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Comparison of Stock Mutual Fund Price Forecasting Results Using ARIMA and Neural Network Autoregressive Model

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Abstract

Stock mutual funds gained popularity among the public as an investment alternative due to the convenience they offer, especially for beginner investors who have limited time and investment knowledge. Compared to money market and bond mutual funds, these mutual funds offer higher potential returns but also come with higher risks due to value fluctuations, so forecasting stock mutual fund prices is essential to minimize losses. Since stock mutual fund prices is time series data, this research employs two forecasting models such as Autoregressive Integrated Moving Average (ARIMA) and Neural Network Autoregressive (NNAR). The objective of this research is to determine the best-performing model between ARIMA and NNAR, and compare their forecasting accuracy using the Mean Absolute Percentage Error (MAPE). The data used consists of daily closing prices of stock mutual funds from March 1, 2022, to March 31, 2025, with the criteria that the selected issuers have been operating for more than five years. The results of this research show that the best ARIMA and NNAR for the RNCN are ARIMA([1],1,0) and NNAR(2,2); for TRAM are ARIMA(0,1,[1]) and NNAR(4,1); for SCHRP are ARIMA(0,1,[1]) and NNAR(4,2); for MICB are ARIMA([1],1,0) and NNAR(2,2); and for BNPP are ARIMA([1],1,0) and NNAR(5,1). The MAPE values in the same order are 6.83% and 5.49%; 6.53% and 5.75%; 8.57% and 7.10%; 8.39% and 8.75%; 8.51% and 7.30%. Based on the comparison, NNAR outperformed ARIMA in four out of five mutual funds, with lower MAPE values and also marked by the ARIMA model tend to produce stable or unchanging values over the long term. The results of this research are expected to assist investors in considering by choosing NNAR model, both in the short and long term, to obtain better stock mutual fund price forecasts.

Keywords: Investment, Stock Mutual Funds, Forecasting, ARIMA, Neural Network Autoregressive.

1. Introduction

The capital market plays a vital role in national development as it facilitates funding for issuers, like government and corporations, while also serves as an investment platform for the public. Stocks are the most popular financial instruments, offering high return potential, but investors have to manage their portfolios independently. For investors with limited time or investment knowledge, mutual funds offer more accessible alternative through professional fund managers. As of 2024, Indonesia has 14.03 million mutual fund investors and 6.38 million stock investors, indicating a growing preference for mutual funds over stocks. Among mutual fund types, stock mutual funds offer higher returns, but also comes with higher risk. Price fluctuation in stock mutual fund prices can affect investor gain or losses, making stock mutual fund prices forecasting essential to avoid potential losses.

Stock mutual fund prices are considered time series data, making them suitable for forecasting using the Autoregressive Integrated Moving Average (ARIMA) model, which effective for linear and stationary data, or data that can be transformed to stationarity through differencing. However, ARIMA may struggle to capture complex non-linear patterns. On the other hand, machine learning based forecasting model such as Neural Network Autoregressive (NNAR) model is better suited to handle non-linearities in time series data.

Several studies have applied ARIMA and NNAR in various forecasting context. Bhardwaj et al. (2021) compared NNAR with classical forecasting models like Moving Average (MA), Double Exponential Smoothing Brown, and Holt's method for predict rice production in India, shows that NNAR yielded more accurate results based on RMSE and MAE values. Prihandi et al. (2024) compared ARIMA and Long Short-Term Memory (LSTM) models for predicting chili prices in Bali. Another research by Melina et al. (2024) compared ARIMA and NNAR for forecasting gold prices and found that the NNAR(1,10) model outperformed ARIMA based on RMSE and MAE values.

Based on previous research, the purpose of this research is to analyze and compare the ARIMA and NNAR models for forecasting stock mutual fund prices. The results of this research are expected to help investors, particularly beginners with limited time and investment knowledge, make informed decisions by identifying the more accurate forecasting model for stock mutual funds.

2. Literature Review

2.1. Investment

Investment refers to the activity of allocating capital by investors through financial instruments with the aim of generating future returns. The parties engaging in capital placement are referred to as investors, also entities that require funding are known as issuers. In Indonesia, the institution that facilitates the interaction between investors and issuers is the Indonesia Stock Exchange (IDX). One of the financial instruments used in investment is mutual funds, which serve to collect funds from investors. These funds are then diversified by an investment manager and held by a custodian bank. According to Bursa Efek Indonesia (2022), among the various types of mutual funds, stock mutual funds carry the highest level of risk, but also offer the potential for greater returns.

