financial security and risk protection for individuals and organizations. The benefits include financial protection against unexpected losses, health coverage for medical treatment, life protection for beneficiaries, education funding preparation, and retirement planning [12]. In addition to these benefits, insurance performs several important functions, such as risk management, financial assurance, and psychological security through risk transfer mechanisms.

To ensure legal certainty, insurance agreements must be documented in written form known as an insurance policy, as regulated in Article 225 of the Indonesian Commercial Code (KUHD). The policy contains contractual rights and obligations of both parties and serves as legal evidence of agreement. Although [4] describes the policy as unilateral in the sense that the insurer commits to indemnification, this contractual relationship remains legally binding once the premium is agreed upon. From an operational standpoint, policy issuance represents a measurable indicator of insurance company performance. Therefore, analyzing and predicting policy sales becomes strategically important for managerial planning and financial sustainability.

2.2 Forecasting

Forecasting is the process of estimating future events based on historical data to support planning and decision-making [13]. Although forecasts are inherently uncertain, they are not merely speculative, as they rely on scientific methods, mathematical modeling, and systematic data analysis. Forecasting can be classified based on time horizon. Long-term forecasting (more than 18 months) is commonly used for investment and infrastructure planning. Medium-term forecasting (3–18 months) is applied in sales and production planning. Short-term forecasting (less than 3 months) is typically utilized for operational decisions such as scheduling and procurement [14]. Methodologically, forecasting approaches can be divided into qualitative and quantitative methods. Qualitative forecasting relies on expert judgment and subjective assessment, whereas quantitative forecasting uses historical data to construct mathematical models.

Quantitative forecasting can be further categorized into causal (explanatory) models and time series models, with the latter focusing on historical pattern recognition without requiring independent variables [15]. A time series consists of sequentially recorded observations collected at specific intervals, such as daily, monthly, or yearly data. Time series analysis aims to identify underlying patterns, including trend, seasonal, cyclical, and irregular components, in order to support accurate forecasting [16]. Proper identification of these components is crucial in selecting an appropriate forecasting model. For instance, exponential smoothing may be suitable for trend-dominated data, whereas ARIMA is typically applied to non-stationary time series requiring differencing [17].

2.3 AutoRegressive Integrated Moving Average (ARIMA)

The AutoRegressive Integrated Moving Average (ARIMA) model was developed within the Box–Jenkins framework during the 1970s. ARIMA is designed for univariate time series

forecasting and does not incorporate external independent variables. It is particularly suitable for short-term forecasting when the data exhibit temporal dependence and require transformation to achieve stationarity [18]. An ARIMA model is denoted as ARIMA(p,d,q), where: p represents the autoregressive (AR) order, d denotes the differencing order, and q indicates the moving average (MA) order.

Autoregressive (AR) Model

The autoregressive model of order *p*, denoted as AR(p) or ARIMA(p,0,0) [19], assumes that the current observation depends linearly on its previous values. The mathematical representation is given in Equation (1):

$$Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \cdots + \phi_p Y_{t-p} + e_t \quad (1)$$

As shown in Equation (1), $Y_t$represents the value of the time series at time t, while $Y_{t-1}, Y_{t-2}, \ldots, Y_{t-p}$ denote observations at previous time periods (lags). The coefficients $\phi_1, \phi_2, \ldots, \phi_p$ are autoregressive parameters that measure the influence of past values on the current observation. The term $e_t$represents the error component at time t, which is assumed to be white noise with zero mean and constant variance.

Moving Average (MA) Model

The moving average model of order *q*, denoted as MA(q) or ARIMA(0,0,q) [19], assumes that the current observation depends on past error terms. The model is expressed in Equation (2):

$$Y_t = e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \cdots - \theta_q e_{t-q} \quad (2)$$

In this formulation, Y_t represents the value of the series at time t, while e_t is the current error term. The terms $e_{t-1}, e_{t-2}, \ldots, e_{t-q}$ represent past errors. The parameters $\theta_1, \theta_2, \ldots, \theta_q$ measure the influence of these past disturbances, and q denotes the order of the moving average process.

ARMA Model

The ARMA(p,q) model combines both autoregressive and moving average components, allowing the model to capture both persistence and shock effects simultaneously [20]. The general form is given in Equation (3):

$$Y_t = \phi_1 Y_{t-1} + \cdots + \phi_p Y_{t-p} + e_t - \theta_1 e_{t-1} - \cdots - \theta_q e_{t-q} \quad (3)$$

In Equation (3), $p$and $q$represent the orders of the autoregressive and moving average components, respectively. The model explains the current value Y_t as a combination of past observations and past error terms, making it suitable for stationary time series data.

ARIMA Model

For non-stationary data, differencing is applied to remove trends and stabilize the mean. The general ARIMA(p,d,q) model can be written as [20]:

$$\phi_p(B)(1-B)^d Y_t = \theta_q(B) e_t \quad (4)$$

In this equation, Bdenotes the backward shift operator defined as $BY_t = Y_{t-1}$, which shifts the series back by one period. The term $(1-B)^d$ represents the differencing operation applied

d times to achieve stationarity. The polynomials $\phi_p(B)$ and $\theta_q(B)$ correspond to the autoregressive and moving average components, respectively, while e_t is the white noise error term.

