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# Regression Models With Arma Errors For Predicting Tabarru Fund In Islamic Insurance: A Normally Distributed Simulation Approach

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***Abstract***

*Islamic insurance is a financial protection system based on mutual assistance and risk-sharing, facilitated by a tabarru fund among participants. Effective management of this fund is essential to prevent financial deficits while ensuring sustainability and compliance with Sharia principles. This study aims to predict the value of the tabarru fund by developing a regression model with ARMA errors, incorporating variables such as participant contributions, claim amounts, and investment returns. The Regression model with ARMA errors is a hybrid approach that combines multiple linear regression with ARMA-based residual modeling, effectively addressing autocorrelation in regression residuals. The data used in this study were generated through a normal distribution simulation based on the monthly financial records of a Sharia insurance company over a ten-year period. The analysis results indicated that the regression model with ARMA(1,0) errors could provide predictive values with minimum error of prediction (MAPE value 0.022%). These findings demonstrate the model's potential for strategic financial planning in Islamic insurance institutions, particularly in optimizing fund allocation and supporting risk-sensitive investment decisions*

***Keywords:*** *ARMA, Islamic insurance, Regression, Tabarru, Time Series*

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## 1. INTRODUCTION

In Islamic insurance, the concept of mutual assistance and risk-sharing among participants for the collective benefit is facilitated through the tabarru fund. The tabarru fund is a core element of Islamic insurance, functioned as a donation from participants to assist one another in managing financial risks [1] . Management of the tabarru fund in Islamic insurance is crucial to prevent financial deficits. Managing the tabarru fund involves overseeing mutual contributions among participants in accordance with Islamic principles. This fund is managed by the Islamic insurance company with the principles of trust and transparency, where suboptimal management can impact business sustainability and participant trust. If the tabarru fund is not well-managed, an imbalance between income and expenditure may lead to a deficit, requiring the company to cover the shortfall through qardh (loan) [2]. Therefore, Islamic insurance companies must implement effective fund management strategies to ensure adequate funds for claim payments and maintain long-term financial stability [3]. Furthermore, Islamic insurance companies need reliable forecasting tools to anticipate future fund needs and ensure adequate reserves [4].

One of the main challenges in managing tabarru funds is the fluctuation of participant contributions and unpredictable claims. To address this challenge, this study proposes the use of a regression model with ARMA errors as a predictive tool for tabarru fund values. Therefore, more accurate analytical and predictive methods are needed to understand the fund's movement patterns. A regression model with errors modeled using an Autoregressive Moving Average (ARMA) process is one potential approach to address this issue. Regression models with ARMA errors combine multiple linear regression with Autoregressive Moving Average (ARMA) processes [5]. This hybrid approach allows for more accurate modeling by capturing the relationships among key financial variables such as contributions, claims, and investment returns while also accounting for time-dependent patterns and autocorrelation in the residuals [6]. By improving prediction accuracy, this model can support more effective tabarru fund management and contribute to the long-term financial stability of Islamic insurance institutions. This model not only captures trends and seasonal patterns in financial data but also accounts for volatility and heteroscedasticity, which are common in Sharia financial data [2]. Thus, this approach enables Sharia insurance companies to make more accurate, data-driven decisions in managing tabarru funds.

The implementation of regression models with ARMA errors in forecasting tabarru fund dynamics offers deeper insights into the underlying risks and uncertainties associated with fund movements. By examining the residual structures of the fitted regression models, Sharia insurance companies can enhance the flexibility and responsiveness of their investment strategies in the face of market fluctuations. This capability is particularly critical, as maintaining financial stability in Islamic insurance must remain consistent with Sharia principles, notably the prohibition of speculation (gharar) and interest (riba) [1].

Previous models in forecasting tabarru funds have primarily relied on classical time series approaches, such as ARIMA or simple regression techniques, which assume that the error terms are white noise and independent [7]. However, this assumption often does not hold in real-world financial data, where residuals frequently exhibit autocorrelation and volatility clustering [8]. Such limitations can lead to biased parameter estimates and inaccurate prediction intervals, ultimately reducing the reliability of risk assessment and fund management decisions [4]. Recent studies in

Islamic insurance forecasting highlight similar challenges, particularly when applying ARIMA or exponential smoothing methods, which often fail to capture complex dependency structures in residuals [5], [6].