2.2. Autoregressive Integrated Moving Average (ARIMA)

According to Box & Jenkins (1977), the ARMA model combines two components, such as Autoregressive (AR) and Moving Average (MA) model, and denoted as ARMA(p,q). The AR model assumes that the current value of the series is determined by a linear combination of its past values, while MA model assumes that the current value of a time series is determined by a linear combination of past residuals. The ARMA model is used for stationary time series data, whereas the ARIMA model is used for non-stationary time series data, so this model requires the data to be transformed into a stationary through a differencing process. In addition to stationarity, the ARIMA model also assumes that the data follows a white noise process (Wei et al., 2006). The ARIMA model consists of 3 components, where p is the order of the AR model, q is the order of the MA model, and d is the order of differencing and denoted as ARIMA(p,d,q). The general form of the ARIMA(p,d,q) is defined as (Box & Jenkins, 1977):

$$\phi(B)(1-B)^d Z_t = \mu + \theta(B)\varepsilon_t \tag{1}$$

were,
$\phi(B)$: AR operator, where $\phi(B) = 1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p$,
$\theta(B)$: MA operator, where $\theta(B) = 1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q$,
B : backshift operator,
Z_t : observation at time t,
μ : intercept,
ε_t : residual at time t,
p : AR order,
d : differencing order,
q : MA order.

2.2.1. Stationary Test

Stationarity is a fundamental property in time series analysis, as it ensures that the mean and variance of the data remain constant over time (Tong & Chatfield, 1996). Time series models such as ARIMA require stationary data to produce reliable forecasts (Wei et al., 2006). The Augmented Dickey Fuller (ADF) test is used to assess whether a time series is stationary in its mean by applying significant level of $\alpha = 5\%$, with the following hypotheses criteria:
H_0 : $\delta = 0$ (data is not stationary)
H_1 : $\delta < 0$ (data is stationary).
The test statistic used is:

$$t = \frac{\hat{\delta}}{SE(\hat{\delta})}, \tag{2}$$

where $SE(\hat{\delta})$ is the standard error of δ. The test criteria are to reject null hypothesis if p-value < 0.05.

According to Wei et al. (2006) and Anjuita et al. (2023), the Box-Cox transformation can be applied to stabilize the variance of the series. The Box-Cox transformation is defined as:

$$T(Z_t) = \frac{Z_t^{\lambda} - 1}{\lambda}, \tag{3}$$

where Z_t is the observation at the time t and λ is a parameter estimated from the data. If λ is equal to 1, the data is already stationary in variance. Otherwise, tranformation is required to achieve approximate variance stationary.

2.2.2. ARIMA Model Identification

According to Box & Jenkins (1977), this identification process uses visualization of the Autocorrelation Function (ACF) and the Partial Autocorrelation Function (PACF) plots. The Autocorrelation Function (ACF) measures the correlation between observations in a time series at different lags and defined as:

$$\hat{\rho}_k = \frac{\hat{\gamma}_k}{\hat{\gamma}_0} = \frac{\sum_{t=k+1}^{n}(Z_t - \bar{Z})\,(Z_{t-k} - \bar{Z})}{\sum_{t=1}^{n}(Z_t - \bar{Z})^2} \tag{4}$$

where $\hat{\rho}_k$ is the estimated ACF at lag k, $\hat{\gamma}_k$ is the estimated autocovariance at lag k, and $\bar{Z}$ is the mean of observations.

The Partial Autocorrelation Function (PACF) measures the correlation between Z_t and Z_{t-k} after removing the linear influence of intermediate lags $Z_{t-1}, Z_{t-2}, \dots, Z_{t-k-1}$ and defined as:

$$\hat{\phi}_{pp} = \frac{\hat{\rho}_p - \sum_{j=1}^{k-1}\hat{\phi}_{p-1,j}\hat{\rho}_{k-j}}{1 - \sum_{j=1}^{k-1}\hat{\phi}_{p-1,j}\hat{\rho}_j} \tag{5}$$

where $\hat{\phi}_{pp}$ is the estimated PACF at lag p, and $\hat{\phi}_{p-1,j}$ is the estimated PACF at lag $p-1$ and lag j.