2.4 ARIMA Modeling Procedure

Stationarity Test

Stationarity is a fundamental requirement in ARIMA modeling, as it ensures that the statistical properties of the series remain constant over time [21]. Variance stationarity can be achieved using the Box–Cox transformation, while mean stationarity is typically addressed through differencing. To formally assess mean stationarity, the Augmented Dickey–Fuller (ADF) test is applied. The null hypothesis (H0) states that the time series is non-stationary and contains a unit root, while the alternative hypothesis (H1) states that the time series is stationary and does not contain a unit root. The test is conducted at a 5% significance level, where the null hypothesis is rejected when the p-value is less than 0.05. The ADF test statistic is defined in Equation (5):

$$ADF = \frac{\hat{\phi}}{SE(\hat{\phi})} \tag{5}$$

Here, $\hat{\phi}$ represents the estimated coefficient obtained from the regression model, and $SE(\hat{\phi})$ is its standard error. The ADF statistic is used to determine whether the series contains a unit root, where a smaller p-value (typically less than 0.05) indicates stationarity.

Model Identification

Model identification is conducted using the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF). The sample ACF is calculated as:

$$\hat{\rho}_k = \frac{\sum_{t=1}^{n-k}(Y_t - \bar{Y})(Y_{t+k} - \bar{Y})}{\sum_{t=1}^{n}(Y_t - \bar{Y})^2} \tag{6}$$

In Equation (6), $\hat{\rho}_k$ denotes the estimated autocorrelation at lag k, Y_t represents the observation at time t, $\bar{Y}$ is the sample mean, and n is the total number of observations. The PACF is computed recursively as shown in Equation (7):

$$\hat{\phi}_{k+1,k+1} = \frac{\hat{\rho}_{k+1} - \sum_{j=1}^{k} \hat{\phi}_{k,j}\, \hat{\rho}_{k+1-j}}{1 - \sum_{j=1}^{k} \hat{\phi}_{k,j}\, \hat{\rho}_j} \tag{7}$$

In this equation, $\hat{\phi}_{k+1,k+1}$ represents the partial autocorrelation at lag $k+1$, while $\hat{\rho}_k$ denotes the autocorrelation at lag k. These functions help identify the appropriate AR and MA orders.

Parameter Estimation

Parameter estimation is performed using the Conditional Sum of Squares (CSS) method [22], which estimates the model parameters by minimizing the sum of squared residuals between the observed and fitted values. In this study, the CSS method was implemented in R using the arima() function with the method = "CSS" option. The objective function is given in Equation (8):

$$CSS = \sum_{t=1}^{n} (Y_t - \hat{Y}_t)^2 \quad (8)$$

Here, Y_t represents the actual observation, $\hat{Y}_t$ is the predicted value from the model, and n denotes the number of observations. The goal is to obtain parameter estimates that minimize the overall prediction error.

Parameter Significance Test

The significance of model parameters is evaluated using the Wald (z) test [22]. The test statistic is defined as:

$$z = \frac{\hat{\beta}}{SE(\hat{\beta})} \quad (9)$$

In this equation, $\widehat{\beta}$ represents the estimated parameter and $SE(\hat{\beta})$ is its standard error. A parameter is considered statistically significant if the absolute value of $z$exceeds the critical value or if the p-value is less than 0.05.

Residual Normality Test

Residual normality is tested using the Shapiro–Wilk statistic [23], as shown in Equation (10):

$$W = \frac{\left(\sum_{i=1}^{n} a_i Y_{(i)}\right)^2}{\sum_{i=1}^{n} (Y_i - \bar{Y})^2} \quad (10)$$

Here, W is the test statistic, $Y_{(i)}$ represents the ordered sample values, a_i are constants determined by the sample size, and $\bar{Y}$ is the sample mean.

Model Adequacy Test

The Ljung–Box test is used to assess whether residuals are independent (white noise) [19]. The test statistic is given by:

$$Q = n(n+2) \sum_{j=1}^{k} \frac{\hat{\rho}_j^2}{n-j} \quad (11)$$

In this equation, Q represents the test statistic, n is the number of observations, k is the number of lags considered, and $\hat{\rho}_j$ is the autocorrelation at lag j. A p-value greater than 0.05 indicates that the model residuals are independently distributed.

2.5 Forecast Accuracy

Forecast accuracy is commonly evaluated using the Mean Absolute Percentage Error (MAPE) [24]. In this study, MAPE was calculated using the in-sample fitted values based on the training data to evaluate the model fit. The MAPE is defined as follows:

$$\text{MAPE} = \frac{100}{n} \sum_{t=1}^{n} \left| \frac{Y_t - \hat{Y}_t}{Y_t} \right| \quad (12)$$

In this equation, Y_t represents the actual value, $\hat{Y}_t$ represents the fitted value, and n denotes the number of observations. MAPE expresses the average absolute percentage error between the actual and fitted values, making it easy to interpret the magnitude of the prediction error. Since no separate testing or out-of-sample validation set was used, the reported MAPE represents the in-sample error of the fitted model.

