

Enhancing Working Capital Financing Forecasting In Indonesian Islamic Banks: Arima Model Insights

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ABSTRACT

This study aims to forecast working capital financing for Islamic Commercial Banks (BUS) and Sharia Business Units (UUS) in Indonesia using the ARIMA model as a basis for strategic decision-making. The research object is the total working capital financing of BUS and UUS based on monthly data from January 2017 to March 2025. The research stages include descriptive statistical analysis, stationarity testing with Augmented Dickey-Fuller, identification of ACF/PACF patterns, parameter estimation and significance testing, residual validation, and selection of the best model based on AIC, SBC, and MSE criteria. The analysis results show the ARIMA(8,1,7) model as optimal with AIC 18.6304 and MSE 6,792,148, while residuals meet white noise and normality assumptions. The 12-month forecast (April 2025–March 2026) indicates an increasing financing trend from Rp130.3 trillion to Rp148.98 trillion, despite moderate fluctuations in some months. The discussion confirms that ARIMA captures historical dynamics and external volatility, enabling forecast integration into decision systems for fund allocation optimization and liquidity risk mitigation. In conclusion, ARIMA(8,1,7) proves accurate for predicting BUS-UUS working capital financing and supports Islamic banking management strategies in Indonesia.

Keywords: Working capital financing; Islamic bank; ARIMA; Time series forecasting; Decision support system

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INTRODUCTION

The development of Islamic banking in Indonesia continues to show positive progress, with assets of Sharia Commercial Banks (BUS) and Sharia Business Units (UUS) reaching IDR 955.263 trillion in 2024 (Otoritas Jasa Keuangan, 2024). This growth is driven by the rising demand for sharia-compliant financial products, particularly working capital financing, which constitutes a crucial part of the real sector. Profit-sharing-based working capital financing contributes 21.75% to the BUS-UUS financing portfolio. Nonetheless, global economic volatility and risks from non-performing financing (NPF) remain critical challenges, making strategic fund allocation necessary to sustain growth.

Indonesian regulations mandate that UUS must transform into BUS if their assets reach 50% of the parent company's total assets or by 2023 at the latest, following Law No. 21 of 2008 (Republik Indonesia, 2008). This has urged UUS to prepare, focusing on enhancing working

capital financing strategies. Becoming a BUS provides greater flexibility in product innovation, market expansion, and competitive readiness. Additionally, transformation requires a shift in financing strategy emphasizing long-term sustainability alongside short-term goals. This change also demands improved human resources and infrastructure to meet BUS operational standards, enabling UUS to better compete in Indonesia's dynamic financial market. The transition supports diverse business models, including large-scale financing and investment, thereby strengthening Islamic banking's national economic role.

PT Bank Syariah Indonesia Tbk (BSI), formed from the merger of three state-owned Islamic banks, leads the national Islamic banking industry with the largest market share in working capital financing. In 2024, BSI's financing reached IDR 278.48 trillion, a 15.88% increase over 2023, exceeding industrial growth rates (Bank Syariah Indonesia, 2024). Asset size rose to IDR 401 trillion by March 2025, and the customer base expanded from 5 million to 20 million by March 2024, making it the world's largest Islamic bank by clientele (iTrade CGS International, 2025). BSI digitalized its forecasting process using artificial intelligence, big data, and automation, enhancing accuracy and responsiveness to market demands (Fachri et al., 2023).

Accurate forecasting of working capital financing is paramount to avoiding liquidity imbalances and rising NPF. The ARIMA model helps Islamic banks detect seasonal and trend patterns in financing demand, better optimizing fund allocation and minimizing risk (Syarif, 2020). Forecasting also impacts liquidity management and risk mitigation, vital for Islamic banks which operate without interest through alternative financing like murabahah. This approach aligns with sharia principles while enhancing operational stability and customer trust (Abedifar et al., 2013; Dusuki, 2008; Hassan & Aliyub, 2018). Effective liquidity management ensures resilience amid market fluctuations, regulatory changes, and rising competition ((Wati & Fasa, 2024). Diversifying financing schemes via murabahah, salam, and istishna' maintains cash flow predictability and strengthens sector resilience under varying conditions (Abedifar et al., 2013).

Time series analysis is a key quantitative tool for identifying trends and seasonal components in financial data. The ARIMA model, preferred for its ability to handle non-stationary data via differentiation and transformations (Tiao, 2015), is widely used in financial

forecasting (Wagner & Cleland, 2023). Its use of Box-Cox transformation stabilizes variance and normalizes data distributions, enhancing model effectiveness (Wagner & Cleland, 2023). ARIMA's application improves forecast accuracy over traditional methods by reducing errors like MSE and RMSE (Arumugam & Natarajan, 2023).