2.2.3. Parameter Estimation

Maximum Likelihood Estimation (MLE) is the method used for parameter estimation in ARIMA that maximize the likelihood function of the observed data. The likelihood function of the ARMA(p,q) model is defined as:

$$L(\mu, \phi_p, \theta_q, \sigma_e^2; \varepsilon_t) = (2\pi\sigma_\varepsilon^2)^{-\frac{n}{2}} \exp\left(-\frac{1}{2\sigma_\varepsilon^2}\sum_{t=1}^{n}\varepsilon_t^2\right) \tag{6}$$

where μ, ϕ_p, θ_q are the parameters used in the model.

2.2.4. Parameter Significance Test

According to Anjuita et al. (2023), a parameter is considered significant if it has a meaningful contribution to the model's predictive accuracy. The test hypotheses used are:

H_0 : $\phi_p = 0$ or $\theta_q = 0$ (the model parameter is not significant)

H_1 : $\phi_p \neq 0$ or $\theta_q \neq 0$ (the model parameter is significant).

The test statistic used is:

$$t = \frac{\hat{\phi}_p}{SE(\hat{\phi}_p)} \text{ or } t = \frac{\hat{\theta}_q}{SE(\hat{\theta}_q)} \tag{7}$$

were,

$\hat{\phi}_p$: is the estimated order p,

$\hat{\phi}_p$: is the estimated order q,

$SE(\hat{\phi}_p)$: is the standard error of $\hat{\phi}_p$,

$SE(\hat{\theta}_q)$: is the standard error of $\hat{\theta}_q$.

The test criteria is to reject H_0 if $|t| > t_{\frac{\alpha}{2}, n-n_p}$ or p-value < 0.05.

2.2.5. Selecting Best ARIMA Model

According to Wei et al. (2006), the selection of the best ARIMA model is based on the Akaike's Information Criterion (AIC). A lower AIC value indicates a better model fit. The AIC is calculated using the following formula:

$$AIC(M) = 2M - 2\ln(L) \tag{8}$$

where M is the number of parameters in the model and L is the likelihood function of the model.

2.2.6. Diagnostic Test

Model diagnostics are conducted using residual analysis to assess the absence of autocorrelation and to verify the normality of the residuals. The Ljung-Box test is used to examine whether the residuals from the fitted ARIMA model exhibit white noise properties and to check the normality assumption of the residuals, a Quantile-Quantile (Q-Q) plot serves as a useful visual aid to assess the extent to which the residuals align with a normal distribution (Gedeck et al., 2020). The hypotheses for the Ljung-Box test are as follows (Tsay, 2005):

H_0 : $\rho_1 = \cdots = \rho_k = 0$ (residuals are white noise)

H_1 : $\exists \rho_k \neq 0, k \in \{1, \dots, K\}$ (residuals are not white noise).

The test statistic used is:

$$Q = n(n+2)\sum_{k=1}^{K}\frac{\hat{\rho}_k^2}{n-k} \tag{9}$$

where n is the number of observations, K is the number of lags used, $\hat{\rho}_k$ is the estimated ACF at lag k. The test criteria are to reject H_0 if $Q \geq \chi^2_{(\alpha,K-p-q)}$ or p-value < α.

2.3. Neural Network Autoregressive (NNAR)

A Neural Network (NN) is a computational system designed to mimic the workings of the human brain's neural structure, especially in capturing non-linear relationships in data (Hyndman & Athanasopoulos, 2018). The NN consists of three main layers such as input layer to receive the input data, hidden layer to processes inputs through weighted connections to produce non-linear outputs, and output layer to generates the final forecasting.

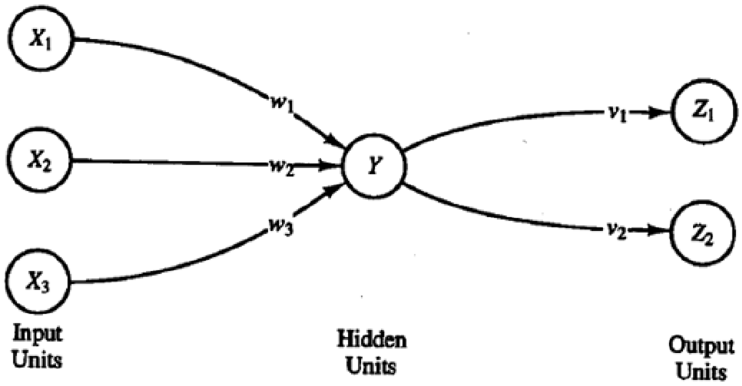

Figure 1: Neural network architecture (Fausett, 1994)