2.6 Data Description

This study utilized secondary data obtained from PT Avrist Assurance KPA Lampung, a company operating in the insurance sector. The data consisted of monthly insurance policy sales, comprising a total of 55 observations covering the period from January 2021 to July 2025. Given the monthly frequency of the data, seasonality was examined by considering the monthly time-series pattern and the autocorrelation structure, particularly at the seasonal lag of 12 months. No clear and consistent annual seasonal pattern was identified. Therefore, a non-seasonal ARIMA model was considered appropriate for the analysis, and a seasonal ARIMA (SARIMA) model was not employed. These data were used as the basis for analysis and for forecasting the next five periods. An overview of the data used in this study is presented as follows:

Table 1. Historical Data

Year	Month	Total Policies
2021	January	6
	February	9
	March	8
	April	6
	May	7
	June	5
⋮	⋮	⋮
2025	February	5
	March	5
	April	6
	May	8
	June	7
	July	7

This data represents the number of insurance policies sold each month and is used to identify patterns, trends, and fluctuations over time.

2.7 Research Object

The object of this study is the total sales of insurance policies at PT Avrist Assurance KPA Lampung. This object was selected due to its ability to represent the company's sales performance over time. In addition, time series data such as this are well-suited for analysis using the ARIMA method, as they allow for the identification of historical patterns and the forecasting of future values.

2.8 Estimation Procedure

The research was conducted through a systematic procedure to model and forecast monthly insurance policy sales using the ARIMA method. The stages of the analysis are described as follows:

1. **Input Data**
   The insurance policy sales data were entered into RStudio. The dataset consisted of 55 monthly observations from January 2021 to July 2025, which were used as the basis for the analysis and forecasting.
2. **Descriptive Statistics**
   Descriptive analysis was performed to determine the minimum, maximum, mean, and standard deviation of the insurance policy sales data. This stage aimed to provide an overview of the characteristics and variability of the data before model development
3. **Stationarity Test**
   The stationarity of the time series was assessed using the Augmented Dickey–Fuller (ADF) test. The null hypothesis of the ADF test states that the time series is non-stationary and contains a unit root, while the alternative hypothesis states that the time series is stationary. If the series was not stationary, differencing was applied to achieve stationarity in the mean. The Box–Cox transformation was used, when necessary, to stabilize the variance and was not considered a stationarity test.
4. **Model Identification**
   Model identification was conducted by examining the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots of the stationary series. The patterns observed in the ACF and PACF were used to determine the candidate orders (p, d, q) of the ARIMA models.
5. **Parameter Estimation**
   The parameters of the candidate ARIMA models were estimated using the Conditional Sum of Squares (CSS) method. The estimated parameters were evaluated based on their statistical significance to determine whether the corresponding model specification was appropriate.
6. **Model Diagnostic Checking**
   Diagnostic checking was performed on the residuals of the candidate ARIMA models to assess model adequacy. The Ljung–Box test was used to examine whether the residuals were free from significant autocorrelation. A model was considered adequate when its residuals behaved approximately as white noise, indicated by the absence of significant autocorrelation. Residual normality was also examined as an additional diagnostic, but it was not considered the primary criterion for model adequacy.
7. **Model Selection**
   The candidate ARIMA models were compared based on parameter significance, residual diagnostic results, and Mean Absolute Percentage Error (MAPE). The MAPE was calculated using the in-sample fitted values because no separate testing or out-of-sample validation set was used. Among the candidate models, ARIMA (3,1,0) was selected because it satisfied the residual diagnostic requirements and produced the lowest in-sample MAPE of 12.11%.

8. **Forecasting**
   The selected ARIMA (3,1,0) model was used to generate forecasts for the next five periods, namely August to December 2025. The forecasting results were presented in tabular and graphical form to illustrate the expected movement of monthly insurance policy sales.

3. Result and Discussion

Descriptive Statistics

The monthly insurance policy sales data of PT Avrist Assurance KPA Lampung for the period January 2021 to July 2025 were analyzed using RStudio to obtain a general overview through descriptive statistics. The results of the analysis are summarized in Table 2.

Table 2. Descriptive Statistics of Insurance Policy Sales

Statistics	Values
Minimum	5
Maximum	13
Mean	7.91
Median	7
Standar Deviasi	2.55
Q1	6
Q3	9

Based on Table 2, the maximum value of 13 and the minimum value of 5 indicate a relatively wide range of variation. The mean value of 7.91, which is slightly higher than the median, suggests a mildly positively skewed distribution, although not extreme. The standard deviation of 2.55 reflects a moderate level of variability, indicating that the data are neither fully stable nor highly volatile. From an analytical perspective, the implicit assumption that this level of variation is “normal” should be examined more critically. A more skeptical view would question whether these fluctuations truly reflect natural market dynamics or are instead driven by structural factors, such as changes in company policies or unmodeled seasonal effects. This consideration is important, as ARIMA models are sensitive to patterns that are not explicitly captured in the modeling process.