Rosyidah and Sukmana (2018) found ARIMA (24,1,5) highly effective in forecasting Indonesian Islamic bank stability using z-score methods, capturing variations tied to retained earnings and capitalization changes during 2017 (Rosyidah & Sukmana, 2018). Building on this, the present study analyzes historical working capital financing patterns using decomposition, stationarity tests, and optimized ARIMA models. It innovatively integrates sharia principles with ARIMA forecasting, aiming to support decision-making for liquidity risk management.

Based on the main problem description, this study identifies two research questions:

1. What are the historical patterns of working capital financing in Islamic commercial banks?
2. How can the ARIMA model be used to forecast working capital financing?

LITERATURE REVIEW

The Concept of Working Capital Financing in Sharia Commercial Banks

Working capital financing in Sharia Commercial Banks is funding provided to customers to support business development and operational activities. It is founded on the principle of trust where the bank, as shahib al-mal, entrusts funds to customers to manage transparently and fairly, under mutually agreed terms compliant with Islamic law. The essence of all Sharia financial institutions is to seek the pleasure of Allah SWT by avoiding any activities that violate religious teachings (Haniffa & Hudaib, 2010; Ilyas, 2015). This financing is categorized as productive assets, typically short-term (one month to one year), and designed to cover operational needs such as acquiring raw materials, paying wages, or other liquidity support vital for smooth business functioning (Abedifar et al., 2013; Ahmed, 2011; Ilyas, 2015). It has contributed significantly to the growth of micro, small, and medium enterprises (MSMEs) and has promoted financial inclusion in various countries (Abedifar et al., 2013).

Sharia operational principles require financing to comply with two main aspects: sharia and economic. The sharia aspect prohibits elements of gambling (maysir), uncertainty (gharar), interest (riba), and mandates financing only for halal businesses. This differentiates Islamic banks from conventional banks that operate on interest, as all contracts and financing mechanisms must align with Islamic muamalah principles, supervised by the Sharia Supervisory Board (Ahmed, 2011; Hassan & Lewis, 2007; Ilyas, 2015; Abedifar et al., 2013). Economically, Sharia banks act as intermediaries channeling funds responsibly, evaluating business feasibility, repayment capacity, and risks. A comprehensive feasibility assessment uses the 5C approach: Character, Capacity, Capital, Collateral, and Condition, supported by cash flow and market sensitivity analyses to minimize risks (Ilyas, 2015; T. Khan & Ahmed, 2001; Čihák & Hesse, 2010).

Working capital financing in Sharia banking follows three main contractual principles: profit-sharing, sale and purchase, and lease. Profit-sharing includes mudharabah, where the bank provides the capital and the customer manages the business, sharing profits proportionally while losses are borne by the capital owner unless caused by negligence (Tiao, 2015; Wagner & Cleland, 2023), and musyarakah, where both parties contribute capital and share profits or losses accordingly (Abedifar et al., 2013; Ilyas, 2015; F. Khan, 2010). The sale and purchase principle applies murabahah, salam, and istishna' contracts. Murabahah involves the bank purchasing goods for the customer and selling them at an agreed profit margin. Salam and istishna' contracts deal with future delivery of goods or services with advance or staged payments (Ahmed, 2011; Dusuki, 2008; Ilyas, 2015). These contracts are particularly flexible and effective for MSME working capital support (Dusuki, 2008). The lease principle (ijarah) applies where the bank leases assets or services without transferring ownership. In ijarah muntahiya bittamlik contracts, ownership transfers to the customer eventually. This scheme suits financing production equipment or operational vehicles (Hassan & Lewis, 2007).

Theory of Time Series Forecasting

The ARIMA (Autoregressive Integrated Moving Average) model, developed by Box and Jenkins in the early 1970s, enhances previous AR and MA models by adding an integrated

component to handle non-stationary data through differencing (Bello-Angulo et al., 2022; Zhang, 2003). ARIMA is widely used in economics and finance for its flexibility in modeling linear patterns, trends, seasonality, and random fluctuations.

Advanced models like SARIMA and hybrid ARIMA-ANN derive from ARIMA to handle seasonal and nonlinear patterns respectively. ARIMA's notation $ARIMA(p, d, q)$ represents its autoregressive order (p), differencing degree (d), and moving average order (q). The model assumes future values as linear functions of past observations and random errors, with parameters estimated from data. ARIMA's advantage lies in its effectiveness for short- and medium-term univariate forecasting without external variables and its ease of implementation with available statistical software (Zhang, 2003). This makes it a primary tool for researchers and practitioners addressing financial time series.

METHOD

This study uses secondary data in the form of monthly time series of working capital financing from Sharia Commercial Banks and Sharia Business Units in Indonesia, obtained from official reports of the Financial Services Authority (OJK) for the period January 2017–March 2025. The data includes the total nominal value of working capital financing. The data source was chosen because of its credibility and consistency in reporting.