Furthermore, by incorporating a normally distributed simulation approach, this study ensures controlled experimental conditions that allow for a comprehensive evaluation of the model's performance under different scenarios of mean and variance assumptions. This methodological enhancement not only mitigates the issues of residual dependence found in earlier models but also offers a practical tool for Sharia insurance companies to manage uncertainty without violating Islamic financial principles [9].

This study aims to develop a predictive model for tabarru funds using regression models with ARMA errors to improve the accuracy of future fund adequacy estimates. By employing this approach, Sharia insurance companies are expected to optimize the management of tabarru funds and improve the efficiency of their investment strategies. The findings of this research are also expected to contribute to the advancement of quantitative methods in supporting the long-term sustainability of the Sharia insurance industry.

## 2. RESEARCH METHODS

The data were simulated using a normal distribution for simplicity and analytical tractability, with the mean ($\mu$) is assumed to be in the range between IDR 147 million to 150 million, also standard deviation was set between IDR 6 million to 7 million to reflect moderate volatility typical of tabarru fund flows. These assumptions were based on estimation from ten years of monthly financial data of a Sharia insurance company. All simulations and analyses were performed using R software with sample size n = 100. The error process is assumed to be stationary after differencing if required.

The variables involved in this study include the tabarru fund ($Y_t$) as the response variable, contributions/premiums ($X_{1,t}$), claim amounts ($X_{2,t}$), and investment returns ($X_{3,t}$) as predictor variables, all measured in millions of rupiah. All simulated variables and assumptions are aligned with Sharia principles, avoiding any elements of speculative return or interest-bearing features.

### 2.1. Regression Models with ARMA errors

Regression models with ARMA errors combine linear regression and ARMA processes to forecast time series data by incorporating various relevant information as independent variables [5]. This model consists of two errors, which is multiple linear regression ($\eta_t$) and ARMA ($\varepsilon_t$) errors. Equation $\eta_t$with $k$ predictor variables ($X_1$ ... $X_k$) expressed by **Equation (1)** [5], [10], [11]

$$\eta_t = Y_t - \beta_0 + \beta_1 X_{1,t} + \cdots + \beta_k X_{k,t} \quad (1)$$

If multiple linear regression error ($\eta_t$) in **Equation (1)** follow ARIMA(p,d,q) processes with parameter of Autoregressive $\phi_p(B)$ and Moving Average $\theta_q(B)$ then $\eta_t$ can be expressed by **Equation (2)** [12], [13]

$$\phi_p(B)(1-B)^d \eta_t = \theta_q(B)\varepsilon_t$$

$$\eta_t = \frac{\theta_q(B)\varepsilon_t}{\phi_p(B)(1-B)^d} \quad (2)$$

The effect of multiple linear regression error ($\eta_t$) modeled by ARMA(p,q) give *Regression model with ARMA errors* ($Y_t$) as shown in **Equation (3)** [5], [12], [9].

$$Y_t = \beta_0 + \beta_1 X_{1,t} + \cdots + \beta_k X_{J,t} + \frac{\theta_q(B)\varepsilon_t}{\phi_p(B)(1-B)^d}$$

$$\phi_p(B)(1-B)^d Y_t = \phi_p(B)(1-B)^d \beta_0 + \phi_p(B)(1-B)^d X_{1,t} + \cdots + \phi_p(B)(1-B)^d X_{k,t} + \theta_q(B)\varepsilon_t$$

$$Y_t^* = \beta_0^* + \beta_1 X_{1,t}^* + \cdots + \beta_k X_{k,t}^* + \theta_q(B)\varepsilon_t,\ \varepsilon_t \ white\ noise \quad (3)$$

## 2.2. Parameter Estimation of *Regression Models with ARMA errors*

The regression models with ARMA errors were estimated using the Maximum Likelihood Estimation (MLE) method. MLE is an estimation technique that identifies parameter values by maximizing the likelihood function. The likelihood function with variance of ARMA errors ($\boldsymbol{\sigma_\varepsilon^2}$) can be expressed by **Equation** (4) **[9], [12].**

$$L(\beta, \phi, \theta, \sigma_\varepsilon^2) = \prod_{t=1}^{n} \frac{1}{\sqrt{2\pi\sigma_\varepsilon^2}} exp\left(-\frac{\varepsilon_t^2}{2\sigma_\varepsilon^2}\right) \quad (4)$$