4.2 Time Series Model Identification

Following the descriptive analysis, the next step involved identifying the pattern of insurance policy sales over time. This stage aimed to understand monthly changes in sales as well as to detect any underlying trends during the observation period. Identifying these patterns is essential to determine the appropriate time series model for forecasting.

Time Series Plot

The monthly insurance policy sales data of PT Avrist Assurance KPA Lampung for the period January 2021 to July 2025 were presented in the form of a time series plot. Figure 1 illustrates the movement of policy sales for each month throughout the observation period. Through this

visualization, the pattern of changes in sales becomes more apparent, including periods of increase, decrease, and fluctuations at certain points in time.

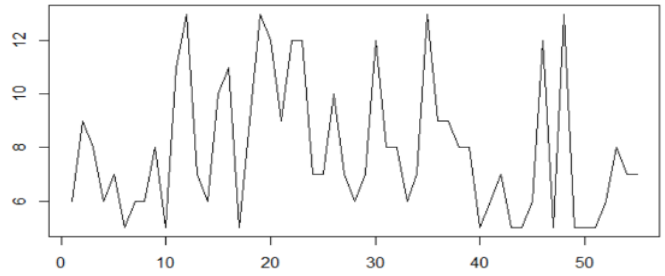


Figure 1. Time Series Plot of Insurance Policy Sales

Based on Figure 1, insurance policy sales exhibited noticeable fluctuations throughout the observation period, indicating instability from month to month. Sales generally ranged between 6 and 10 policies, although several periods showed significant increases, reaching a peak of 13 policies, as well as declines to around 5 policies. These variations suggest a considerable gap between the highest and lowest sales levels. Such fluctuations may be influenced by factors such as promotional activities, marketing strategies, or changes in consumer purchasing power. Overall, the pattern indicates that sales remain dynamic and have not yet reached a stable trend.

Stationarity Test

a. Variance Stationarity (Box-Cox Test)

The variance stationarity of the data was assessed using the Box–Cox transformation, with the Probability Plot Correlation Coefficient (PPCC) used as the evaluation criterion. The results are presented in Table 3, which compares PPCC values for the initial data and after transformation across different values of λ.

Table 3. Box-Cox Test Results

Lambda	PPCC Value (Initial Data)	PPCC Value (After Transformation)
-2.0	0.9525510	0.9452605
-1.5	0.9613545	0.9514339
-1.0	0.9666069	0.9567377
-0.5	0.9677116	0.9610795
0.0	0.9643858	0.9643858
0.5	0.9567377	0.9666053
1.0	0.9452605	0.9677116
1.5	0.9307391	0.9677040
2.0	0.9141051	0.9666069

Based on Table 3, the initial data produced the highest PPCC value of 0.9677 at λ = −0.5. A Box–Cox transformation was then evaluated over a range of λ values to determine an appropriate transformation parameter. After transformation, the highest PPCC value was 0.9677 at λ = 1.0.

Thus, λ = 1.0 was selected as the final value based on the PPCC criterion. The resulting series was subsequently used in the ARIMA analysis. Because λ = 1.0 corresponds to an identity transformation, no further nonlinear transformation was applied before the ARIMA modeling.

b. Mean Stationarity (ADF Test)

After achieving variance stationarity, mean stationarity was tested using the Augmented Dickey–Fuller (ADF) test. The initial test yielded a p-value of 0.3533 (> 0.05), indicating that the data were not stationary in the mean. To address this, first-order differencing was applied. The subsequent ADF test produced a p-value of 0.01 (< 0.05), indicating that the data had become stationary in the mean. Thus, one level of differencing was sufficient, and the data satisfied the stationarity requirement for ARIMA modeling.

ACF and PACF Identification

After the data were confirmed to be stationary in both variance and mean, the next step was to identify the appropriate time series model using the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots. These tools are commonly used to determine the underlying structure of time series data. The ACF reflects the correlation between observations at different lags, while the PACF measures the direct relationship between observations after removing the influence of intermediate lags. Based on the Figure 2, the ACF plot exhibits significant cut-offs at lag 1 and lag 7, suggesting the possible presence of moving average components. Meanwhile, the PACF plot shows significant spikes at lags 1, 2, 3, and 6, indicating the presence of autoregressive components. The application of first-order differencing confirms that the integration order of the model is $d = 1$. Rather than testing all possible combinations of AR and MA orders, the model identification process focuses on selecting parsimonious models that reflect the dominant lag structures observed in the data.