ARIMA analysis will be conducted using the E-views 13.0 application and consists of several stages (Bello-Angulo et al., 2022; Huruta, 2024; Zhang, 2003):

1. Descriptive Statistical Analysis

Descriptive statistical analysis at the initial stage of ARIMA analysis is very important to understand the basic characteristics of the time series data to be modeled. Descriptive statistics such as mean, median, standard deviation, minimum, maximum, skewness, and kurtosis provide an overview of the central tendency, dispersion, and distribution shape of working capital financing data before further modeling is carried out.

2. Stationarity Test (ADF Test)

The data is tested for stationarity using the Augmented Dickey-Fuller (ADF) Test to determine differencing (parameter d). If the ADF statistic is smaller than the critical value ($\alpha = 5\%$), the data is declared stationary.

3. ARIMA Model Identification (ACF and PACF)

The patterns of the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) are analyzed to determine the values of p (AR) and q (MA). For example, if the ACF shows a cut-off at lag 2 and the PACF cut-off at lag 1, the candidate model tested is ARIMA(1,d,2).

4. Parameter Estimation and Significance Testing

The ARIMA model is estimated using Maximum Likelihood Estimation (MLE). AR and MA coefficients must be statistically significant ($p\text{-value} < 0.05$). If insignificant, the model is revised by reducing the order of p or q .

5. Model Validation

Diagnostic checks are conducted to assess the suitability of the ARIMA model for forecasting by verifying two key assumptions: Residuals exhibit white noise (no autocorrelation) and residuals are normally distributed. In EViews 13.0, diagnostic tests involve Correlogram Q-statistic analysis to detect residual autocorrelation. The model satisfies the white noise assumption if all Q-statistic lags are insignificant ($p\text{-value} > 0.05$), indicating no residual patterns or extractable information for further modeling. Next, the optimal ARIMA model is selected by comparing AIC (Akaike Information Criterion) and SBC (Schwarz Bayesian Criterion), where AIC and SBC balance goodness-of-fit and model complexity. The lowest AIC and SBC values indicate the most efficient model. Additionally, the optimal ARIMA model is chosen based on the lowest MSE (Mean Squared Error), a prediction accuracy metric where lower values signify smaller forecasting errors.

6. Forecasting

The best model forecasts working capital financing for 12–24 months ahead. Results are visualized with 95% confidence intervals to estimate uncertainty ranges.

RESULTS AND DISCUSSION

Descriptive Statistical Analysis

Descriptive analysis provides an overview of the characteristics of working capital financing in Sharia Commercial Banks (BUS) and Sharia Business Units (UUS) during the observation period. It identifies tendencies in mean values, dispersion, and distribution patterns over time,

forming a basis for further analysis. **Table 1** shows a mean working capital financing value of IDR 115,689.4 billion, with a median close to the mean, indicating a relatively symmetrical distribution despite slight right skewness (skewness = 0.303). Financing amounts ranged from a minimum of IDR 84,040.34 billion to a maximum of IDR 147,414.2 billion with a moderate standard deviation of IDR 17,066.46 billion. Kurtosis value of 2.212 suggests a flat distribution and Jarque-Bera test results (JB = 4.081, $p = 0.130$) confirm no significant deviation from normal distribution. Total financing summed to IDR 11,453,255 billion, with variability controlled over the period, showing relative stability and a positive trend but vulnerability to external shocks.

Table 1. Descriptive Statistics of Working Capital Financing in Sharia Commercial Banks and Sharia Business Units for the Period January – March 2025

Working Capital Financing	
Mean	115689.4
Median	112877.4
Maximum	147414.2
Minimum	84040.34
Std. Dev.	17066.46
Skewness	0.303471
Kurtosis	2.212063
Jarque-Bera	4.080544
Probability	0.129993
Sum	11453255
Sum Sq. Dev.	28543893734
Observations	99

Source: Data analyzed by the researcher, 2025



Source: Otoritas Jasa Keuangan, 2025

Figure 1. Historical Data of Working Capital Financing for Sharia Commercial Banks and Sharia Business Units, January 2017 – March 2025

The historical plot of working capital financing from January 2017 to March 2025 reveals consistent growth with intermittent sharp fluctuations. Initially under IDR 90,000 billion, financing steadily increased until 2021, then surged significantly in 2022, likely due to economic recovery and increased real sector demand post-pandemic. From mid-2023 to early 2024, volatility rose with sharp declines before recovering in 2025. Monthly fluctuations conformed to a stable pattern, supporting the stationarity assumption of the time series data, an important requisite for robust forecasting and strategy formulation.

Stationarity Test Results

Valid ARIMA modeling requires the data to be stationary, meaning constant mean and variance over time. The Augmented Dickey-Fuller (ADF) test is applied to verify stationarity before model building. When the ADF test indicates non-stationary data, transformations like differencing are necessary.