The Neural Network Autoregressive (NNAR) model is a specific application of NN in time series analysis, using p-lagged values of the time series $(x_1, x_2, \ldots, x_p)$ as inputs (As'ad et al., 2020; Hyndman & Athanasopoulos, 2018). The NNAR model typically adopts a feed-forward architecture, meaning information flows in one direction from the input layer to the output layer, with no feedback loops (Shmueli et al., 2018) and trained by backpropagation algorithm to estimate weights and biases (Fausett, 1994). The model is denoted by NNAR(p,k), where p is the number of input nodes (determined using the PACF plot) and k is the number of hidden nodes (determined by trial and error) (Maier et al., 2023). This structure allows the NNAR model to effectively capture both linear and non-linear dependencies in the time series data.

2.3.1. Activation Function

The activation function is a crucial component of a neural network, enabling the model to capture non-linear relationships in the data. One of the most commonly used activation functions is the sigmoid function. As highlighted by Shmueli et al. (2018), the sigmoid function effectively maps input values to the range $[0,1]$, facilitating convergence during training. Sigmoid function defined as:

$$f(z) = \frac{1}{1+e^{-z}} \tag{10}$$

where z is an input to the function. Sigmoid function takes the derivative with respect to z:

$$f'(z) = f(z)[1-f(z)] \tag{11}$$

2.3.2. Normalization and Denormalization

Normalization ensures that all input variables are scaled between $[0,1]$ before being input to the NNAR model. According to Hapsari *et al.* (2023), normalization is performed using the following formula:

$$x_i^* = \frac{x_i - x_{min}}{x_{max} - x_{min}} \tag{12}$$

Denormalization converts normalized outputs back to the original scale before the normalization process using the following formula:

$$x_i = x_i^*(x_{max} - x_{min}) + x_{min} \tag{13}$$

where x^* is the normalized value, x_{min} and x_{max} are the minimum and maximum of the data respectively, and x_i is the actual data at the time i.

3. Materials and Methods

3.1. Materials

This research used the daily closing prices of stock mutual funds: (i) Rencana Cerdas (RNCN), (ii) Tram Consumption Plus (TRAM), (iii) Schroder Dana Prestasi Plus (SCHRP), (iv) Mandiri Investa Cerdas Bangsa (MICB), and (v) BNP Paribas Pesona (BNPP), with a total of 741 observations from March 1, 2022, to March 31, 2025. The data was collected from the websites www.investing.com and https://www.bareksa.com/id/data, with the criteria that the selected issuers have been operating for more than five years.

3.2. Methods

This research uses ARIMA and NNAR models to forecast stock mutual funds and determine which model provide the highest accuracy using Mean Average Percentage Error (MAPE). The steps of ARIMA model are as follows:

a) Test the stationarity of mean using the Augmented Dickey-Fuller (ADF) test and the stationarity of variance using the Box-Cox transformation.
b) Identify the model by Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots.
c) Estimating the model's parameters using Maximum Likelihood Estimation (MLE).
d) Selecting the optimal ARIMA model based on the smallest Akaike Information Criterion (AIC) value.
e) Residual diagnostic tests using the Ljung-Box test and Q-Q plot.
f) Calculate the Mean Absolute Percentage Error (MAPE).

The steps of NNAR model are as follows:

a) Normalize the training dataset using equation (4).
b) Identifying the order p by analyzing the PACF plot.
c) Selecting the order p based on the smallest AIC value.
d) Training the NNAR model with feedforward and backpropagation processed using various order k.
e) Testing the model using the selected of order k.
f) Applying denormalization to the training dataset.
g) Selecting the most accurate model NNAR based on the smallest MAPE value.

Then, both models are compared using the smallest MAPE values to determine which one more accurate, and generate the stock mutual fund price forecasts using the best model.

4. Results and Discussion

4.1. Stock Mutual Fund Data

According to Hyndman & Athanasopoulos (2018), forecasting accuracy can be determined by evaluating the model's performance on new data that was not used during model training. In this research, 741 data were divided into 80% as training data from March 1, 2022, to August 20, 2024; and 20% as testing data from August 21, 2024, to March 31, 2025. An illustration of the stock mutual fund data can be seen in Figure 2, which RNCN is used as the example issuer throughout the calculation and analyses.