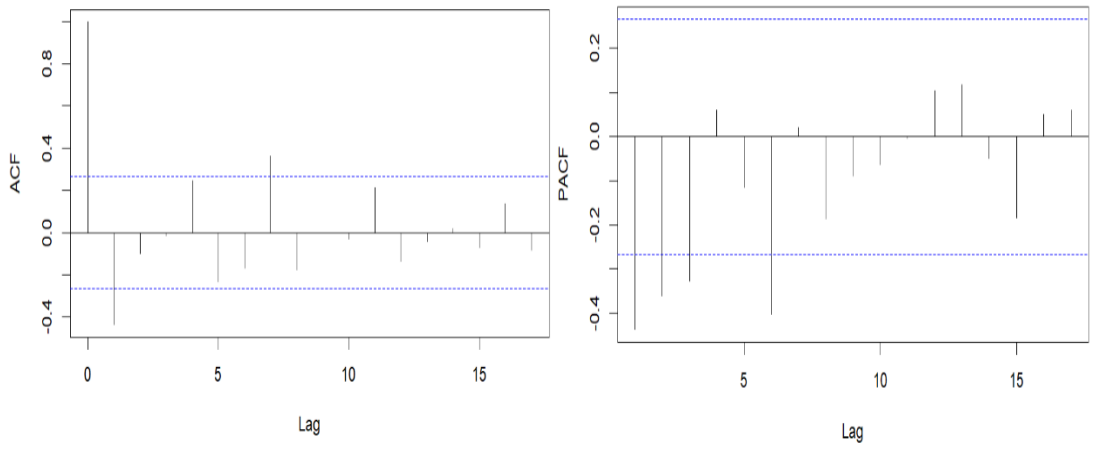


Figure 2. ACF and PACF Plots

Although a spike was observed at lag 7 in the ACF, this pattern does not correspond to the annual seasonal cycle expected for monthly data. Therefore, seasonality was further examined by considering the monthly time-series pattern and the autocorrelation structure at the seasonal lag of 12 months. No clear and consistent annual seasonal pattern was identified. Consequently, there was insufficient evidence to justify the inclusion of seasonal terms, and a non-seasonal

ARIMA framework was retained rather than a seasonal ARIMA (SARIMA) model. Based on these considerations, a set of candidate non-seasonal ARIMA models was formulated, consisting of autoregressive (AR), moving average (MA), and mixed ARIMA structures. The refined candidate models are presented in Table 4.

Table 4. Candidate ARIMA Models

Model Type	ARIMA Specification
AR Model	ARIMA (1,1,0), ARIMA (2,1,0), ARIMA (3,1,0)
MA Model	ARIMA (0,1,1)
Mixed Model	ARIMA (1,1,1), ARIMA (2,1,1), ARIMA (3,1,1)

These models were selected to balance flexibility and parsimony, ensuring that only meaningful lag structures are considered in the subsequent estimation stage while reducing the risk of overfitting.

4.3 Parameter Estimation and Significance Test

Following model identification, parameter estimation was conducted using the Conditional Sum of Squares (CSS) method to obtain the coefficient estimates for each candidate ARIMA model. In this study, the CSS method was implemented in R using the arima() function with the argument method = "CSS". The statistical significance of each estimated parameter was then evaluated using the Wald (z) test at a 5% significance level ($\alpha = 0.05$). A parameter was considered statistically significant when its p-value was less than 0.05. Models containing statistically insignificant parameters were excluded from further consideration. Table 5 presents the estimation results for the candidate models with statistically significant parameters. Several other candidate models, particularly mixed ARIMA specifications, were initially estimated but excluded because they contained statistically insignificant coefficients.

Table 5. Parameter Estimation Results

Model	Parameter	Coefficient	z-value	p-value	Decision
ARIMA (1,1,0)	AR(1)	-0.4370	-3.6152	0.0003001	Significant
ARIMA (2,1,0)	AR(1)	-0.6030	-4.7654	1.885×10^{-6}	Significant
	AR(2)	-0.3644	-2.9059	0.003662	Significant
ARIMA (3,1,0)	AR(1)	-0.7217	-5.6444	1.657×10^{-8}	Significant
	AR(2)	-0.5509	-3.8883	0.0001009	Significant
	AR(3)	-0.3281	-2.5794	0.0098982	Significant
ARIMA (0,1,1)	MA(1)	-0.8373	-11.827	$<2.2\times10^{-16}$	Significant

Based on Table 4, the ARIMA (1,1,0), ARIMA (2,1,0), ARIMA (3,1,0), and ARIMA (0,1,1) models exhibit statistically significant parameters at the 5% level. In contrast, mixed ARIMA models contain insignificant coefficients, suggesting that the inclusion of additional parameters does not substantially improve the model. From a statistical perspective, this finding supports the principle of parsimony, where simpler models with significant parameters are preferred over

more complex models that may lead to overfitting. Therefore, only the models with statistically significant parameters are retained for further diagnostic checking in the next stage of analysis.