Table 2. Unit Root Test (Augmented Dickey-Fuller / ADF) Results at Level

	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-1.579112	0.4894
Test critical values: 1% level	-3.498439	
5% level	-2.891234	
10% level	-2.582678	

Source: Data analyzed by the researcher, 2025

The ADF test results on working capital financing data at the original level showed a t-statistic of -1.579 and a p-value of 0.4894, which is greater than the 5% significance level, indicating non-stationarity (**Table 2**). After first differencing, the ADF test produced a t-statistic of -9.354 with a p-value of 0.000, indicating stationarity at this level (**Table 3**). Thus, the data fulfills the stationarity requirement for ARIMA modeling after differencing.

Table 3. Unit Root Test (Augmented Dickey-Fuller / ADF) Results at First Differencing Level

	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-9.354424	0.0000
Test critical values: 1% level	-3.498439	
5% level	-2.891234	
10% level	-2.582678	

Source: Data analyzed by the researcher, 2025

ARIMA Model Identification (ACF and PACF)

ARIMA depends on three parameters: autoregressive order (p), differencing order (d), and moving average order (q). Differencing degree (d) is set to 1 based on stationarity results. Parameters p and q are identified by analyzing the patterns in Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots post-differencing.

Observations in ACF and PACF (**Supplement 1**) suggest candidate values for **p as 6, 7, 8, or 9**, while **q candidates include 7, 8, 12, 19, 24, or 36**. These parameters form multiple ARIMA model combinations for further evaluation.

Parameter Estimation and Significance Testing

Using Maximum Likelihood Estimation (MLE), ARIMA model parameters are estimated with significance testing based on p-values (<0.05) to avoid overfitting.

Tabel 4. ARIMA Model Combinations and Maximum Likelihood Estimation Test Results

Lag pada d=1	AR (Partial Autocorrelation)							
	0	6	7	8	9			
MA (Autocorrelation)	0	Model (6,1,0) AR 0.021	Model (7,1,0) AR 0.0115	Model (8,1,0) AR 0.0686	Model (9,1,0) AR 0.14			
	7	Model (0,1,7) AR 0.0751	Model (6,1,7) AR 0.7411	Model (7,1,7) AR 0.0323	Model (8,1,7) AR 0.1432			
	8	MA 0.0003	MA 0.0035	MA 0.1233	MA 0.0000	MA 0.0015		
	12	Model (0,1,8) AR 0.023	Model (6,1,8) AR 0.0078	Model (7,1,8) AR 0.9293	Model (8,1,8) AR 0.3518	Model (9,1,8) AR 0.1023		
	19	MA 0.0226	MA 0.0298	MA 0.0179	MA 0.5241	MA 0.1023		
	24	Model (0,1,12) AR 0.025	Model (6,1,12) AR 0.061	Model (7,1,12) AR 0.1969	Model (8,1,12) AR 0.2007	Model (9,1,12) AR 0.0059		
	36	MA 0.0052	MA 0.0102	MA 0.0172	MA 0.0117	MA 0.0059		
	24	Model (0,1,19) AR 0.0289	Model (6,1,19) AR 0.0247	Model (7,1,19) AR 0.1059	Model (8,1,19) AR 0.1683	Model (9,1,19) AR 0.0355		
	36	MA 0.0278	MA 0.0222	MA 0.0667	MA 0.0733	MA 0.0355		
	24	Model (0,1,24) AR 0.0337	Model (6,1,24) AR 0.0271	Model (7,1,24) AR 0.1387	Model (8,1,24) AR 0.1381	Model (9,1,24) AR 0.076		
	36	MA 0.0826	MA 0.0885	MA 0.1899	MA 0.1653	MA 0.076		
	36	Model (0,1,30) AR 0.1894	Model (6,1,36) AR 0.017	Model (7,1,36) AR 0.1313	Model (8,1,36) AR 0.1237	Model (9,1,36) AR 0.1237		
	36	MA 0.0783	MA 0.1716	MA 0.0579	MA 0.1154	MA 0.0735		

Source: Data analyzed by the researcher, 2025

Among the 34 tested models with various (p,d,q) combinations in **Table 4**, only 11 showed statistically significant AR and MA coefficients and are considered viable candidates for forecasting working capital financing. These include models such as (6,1,0), (7,1,0), (0,1,7), (8,1,7), (0,1,8), (6,1,8), (7,1,8), (0,1,12), (6,1,12), (0,1,19), and (6,1,19). The selection of the final model will be based on further comparison using criteria like AIC/BIC and residual analysis, following the Box-Jenkins methodology.

Model Validation

Diagnostic checks validate the adequacy of ARIMA models by examining whether residuals meet assumptions of white noise (lack of autocorrelation) and normal distribution. Using EViews 13.0, the residual autocorrelation is assessed with the Correlogram Q-statistic. A model passes the white noise test if all lagged Q-statistics are insignificant (p-value > 0.05), indicating no temporal patterns remain in residuals.