The log-likelihood in **Equation (4)** can be expressed again by **Equation (5)**

$$\begin{aligned} ln\,L(\beta, \phi, \theta, \sigma_\varepsilon^2) &= \sum_{t=1}^{n} ln\left(\frac{1}{\sqrt{2\pi\sigma_\varepsilon^2}} exp\left(-\frac{\varepsilon_t^2}{2\sigma_\varepsilon^2}\right)\right) \\ &= \sum_{t=1}^{n} \left(-\frac{1}{2} ln\,(2\pi\sigma_\varepsilon^2) - \frac{\varepsilon_t^2}{2\sigma_\varepsilon^2}\right) \\ &= -\frac{n}{2} ln\,(2\pi\sigma_\varepsilon^2) - \frac{1}{2\sigma_\varepsilon^2}\sum_{t=1}^{n} \varepsilon_t^2 \end{aligned} \quad (5)$$

Given Regression models with ARMA(1,1) followed by **Equation (3-5)**, parameter values can be solved by **Equation (6) [12], [9], [14]**

$$\frac{\partial\, ln\, L}{\partial \beta_0} = \frac{\partial}{\partial \beta_0}\left(-\frac{n}{2} ln\,(2\pi\sigma_\varepsilon^2) - \frac{1}{2\sigma_\varepsilon^2}\sum_{t=1}^{n} \varepsilon_t^2\right) = 0 - \frac{\partial}{\partial \beta_0}\left(\frac{1}{2\sigma_\varepsilon^2}\sum_{t=1}^{n} \varepsilon_t^2\right)$$

$$\frac{\partial}{\partial \beta_0}\sum_{t=1}^{n} \varepsilon_t^2 = \frac{\partial}{\partial \beta_0}\sum_{t=1}^{n} \left(Y_t^* - \beta_0^* - \beta_1 X_{1,t}^* + \theta_1 \varepsilon_{t-1}\right)^2 = 0$$

$$\frac{\partial}{\partial \beta_1}\sum_{t=1}^{n} \left(Y_t^* - \beta_0^* - \beta_1 X_{1,t}^* + \theta_1 \varepsilon_{t-1}\right)^2 = 0$$

$$\frac{\partial}{\partial \theta_1}\sum_{t=1}^{n} \left(Y_t^* - \beta_0^* - \beta_1 X_{1,t}^* + \theta_1 \varepsilon_{t-1}\right)^2 = 0$$

$$\frac{\partial}{\partial \phi_1}\sum_{t=1}^{n} \left(Y_t^* - \beta_0^* - \beta_1 X_{1,t}^* + \theta_1 \varepsilon_{t-1}\right)^2 = 0 \quad (6)$$

Thus, the parameter estimates of the regression model with ARMA(1,1) errors in **Equation (6)** are presented in **Equation (7)**

$$\beta_0^* = \sum_{t=2}^{n} (Y_t^* - \beta_1 X_{1,t}^* + \theta_1 \varepsilon_{t-1})$$
$$\beta_1 = \sum_{t=2}^{n} \left( \frac{-Y_t^* + \beta_0^* - \theta_1 \varepsilon_{t-1}}{X_{1,t}^*} \right)$$
$$\theta_1 = \sum_{t=2}^{n} \left( \frac{Y_t^* - \beta_0^* - \beta_1 X_{1,t}^*}{\varepsilon_{t-1}} \right)$$
$$\phi_1 = \sum_{t=2}^{n} \left( \frac{\varepsilon_t Y_{t-1}}{Y_{t-1}^2} \right) \quad (7)$$

### 2.3. The Best Model Selection

An effective approach for identifying the optimal model is the Akaike Information Criterion (AIC). Unlike other criteria such as the Bayesian Information Criterion (BIC), which imposes a stronger penalty for complexity, AIC tends to favor models with better predictive accuracy, making it a standard choice in time series forecasting and simulation studies **[4]**. In the context of tabarru fund modeling, the primary objective is to capture underlying dynamics without over-parameterization, as overfitted models may lead to unreliable forecasts and violate the principle of parsimony. Therefore, the model with the smallest AIC value among the candidate specifications is considered optimal.