4.4 Model Diagnostics

Following parameter estimation and significance testing, the candidate models were subjected to diagnostic checking to ensure that the underlying assumptions of the ARIMA framework were satisfied prior to forecasting. This step is essential to validate whether the residuals behave as white noise and to confirm the statistical adequacy of the model. Residual normality was evaluated using the Shapiro–Wilk test, and the results are summarized in Table 5.

Table 6. Residual Normality Test (Shapiro–Wilk)

Model	W Statistic	p-value	Decision
ARIMA (1,1,0)	0.98466	0.7048	Normal
ARIMA (2,1,0)	0.98463	0.7037	Normal
ARIMA (3,1,0)	0.97692	0.3680	Normal
ARIMA (0,1,1)	0.96758	0.1432	Normal

As shown in Table 6, all models yield p-values greater than the 5% significance level, indicating no evidence to reject the null hypothesis of normally distributed residuals. While normality is not strictly required for unbiased forecasting, it strengthens the reliability of statistical inference and supports the adequacy of the model specification. The independence of residuals was examined using the Ljung–Box test, with results presented in Table 7.

Table 7. Ljung–Box Test Results

Model	Q Statistic	p-value	Decision
ARIMA (1,1,0)	1.5079	0.2195	Adequate Model
ARIMA (2,1,0)	0.7724	0.3795	Adequate Model
ARIMA (3,1,0)	0.0247	0.8750	Adequate Model
ARIMA (0,1,1)	0.0539	0.8164	Adequate Model

All candidate models have p-values greater than 0.05, indicating that there is insufficient evidence to reject the null hypothesis of no significant residual autocorrelation. Thus, the residuals of all candidate models satisfy the Ljung–Box diagnostic requirement and can be considered approximately uncorrelated. Since all candidate models pass the residual diagnostic test, the Ljung–Box results alone do not provide a basis for distinguishing one model as superior to the others. Therefore, model selection was subsequently based on the combined results of parameter significance, residual diagnostics, and in-sample Mean Absolute Percentage Error (MAPE), as presented in Table 8.

Table 8. MAPE Values

Model	MAPE (%)
ARIMA (1,1,0)	14.36
ARIMA (2,1,0)	12.90
ARIMA (3,1,0)	12.11
ARIMA (0,1,1)	13.05

Among the competing models, ARIMA (3,1,0) yields the lowest in-sample MAPE value of 12.11%. Since the MAPE was calculated using the fitted values from the same data used for model estimation, this result represents the in-sample fitting error rather than out-of-sample predictive performance. The candidate models were further compared using information criteria, including AIC and BIC, together with parameter significance and residual diagnostic results. Considering these criteria jointly, ARIMA (3,1,0) was selected as the final model. The estimated equation of the selected ARIMA (3,1,0) model is presented in Equation (13), which was subsequently used to generate the five-step-ahead forecasts.

$$Y_t = 0.2783Y_{t-1} + 0.1708Y_{t-2} + 0.2228Y_{t-3} + 0.3281Y_{t-4} + e_t \quad (13)$$

Accordingly, the one-step-ahead forecasting equation is written as

$$\hat{Y}_{t+1} = 0.2783Y_t + 0.1708Y_{t-1} + 0.2228Y_{t-2} + 0.3281Y_{t-3}, \quad (14)$$

where $(\hat{Y}_{t+1})$ denotes the forecast value at time $(t+1)$. The future error term is omitted because its expected value is assumed to be zero during the forecasting process.

4.5 Forecasting Results and Interpretation

Using the selected ARIMA (3,1,0) model, forecasts were generated for five future periods (August–December 2025). The results are presented in Table 8.

Table 9. Forecast Results

Period	Forecast
August	6.8365
September	7.2572
October	7.0414
November	7.0171
December	7.0129

The forecast results indicate moderate fluctuations with a slight upward movement in the early forecast period followed by a gradual stabilization. This pattern suggests that while short-term growth may occur, the overall trend tends toward equilibrium rather than sustained expansion. To further illustrate the model performance, the comparison between actual and forecasted values is presented in Figure 3.

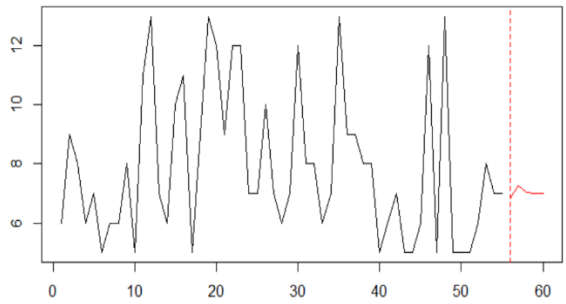


Figure 3. Actual vs Forecasted Values of Insurance Policy Sales

Figure 3 compares the actual insurance policy sales with the forecasts generated by the selected ARIMA (3,1,0) model. The black line represents the observed data, while the red line represents the forecast values beginning after the vertical dashed line. The figure shows that the forecast follows the general pattern of the historical observations without exhibiting abrupt changes. During the initial forecast periods, the predicted values exhibit a slight upward movement before gradually stabilizing around a relatively constant level. This stabilization indicates that, in the absence of additional information, the selected model produces forecasts that converge toward a relatively stable level over the five-period forecast horizon. The smooth transition from the observed series to the forecasted values provides a graphical indication of the continuity of the model forecasts. The reported MAPE of 12.11% represents the in-sample error calculated from the fitted values and therefore should not be interpreted as a measure of out-of-sample forecasting accuracy.