Among the 11 ARIMA models tested, only four met this white noise criterion: ARIMA (0,1,7), (0,1,12), (7,1,8), and (8,1,7). These models exhibited no significant autocorrelation in residuals (**Supplement 2**). Model selection then involved comparing AIC (Akaike Information Criterion), SBC (Schwarz Bayesian Criterion), and MSE (Mean Squared Error) values. These criteria balance goodness of fit against model complexity; lower values indicate better models. SBC imposes harsher penalties for complexity than AIC. The ARIMA (8,1,7) model showed the lowest AIC, SBC, and MSE, emerging as the best model per Box-Jenkins parsimony principle (**Table 5**).

Table 5. AIC, SBC, and MSE Criteria for the Best ARIMA(p,d,q) Model

Model ARIMA	AIC	SBC	S.E. of regression	MSE
(0,1,7)	18.6755	18.75462	2,692.17	7,247,785
(0,1,12)	18.6754	18.75457	2,690.93	7,241,104
(7,1,8)	18.6486	18.75411	2,637.57	6,956,765
(8,1,7)	18.6304	18.73595	2,606.18	6,792,148

Source: Data analyzed by the researcher, 2025

Model Forecasting

Based on the coefficients in **Table 6**, the ARIMA(8,1,7) model equation for working capital financing can be formulated as follows:

$$\Delta Y_t = C + \phi_8 \Delta Y_{t-8} + \varepsilon_t + \theta_7 \varepsilon_{t-7}$$

$$\Delta Y_t = 533.1508 - 0.294872 \Delta Y_{t-8} + \varepsilon_t - 0.420561 \varepsilon_{t-7}$$

Description:

ΔY_t = first difference of working capital financing for time t

C = 533.1508 (constant/drift)

ϕ_8 = -0.294872 (autoregressive coefficient/AR lag 8th)

θ_7 = -0.420561 (moving average coefficient/MA lag 7th)

ε_t = error term for time t

ε_{t-7} = error term for time t-7

Tabel 6. ARIMA Model (8,1,7) Test Result

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	533.1508	137.2331	3.885003	0.0002
AR(8)	-0.294872	0.135705	-2.172888	0.0323
MA(7)	-0.420561	0.097210	-4.326337	0.0000
SIGMASQ	6514917.	759432.4	8.578666	0.0000
R-squared	0.162777	Mean dependent var		476.2701
Adjusted R-squared	0.136058	S.D. dependent var		2803.891
S.E. of regression	2606.175	Akaike info criterion		18.63044
Sum squared resid	6.38E+08	Schwarz criterion		18.73595
Log likelihood	-908.8917	Hannan-Quinn criter.		18.67312
F-statistic	6.092001	Durbin-Watson stat		1.873604
Prob(F-statistic)	0.000781			

Source: Data analyzed by the researcher, 2025

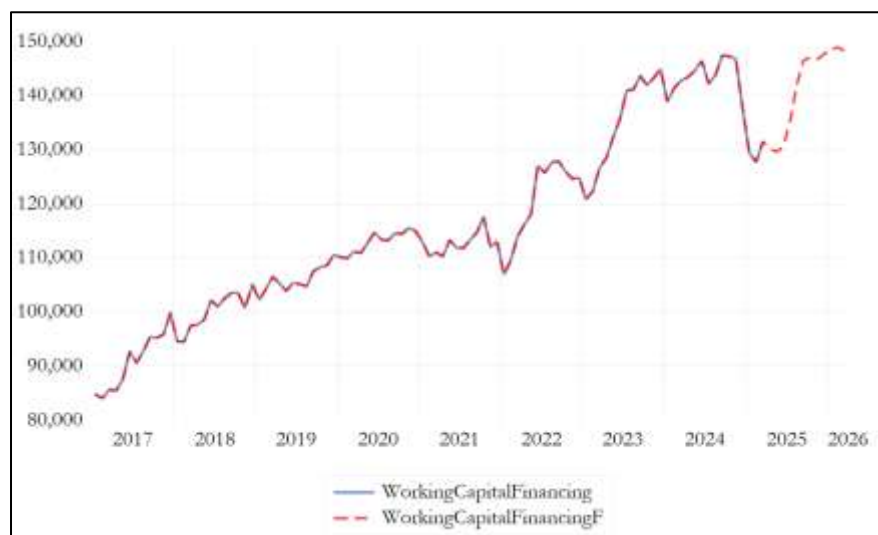
The ARIMA (8,1,7) model shows a significant autoregressive coefficient at lag 8 of -0.294872 (t = -2.17, p = 0.0323), and a highly significant moving average coefficient at lag 7 of -0.420561 (t = -4.33, p = 0.000). The constant term (533.15) is also significant, indicating a deterministic trend in the working capital financing data. The model's overall significance is reflected in an F-statistic of 6.09 (p < 0.001), validating its predictive strength. Despite an Adjusted R-squared of 13.61%, typical for volatile financial time series, the ARIMA (8,1,7) model reliably captures key data variability. The Durbin-Watson statistic (1.87) confirms no serious autocorrelation issues in residuals.