Model selection based on AIC is performed by choosing the model with the lowest AIC value **[4] [15].** AIC can be expressed by **Equation (8)** with M denotes the number of parameters involved in the model, and L represents the likelihood value obtained in **Equation (4) [15], [16], [17], [18]**.

$$AIC = -2\ ln(L) + 2M \quad (8)$$

### 2.4. Forecasting

Forecasting using the regression with ARMA errors method for t+h steps ahead ($\hat{\boldsymbol{Y}}_{t+h}$) with 95% confidence interval corresponding to (1–$\alpha$) level, normal distribution ($\mathbf{z}_{\alpha=5\%}$) and standard deviation of the forecast value for t+h steps ahead (SD($\hat{\boldsymbol{Y}}_{t+h}$)) can be expressed by **Equation (9) [19]**. This forecast value includes lower and upper bound of the 95% confidence interval.

$$\hat{Y}_{t+h} - \left( z_{\frac{\alpha}{2}} \times SD(\hat{Y}_{t+h}) \right) < \hat{Y}_{t+h} < \hat{Y}_{t+h} + \left( z_{\frac{\alpha}{2}} \times SD(\hat{Y}_{t+h}) \right) \quad (9)$$

### 2.5. Mean Absolute Percentage Error (MAPE)

Mean Absolute Percentage Error (MAPE) is an evaluation metric used to assess the predictive accuracy of a model by calculating the average absolute percentage error. A lower MAPE indicates higher predictive accuracy, whereas a higher MAPE reflects reduced model precision. MAPE equation, incorporating $\boldsymbol{Y_t}$ as the actual value at time t and $\hat{\boldsymbol{Y}}_t$as the predicted value at time t, can be expressed by **Equation (10) [16] , [17], [20], ,** Forecast accuracy is considered highly accurate when the MAPE less than 10%, good when it ranges between 10% and 20%, reasonable when it falls between 20% and 50%, and poor when the MAPE exceeds 50% **[21]**.

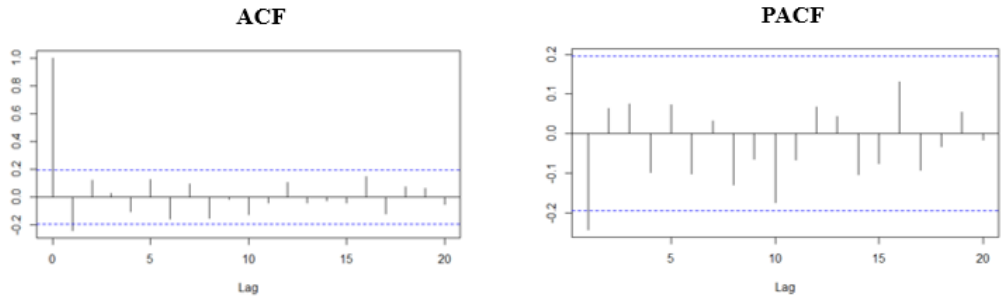
$$MAPE = \frac{100\%}{n} \sum_{t=1}^{n} \left| \frac{Y_t - \hat{Y}_t}{Y_t} \right| \quad (10)$$

## 3. RESULTS AND DISCUSSION

The error term $\eta_t$ of the multiple linear regression model, with the tabarru fund as the response variable ($Y_t$) and contributions($X_{1,t}$), claim amounts($X_{2,t}$), and investment returns ($X_{3,t}$) as predictors, was formulated in **Equation (11),** following the structure outlined in **Equation (1).**

$$\eta_t = Y_t - 1{,}49 \times 10^5 - 0{,}01X_{1,t} - 5{,}86X_{2,t} + 31{,}30X_{3,t} \quad (11)$$

Subsequently, $\eta_t$ was modeled to identify the appropriate ARMA structure by examining the autocorrelation function (ACF) and partial autocorrelation function (PACF) plots. The results of the ACF and PACF residuals of the multiple linier regression analyses were presented in **Figure 1**.




(a) (b)

**Figure 1. Identification ARMA model based on ACF residuals (a), PACF residuals (b)**

Based on the ACF and PACF plots shown in **Figure 1** could be identified several potential ARMA (p,q) models include ARMA(1,0), ARMA(0,1), and ARMA(1,1). The parameter estimates for each model, as specified in **Equation (5),** presented in **Table 1.**

**Table 1. ARMA Errors regressions model estimated parameters.**

| Parameter | ARMA(1,0) | p-value | ARMA(1,1) | p-value | ARMA(0,1) | p-value |
|---|---|---|---|---|---|---|
| $\phi_1$ | -0,26 | 0,008 | -0,36 | 0,182 | - | 0,01 |
| $\theta_1$ | - | $< 2{,}2 \times 10^{-6}$ | 0,09 | 0,724 | -0,229 | $< 2{,}2 \times 10^{-6}$ |
| $\beta_0$ | 147189,27 | 0,51 | 147295,43 | $< 2{,}2 \times 10^{-6}$ | 147247,66 | 0,54 |
| $\beta_1$ | 0,01 | 0,64 | 0,01 | 0,519 | 0,01 | 0,63 |
| $\beta_2$ | 5,36 | 0,57 | 5,36 | 0,639 | 5,6 | 0,56 |
| $\beta_3$ | -13,54 | 0,008 | -14,67 | 0,545 | -14,19 | 0,01 |