4. Discussion

This study developed a univariate ARIMA model to forecast monthly insurance policy sales at PT Avrist Assurance KPA Lampung using historical sales data. Based on model identification, parameter estimation, and residual diagnostic checking, ARIMA (3,1,0) was selected as the final model. The residual diagnostic results indicated that the residuals did not exhibit significant autocorrelation based on the Ljung–Box test, supporting the adequacy of the model in capturing the temporal dependence remaining in the series. The model also produced the lowest in-sample MAPE of 12.11% among the candidate models. However, because this MAPE was calculated from the fitted values using the same observations employed for model estimation, it should be interpreted as an in-sample error measure rather than as evidence of out-of-sample forecasting accuracy.

The forecasting results for August to December 2025 show a slight increase in the initial forecast period followed by a gradual stabilization. This pattern reflects the temporal structure captured by the selected ARIMA model and provides a short-term projection based solely on the historical sales series. The findings are broadly consistent with previous studies that have applied ARIMA models to short-term forecasting in other contexts, including property sales and Bitcoin price forecasting. Previous research reported that ARIMA could capture temporal patterns and generate short-term forecasts in these settings. However, the characteristics of those data differ from insurance policy sales, particularly in terms of the underlying market mechanisms and potential explanatory factors. Therefore, the findings of those studies provide

contextual support for the use of ARIMA as a time-series forecasting framework, but they should not be interpreted as directly equivalent evidence for insurance policy sales.

An important limitation of this study is the univariate nature of the ARIMA model. The model uses only the historical values of insurance policy sales and does not explicitly incorporate external factors that may influence sales, such as marketing activities, promotional programs, economic conditions, changes in insurance products, or other company-specific factors. Consequently, changes in policy sales driven by external variables may not be adequately captured by the model. In addition, the study uses 55 monthly observations and does not employ a separate hold-out or out-of-sample validation set. Therefore, the reported in-sample MAPE should not be interpreted as a direct measure of future forecasting performance. Future studies could address these limitations by incorporating relevant exogenous variables through ARIMAX or other multivariate forecasting approaches and by evaluating forecasting performance using a hold-out sample or rolling-origin validation.

Reference

[1] D. Guntara, "Asuransi dan ketentuan-ketentuan hukum yang mengaturnya," *J. Justisi Ilmu Huk.*, vol. 1, no. 1, pp. 29–46, 2026.

[2] I. Ain, M. Syahbudi, and B. Rahmani, N., A., "Analisis Identifikasi Risiko Klaim Asuransi Jiwa Pada PT. Chubb Life Dengan Metode Risk Meta Language," *JAMBURA Econ. Educ. J.*, vol. 6, no. 1, pp. 142–155, 2024.

[3] T. L. Situngkir, W. Santoso, E. P. Ananda, I. N. Syafarani, M. Y. Anugrah, and I. P. Sukma, *Bank dan Institusi Keuangan Non Bank*. Penerbit Pustaka Rumah C1nta, 2022.

[4] A. Wasita, "Perlindungan Hukum Terhadap Pemegang Polis," *J. BECOSS (bus. Econ. Commun. Soc. Sci.*, vol. 2, no. 1, pp. 105–113, 2020.

[5] G. A. Maulidya, N. Satyahadewi, P. S. Statistika, and U. Tanjungpura, "Analisis Autoregressive Integrated Moving Average (ARIMA) dengan Intervensi Double Input pada Prediksi Harga Saham," *IJAS (Indonesian J. Appl. Stat.*, vol. 7, no. 1, pp. 60–72, 2024, doi: 10.13057/ijas.v7i1.85299.

[6] N. Nurhayati and W. Apriani, "PREDIKSI PRODUKSI CRUDE OIL DENGAN MENGGUNAKAN MODEL DERET," *Amalgamasi J. Math. Appl.*, vol. 2, no. 1, pp. 10–23, 2023.

[7] R. Kruba *et al.*, "Peramalan Saham Indofood di Indonesia Menggunakan Metode Seasonal Autoregressive Integrated Moving Average (SARIMA)," *URNAL Manaj. DAN Keuang.*, vol. 14, no. 1, pp. 102–117, 2025.

[8] W. Apriani and N. Nurhayati, "Pemodelan data curah hujan di kota langsa dengan model ARIMA," *Amalgamasi J. Math. Appl.*, vol. 1, no. 2, pp. 64–70, 2021.

[9] J. J. Pangaribuan, O. B. Barus, and R. Romindo, "Prediksi Penjualan Bisnis Rumah Properti dengan Menggunakan Metode Autoregressive Integrated Moving Average (ARIMA)," *J. Sist. Inf. Bisnis*, vol. 02, pp. 154–161, 2023, doi: 10.21456/vol13iss2pp154-161.