The model forecasts working capital financing from April 2025 to March 2026, showing steady growth from approximately IDR 130.3 trillion to nearly IDR 149 trillion, with moderate monthly fluctuations. Temporary declines in May 2025 and November 2025 reflect responses to external economic factors or business cycles. Historical data from 2017 to March 2025 depict a growth trend with intermittent volatility, including sharp dips in 2021–2022 and early 2024. The forecast projects recovery and sustained growth up to IDR 148–150 trillion by March 2026. These findings indicate positive prospects for Islamic banking's working capital financing, although potential volatility necessitates prudent liquidity risk management and strategic planning by financial institutions.

Table 6. ARIMA (8,1,7) Model Forecast Results for April 2025 – March 2026 (Billion Rupiah)

Month	Working Capital Financing	Month	Working Capital Financing
Apr-25	130,301.76	Oct-25	147,067.63
May-25	129,612.97	Nov-25	146,655.10
Jun-25	130,552.48	Dec-25	147,680.62
Jul-25	135,292.75	Jan-26	148,574.09
Aug-25	142,038.68	Feb-26	148,987.42
Sep-25	146,538.23	Mar-26	148,280.00

Source: Data analyzed by the researcher, 2025



Source: Data analyzed by the researcher, 2025

Figure 2. Forecast of Working Capital Financing for Sharia Commercial Banks and Sharia Business Units, April 2025 – March 2026

Discussion

Working capital financing is a vital aspect of Islamic banking operations. Forecasting it using ARIMA models through time series analysis provides a robust foundation for strategic decision-making, as demonstrated by similar models' proven effectiveness across Indonesian Islamic banking. The identified optimal ARIMA(8,1,7) model (MSE: 6,792,148) enables Islamic banks to project working capital financing fluctuations 12 months ahead (April 2025–March 2026). The projected gradual increase from IDR 130.3 trillion to IDR 148.98 trillion (**Table 6**) offers a strategic basis for optimizing fund allocation and avoiding liquidity mismatch.

Islamic banks can adjust financing composition (*murabahah*, *musyarakah*, *ijarah*) according to projected trends while anticipating volatile periods like the November 2025 dip (IDR 146.65 trillion) through *sukuk* or interbank *mudharabah* instruments. Rising financing trends toward 2026 imply portfolio expansion, particularly for supporting MSMEs and productive sectors. The transformation of Sharia Business Units (UUS) into Sharia Commercial Banks (BUS) under Law No. 21/2008 requires realignment of large-scale financing strategies (\geq IDR 500 billion). ARIMA projections align with BSI's asset growth (IDR 401 trillion in 2025), enabling innovative products like fintech-based supply chain financing. Studies confirm that digitalizing forecasting via AI and big data (as implemented by BSI) enhances market responsiveness (Fachri et al., 2023).

Despite its accuracy, this study has model limitations: the ARIMA(8,1,7) model exhibits a low adjusted R^2 (13.61% in **Table 5**), indicating that 86.39% of financing variation stems from exogenous factors (monetary policy, inflation, UUS→BUS transformation) not captured by the model. Additionally, methodological constraints include undetected extreme volatility (e.g., pandemics). Arumugam & Natarajan (2023) recommend hybrid models (e.g., ARIMA-GARCH) to capture risk asymmetry and volatility clustering. Model validation also relies solely on OJK historical data, neglecting qualitative variables like the Sharia Supervisory Board's policies on business feasibility.

Monthly forecast fluctuations (e.g., the November 2025 dip) highlight the need for financing diversification. A portfolio combining *murabahah* (55%), *musyarakah* (30%), and *ijarah* (15%) enhances resilience, as validated by Fachri et al. (2023). Banks could develop *ijarah muntahiya bittamlik* (lease-to-own) for production equipment financing, proven

effective in maintaining micro-business cash flow. This aligns with *maqasid al-shari'ah* principles emphasizing economic sustainability and justice.

ARIMA projections underscore the need for bank-regulator synergy in monitoring financing dynamics. The Financial Services Authority (OJK) could leverage these findings to design worst-case scenario liquidity stress tests, especially for external fluctuations like conventional interest rate shifts or global crises. Abedifar et al. (2013) emphasize that rigorous sharia oversight of contract compliance and fund allocation minimizes *gharar* (transactional ambiguity).