The parameter estimates in **Table 1** provided candidate models for forecasting. Model selection was based on statistical significance, with only parameters having p-values below 5% being retained. Models containing non-significant parameters were excluded from further consideration. As shown in **Table 2**, the candidate Regression with ARMA Errors models suitable for forecasting tabarru funds h-steps ahead were ARMA(1,0) and ARMA(0,1). The corresponding AIC values in those two candidate models were 2038.9 and 2039.9 respectively.

Based on a significant level of p-value at 5% ($p < 0.05$) ARMA(1,0) model performed best, with the lowest AIC value (2038.9) and two significant parameters: AR(1) and Investment return. This indicated that the previous tabarru fund value and current investment return significantly influenced the fund's movement. In contrast, ARMA(1,1) included additional complexity without improving accuracy, as most parameters are not significant, including MA(1). ARMA(0,1) had two significant parameters (MA(1) and Investment return), but its AIC is slightly higher (2039.9), making it less efficient than ARMA(1,0).

**Table 2. Significance parameter with ARMA Errors models**

| Parameter | ARMA(1,0) | ARMA(1,1) | ARMA(0,1) |
|---|---|---|---|
| $\phi_1$ | Significant | Not significant | Significant |
| $\theta_1$ | Significant | Not significant | Significant |
| $\beta_0$ | Not significant | Significant | Not significant |
| $\beta_1$ | Not significant | Not significant | Not significant |
| $\beta_2$ | Not significant | Not significant | Not significant |
| $\beta_3$ | Significant | Not significant | Significant |

Based on Table 1-2, and considering the lowest AIC value, the best Regression with ARMA Errors model for forecasting tabarru funds h-steps ahead was ARMA(1,0) model. This model was henceforth referred to as the Regression model with ARMA(1,0) errors. According to Equation (3) the Regression model with ARMA(1,0) errors could be expressed as Equation (12).

$$Y_t = \beta_0(1-\phi_1) + \phi_1 Y_{t-1} + \beta_1\left(X_{1,t} - \phi_1 X_{1,t-1}\right) + \beta_2\left(X_{2,t} - \phi_1 X_{2,t-1}\right) + \beta_3\left(X_{3,t} - \phi_1 X_{3,t-1}\right) + \varepsilon_t \quad (12)$$

By substituting the parameter estimates from Table 1, the Regression model with ARMA(1,0) errors expressed in Equation (12) could be reformulated as Equation (13).

$$Y_t = 186341{,}612 - 0{,}26Y_{t-1} + 0{,}01X_{1,t} + 0{,}004X_{1,t-1} + 5{,}36X_{2,t} + 1{,}43X_{2,t-1} - 13{,}54X_{3,t} - 3{,}60X_{3,t-1} + \varepsilon_t \quad (13)$$

Equation (13) indicated that each increase in the tabarru fund at time t ($Y_t$) was influenced by a 0.26 decrease in the previous period's tabarru fund ($Y_{t-1}$), a 13.54 decrease in current investment return ($X_{3,t}$), and a 3.60 decrease in previous period's investment return ($X_{3,t-1}$). This equation could be used to generate h-step-ahead forecasts. Furthermore, the MAPE value calculated using Equation (10) was 0.022%, indicated very high level of predictive accuracy. The MAPE result also confirmed some findings of previous research on the effectiveness of hybrid models in time series analysis. The improvement in predictive accuracy achieved in this study was consistent with the results presented by Hajirahimi and Khashei [20], who observed the advantages of integrating linear regression models with ARMA-based residual structures in addressing autocorrelation in financial data.

The tabarru fund forecasts, along with the 95% confidence intervals for the next three periods, were presented in Table 3.