[10] N. F. B. Pradana and S. Lestanti, "Aplikasi Prediksi Jangka Pendek Harga Bitcoin Menggunakan Metode Arima," *J. Ilm. Inform. Komput.*, vol. 25, no. 3, pp. 160–174, 2020, doi: 10.35760/ik.2020.v25i3.3128.

[11] A. P. Nasution, S. Aisyah, U. Islam, and N. Sumatera, "Analisis Implementasi Pembayaran Klaim Asuransi Kesehatan Berdasarkan Fatwa Nomor 21 / Dsn- Mui / X / 2001 Pada PT. Sun Life Financial Syari ' Ah Cabang Kapten Jumhana Kota Medan," *J. Masharif al-Syariah J. Ekon. dan Perbank. Syariah*, vol. 8, no. 30, pp. 747–763, 2023.

[12] C. S. Kansil and F. A. Sulistio, "Kansil, C. S., & Sulistio, F. A. (2024). Analisis Elemen-Elemen Penting dalam Asuransi Berdasarkan Undang-Undang No. 40 Tahun 2014," *J. Manag. Accounting, Tax Prod.*, vol. 2, no. 1, pp. 24–34, 2024.

[13] A. F. Wiharja and H. F. Ningrum, “Analisis Prediksi Penjualan Produk PT. Joenoes Ikamulya Menggunakan 4 Metode Peramalan Time Series,” *J. Bisnisman Ris. Bisnis dan Manaj.*, vol. 2, no. 1, pp. 43–51, 2020, doi: 10.52005/bisnisman.v2i1.23.

[14] L. Maysofa and K. U. Syaliman, “Jurnal Testing dan Implementasi Sistem Informasi Implementasi Forecasting Pada Penjualan Inaura Hair Care Dengan Metode Single Exponential Smoothing Forecasting Implementation In Inaura Hair Care Sales,” *J. Test. dan Implementasi Sist. Inf.*, vol. 1, no. 2, pp. 82–91, 2023.

[15] T. Yunita, “Peramalan Jumlah Penggunaan Kuota Internet Menggunakan Metode Autoregressive Integrated Moving Average (ARIMA),” *J. Math. Theory Appl.*, vol. 1, no. 2, pp. 16–22, 2019.

[16] G. Ayu, M. Arna, N. Putu, N. Hendayanti, and M. Nurhidayati, “PEMODELAN DATA DERET WAKTU DENGAN A UTOREGRESSIVE INTEGRATED,” *J. Varian*, vol. 1, no. 1, pp. 54–63, 2017.

[17] H. A. Hutomo, “Pemodelan deret waktu dan peramalan curah hujan pada dua belas stasiun di bogor,” *J. Mat. Stat. dan Komputasi*, vol. 15, no. 1, pp. 50–63, 2018.

[18] S. Sismi and M. Y. Darsyah, “Perbandingan Prediksi Harga Saham PT . BRI , Tbk dengan METODE ARIMA dan MOVING AVERAGE,” *Pros. Semin. Nas. Mhs. Unimus*, vol. 1, no. 1, pp. 351–360, 2018.

[19] K. Nurfadila and Ilham Aksan, “Aplikasi Metode Arima Box-Jenkins Untuk Meramalkan Penggunaan Harian Data Seluler,” *J. Math. Theory Appl.*, vol. 2, no. 1, pp. 5–10, 2020, doi: 10.31605/jomta.v2i1.749.

[20] N. Nurhayati and A. Fitriawati, “ARIMA – GGJR – GARCH Modeling of Asymmetric Conditional Volatility in Wind Speed Time Series,” *CAUCHY – J. Mat. Murni dan Apl.*, vol. 11, no. 1, pp. 887–903, 2026.

[21] J. Riza; and S. Akbar, “Perbandingan Uji Stasioner Data Timeseries Antara Metode : Control Chart , Correlogram , Akar Unit Dickey Fuller , dan Derajat Integrasi,” *J. Gradien*, vol. 11, no. 1, pp. 1040–1046, 2015.

[22] I. Aksan and K. Nurfadilah, “Aplikasi Metode Arima Box-Jenkins Untuk Meramalkan Penggunaan Harian Data Seluler,” *JOMTA J. Math. Theory Appl.*, vol. 2, no. 1, pp. 5–10, 2020.

[23] W. W. S. Wei, *Time Series Analysis: Univariate and Multivariate Methods 2nd edn.* New York: Pearson Addison Wesley, 2006.

[24] B. Putro, M. T. Furqon, and S. H. Wijoyo, “Prediksi Jumlah Kebutuhan Pemakaian Air Menggunakan Metode Exponential Smoothing (Studi Kasus : PDAM Kota Malang),” *J. Pengemb. Teknol. Inf. dan Ilmu Komput.*, vol. 2, no. 11, pp. 4679–4686, 2018.