CONCLUSION

This study develops an ARIMA(8,1,7) model to forecast working capital financing for Sharia Commercial Banks (BUS) and Sharia Business Units (UUS) in Indonesia during 2017–March 2025. Analysis confirms the model's accuracy with the lowest AIC (18.6304), SBC (18.73595), and MSE (6,792,148) among candidate models. The 12-month projection (April 2025–March 2026) indicates a gradual increase from IDR 130.3 trillion to IDR 148.98 trillion, despite moderate volatility (e.g., a temporary dip to IDR 146.65 trillion in November 2025). These findings prove ARIMA's efficacy in capturing historical patterns and external fluctuations, providing a strategic basis for fund allocation optimization and liquidity risk mitigation.

Islamic banks should integrate ARIMA(8,1,7) forecasts into Decision Support Systems (DSS) to enhance mid-term liquidity management, particularly for anticipating downturns like November 2025. Future research should incorporate external variables (e.g., inflation, monetary policy) into hybrid ARIMA-machine learning models to improve predictive accuracy and capture unobserved market complexities.

REFERENCES

- Abedifar, P., Molyneux, P., & Tarazi, A. (2013). Risk in Islamic Banking. *Review of Finance*, 17(6), 2035–2096.
- Ahmed, H. (2011). Maqasid al-Shari'ah and Islamic Financial Products: A Framework for Assessment. *ISRA International Journal of Islamic Finance*, 3(1), 149–160.
- Arumugam, V., & Natarajan, V. (2023). Time Series Modeling and Forecasting Using Autoregressive Integrated Moving Average and Seasonal Autoregressive Integrated Moving Average Models. *Instrumentation Mesure Métrologie*, 22(4), 161–168.
- Bank Syariah Indonesia. (2024). *Laporan Tahunan 2024*.





















































- Bello-Angulo, D., Mantilla-Duarte, C., Montes-Paez, E., & Guerrero-Martin, C. (2022). Box-Jenkins Methodology Application to Improve Crude Oil Production Forecasting: Case Study in a Colombian Field. *Arabian Journal for Science and Engineering*, 47(9), 11269–11278. <https://doi.org/10.1007/s13369-021-05997-7>
- Čihák, M., & Hesse, H. (2010). Islamic Banks and Financial Stability: An Empirical Analysis. *Journal of Financial Services Research*, 38(2), 95–113.
- Dusuki, A. W. (2008). Understanding the objectives of Islamic banking: a survey of stakeholders' perspectives. *International Journal of Islamic and Middle Eastern Finance and Management*, 1(2), 132–148.
- Fachri, S., Sulistiana, I., Nurhayadi, W., & Wahyuni, I. (2023). The Effect Of Working Capital Financing, MSME Investment Financing And Non-Performing Financing On Bank Profit Growth General Sharia. *Jurnal Ekonomi*, 12(03), 2023. <http://ejournal.seaninstitute.or.id/index.php/Ekonomi>
- Haniffa, R., & Hudaib, M. (2010). Islamic finance: from sacred intentions to secular goals? *Journal of Islamic Accounting and Business Research*, 1(2), 85–91.
- Hassan, M. K., & Aliyub, S. (2018). A contemporary survey of islamic banking literature. *Journal of Financial Stability*, 34, 12–43. <https://doi.org/https://doi.org/10.1016/j.jfs.2017.11.006>
- Hassan, M. K., & Lewis, M. K. (2007). *Handbook of Islamic Banking*. Edward Elgar Publishing Limited.
- Huruta, A. D. (2024). Predicting the unemployment rate using autoregressive integrated moving average. *Cogent Business and Management*, 11(1). <https://doi.org/10.1080/23311975.2023.2293305>
- Ilyas, R. (2015). Konsep pembiayaan dalam perbankan syari'ah. *Jurnal Penelitian (P3M STAIN Kudus)*, 9(1).
- iTrade CGS International. (2025, May 2). *Laba BSI Triwulan I 2025 Tumbuh Double Digit*.
- Khan, F. (2010). How 'Islamic' is Islamic Banking? *Journal of Economic Behavior & Organization*, 76(3), 805–820.
- Khan, T., & Ahmed, H. (2001). Risk Management: An Analysis of Issues in Islamic Financial Industry (Occasional Papers). *Occasional Paper The Islamic Research and Teaching Institute (IRTI)*, 91.
- Otoritas Jasa Keuangan. (2024). *Statistik Perbankan Syariah*.
- Republik Indonesia. (2008). *Undang-undang Republik Indonesia No. 21 Tahun 2008 tentang Perbankan Syariah*.
- Rosyidah, & Sukmana, R. (2018). Aplikasi Metode Autoregressive Integrated Moving Average (Arima) Pada Peramalan Stabilitas Bank Syariah Di Indonesia. *Jurnal Ekonomi Syariah Teori Dan Terapan*, 5(3), 200–215.
- Syarif, A. (2020). Forecasting the Development of Islamic Bank in Indonesia: Adopting ARIMA Model. *JTAM (Jurnal Teori Dan Aplikasi Matematika)*, 4(2), 190. <https://doi.org/10.31764/jtam.v4i2.2790>
- Tiao, G. C. (2015). Time Series: ARIMA Methods. In *International Encyclopedia of the Social & Behavioral Sciences* (Second Edition, Vol. 96, pp. 316–321).
- Wagner, B., & Cleland, K. (2023). Using autoregressive integrated moving average models for time series analysis of observational data. *E-BMJ*, 383.