**Table 3. Tabarru funds prediction ( $Y_t$) for h=5**

| h | $Y_{t+h}$ | Lower bound | Upper bound |
|---|---|---|---|
| 1 | 150.078,2 | 137.822,1 | 162.334,3 |
| 2 | 147.412,9 | 134.730,2 | 160.095,6 |
| 3 | 148.122,2 | 135.409,9 | 160.834,5 |

The forecasted values in Table 3 exhibited a declining trend. The predicted value for period 1 (h=1) was higher than those of subsequent periods, with a downward trend observed from h=1 to h=2, followed by a slight increase at h=3. The prediction intervals, ranging from the lower bound to the upper bound, were relatively narrow, indicating a high level of accuracy and confidence in the forecasting model. The fluctuations in the tabarru fund values ($Y_t$), from the observed data through the h=3-step-ahead forecast, were illustrated in **Figure 2**.

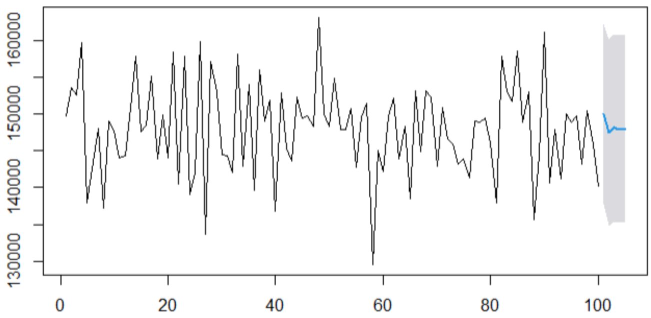



**Figure 2. Prediction results with ARMA(1,0) error regression model**

Although the projected forecast value in **Figure 2** for the first period appeared higher than in subsequent periods, it remained within a reasonable range, supported by a narrow prediction interval indicating high accuracy. This forecast was particularly valuable for informing strategic decision-making in Sharia insurance management, such as anticipating potential deficit or surpluses in tabarru funds. Based on the estimated prediction intervals, Sharia insurance companies could ensure the adequacy of the tabarru funds in meeting participants' financial needs.

Furthermore, this study supported findings of Owusu-Ansah et al. **[14],** which found that regression models with ARIMA errors were effective when applied to volatile data, such as transportation accident statistics and dynamic financial data like tabarru fund. The results obtained in this research reinforced model's relevance in the context of Islamic finance by showed its capability to handle volatility and enhanced predictive accuracy, even when using simulated data that resembling real-world patterns.

Compared to the simple linear regression model used in the previous study by our previous work on tabarru funds, the inclusion of the ARMA component in this research significantly improved predictive reliability **[8][19]**. While earlier models could only capture basic trends, the model developed here effectively addresses autocorrelation in regression. Therefore, this approach offered both theoretical and practical contributions to the implementation of tabarru fund forecasting in Islamic insurance.

Moreover, low MAPE value obtained in this study surpassed the threshold for highly accurate forecasting (which is less than 10%), as outlined by Vivas et al. **[21],** indicated that the proposed model is not only theoretically but also practically viable for real-world implementation.

## 4. CONCLUSION

This study explores the implementation of regression models with ARMA errors for forecasting tabarru funds in Sharia insurance. This model was chosen for its ability to address autocorrelation in the residuals, thereby improving prediction accuracy compared to standard linear regression models, which shows comprehensive results. The optimal selection of ARMA orders significantly affects model performance, making model selection using the Akaike Information Criterion (AIC) essential. By accounting for time-dependent patterns and fluctuations in historical data, regression models with ARMA errors provide more accurate short-term forecasts of tabarru funds. Our results also indicate that this model yields high predictive accuracy, as reflected by lower Mean Absolute Percentage Error (MAPE) values. Therefore, the use of regression models with ARMA errors offers an effective approach for forecasting tabarru fund values in Sharia insurance, supporting better risk management and financial planning for insurance companies. Accurate short-term forecasts of tabarru fund dynamics allow companies to anticipate potential deficits or surpluses, enabling better financial planning, strategic investment decisions, and efficient resource allocation.

For future research, several directions can be explored. First, incorporating real-world data from multiple Sharia insurance providers would improve the robustness and generalizability of the model. This will also reveal practical challenges such as missing data, seasonality, and structural breaks that are often present in actual financial series. Second, extending the model to include non-linear relationships, regime-switching behaviors, or integrating volatility models such as GARCH could further enhance predictive performance in more complex environments. Finally, the development of adaptive or machine learning-based hybrid approaches may provide additional flexibility for real-time applications in risk-sensitive decision-making.

By addressing these aspects, the proposed framework can evolve from a simulation-based model to a practical decision-support tool, offering substantial benefits for long-term financial planning and risk management in the Islamic insurance sector.

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