Wati, R., & Fasa, M. I. (2024). Manajemen Risiko Likuiditas : Jaminan Keberlanjutan dan Ketahanan Bank Syariah di Era Krisis Moneter. *Jurnal Manajemen*, 3(4).









































































Zhang, G. P. (2003). Time series forecasting using a hybrid ARIMA and neural network model. In *Neurocomputing* (Vol. 50). www.elsevier.com/locate/neucom

Supplement

Supplement 1. Correlogram Test Results

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.034	0.034	0.1193	0.730
		2	0.045	0.044	0.3289	0.848
		3	0.055	0.052	0.6370	0.888
		4	-0.163	-0.169	3.4002	0.493
		5	-0.176	-0.175	6.6776	0.246
		6	0.179	0.214	10.086	0.121
		7	-0.224	-0.221	15.512	0.030
		8	-0.190	-0.231	19.427	0.013
		9	0.177	0.195	22.882	0.006
		10	-0.049	0.017	23.151	0.010
		11	0.090	0.060	24.055	0.013
		12	0.295	0.144	33.991	0.001
		13	0.011	0.061	34.005	0.001
		14	-0.074	-0.054	34.644	0.002
		15	0.136	0.011	36.836	0.001
		16	-0.129	0.008	38.824	0.001
		17	-0.187	-0.145	43.060	0.000
		18	0.003	-0.087	43.061	0.001
		19	-0.201	-0.056	48.056	0.000
		20	-0.173	-0.099	51.810	0.000
		21	0.119	-0.015	53.610	0.000
		22	-0.107	-0.146	55.089	0.000
		23	0.008	0.015	55.099	0.000
		24	0.227	0.080	61.930	0.000
		25	-0.050	-0.122	62.267	0.000
		26	0.018	0.044	62.309	0.000
		27	0.094	-0.022	63.536	0.000
		28	-0.127	-0.029	65.802	0.000
		29	-0.080	0.025	66.710	0.000
		30	0.039	-0.033	66.932	0.000
		31	-0.145	0.037	70.003	0.000
		32	-0.111	-0.102	71.849	0.000
		33	0.013	-0.088	71.874	0.000
		34	-0.144	-0.076	75.036	0.000
		35	0.022	-0.044	75.112	0.000
		36	0.226	0.109	83.216	0.000

Supplement 2. Correlogram Q-Statistic Residuals Results for ARIMA (8,1,7)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.060	0.060	0.3661	
		2	0.108	0.105	1.5586	
		3	-0.012	-0.024	1.5730	0.210
		4	-0.091	-0.102	2.4315	0.296
		5	-0.075	-0.062	3.0276	0.387
		6	0.128	0.161	4.7716	0.312
		7	0.003	0.001	4.7726	0.444
		8	-0.048	-0.101	5.0279	0.540
		9	0.115	0.118	6.4762	0.485
		10	-0.070	-0.042	7.0196	0.535
		11	0.027	0.024	7.1019	0.627
		12	0.130	0.119	9.0414	0.528
		13	-0.051	-0.072	9.3470	0.590
		14	-0.060	-0.066	9.7716	0.636
		15	0.047	0.049	10.033	0.691
		16	-0.061	-0.015	10.481	0.726
		17	-0.131	-0.142	12.548	0.637
		18	-0.041	-0.095	12.757	0.690
		19	-0.155	-0.086	15.734	0.543
		20	-0.178	-0.151	19.704	0.350
		21	0.068	0.049	20.291	0.377
		22	-0.109	-0.094	21.826	0.350
		23	-0.018	-0.043	21.868	0.407
		24	0.108	0.096	23.415	0.379
		25	-0.129	-0.121	25.644	0.318
		26	-0.050	-0.010	25.987	0.354
		27	-0.014	-0.033	26.014	0.407
		28	-0.052	-0.005	26.399	0.441
		29	0.018	0.103	26.447	0.494
		30	0.038	-0.059	26.657	0.537
		31	-0.103	-0.068	28.224	0.506
		32	-0.138	-0.115	31.053	0.413
		33	-0.048	-0.095	31.402	0.446
		34	-0.149	-0.091	34.811	0.336
		35	-0.018	-0.085	34.861	0.380
		36	0.140	0.064	37.941	0.294