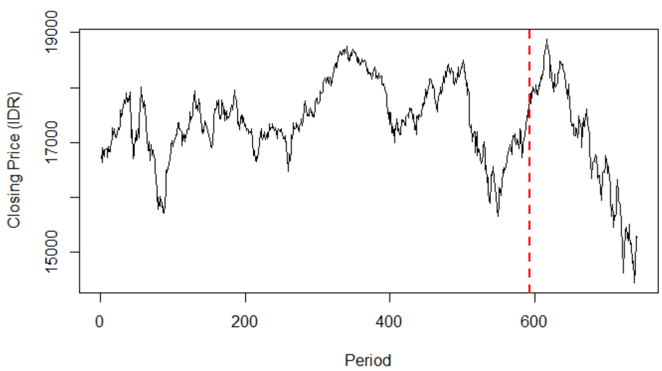

Figure 2: RNCN closing price

In Figure 2 displays the stock mutual fund price movements for the RNCN issuer up to period 741. The plot shows a characteristic pattern of price fluctuations that eventually exhibit a downward trend after period 600.

4.2. ARIMA Model

4.2.1. Stationary Test

The stationarity test using the Augmented Dickey Fuller (ADF) in equation (2) and Box-Cox Transformation were performed using RStudio and the results are presented in Table 1.

Table 1: Stationarity Test Results

Issuer	ADF test (1)	ADF test (2)	λ
RNCN	0.1824	0.01	$0.97 \approx 1$

ADF (1) in Table 1 showed that RNCN was not stationary (p-value = 0.1162 > 0.05), which failure to reject H_0. After first differencing ($d = 1$) was applied, ADF (2) showed that RNCN became stationary (p-value = 0.01 < 0.05). Furthermore, the Box-Cox transformation yielded λ = 0.97, which is approximately to 1. Consequently, it can be concluded that the RNCN series satisfies the assumptions of stationarity in both the mean and variance.

4.2.2. ARIMA Model Identification

From the ADF test results after applying first differencing, it was found that d = 1. The identification of the order p and q were identified using ACF and PACF plot, which are shown in Figure 3.

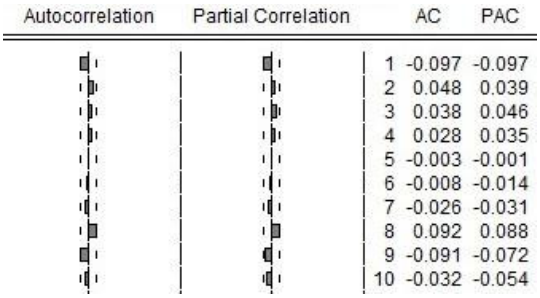

Figure 3: ACF and PACF plot of RNCN

Based on the ACF and PACF plots, significant lags were observed at lag 1, indicating three candidate ARIMA models are ARIMA(1,1,0), ARIMA(0,1,1), and ARIMA(1,1,1).

4.2.3. Parameter Significance Test

The candidate ARIMA models were estimated using the Maximum Likelihood Estimation (MLE) method in RStudio. The significance of each parameter was tested at a 5% significance level, results are presented in Table 2.

Table 2: Parameter Estimation and Significance Test (1)

Model	Parameter	Parameter Estimation	p-value	Description
ARIMA(1,1,0)	$\hat{\mu}$	1.808686	0.72031	Not Significance
	$\hat{\phi}_1$	-0.0978	0.01711	Significance
ARIMA(0,1,1)	$\hat{\mu}$	1.81021	0.72026	Not Significance
	$\hat{\theta}_1$	-0.08891	0.02177	Significance
ARIMA(1,1,1)	$\hat{\mu}$	1.81419	0.7238	Not Significance
	$\hat{\phi}_1$	-0.31854	0.3012	Not Significance
	$\hat{\theta}_1$	0.22132	0.4835	Not Significance

Table 3: Parameter Estimation and Significance Test (2)

Model	Parameter	Parameter Estimation	p-value	Description
ARIMA(1,1,0)	$\hat{\phi}_1$	-0,0976	0,01732	Significance
ARIMA(0,1,1)	$\hat{\theta}_1$	-0,0887	0,02205	Significance

The estimation results showed that parameter $\hat{\phi}_1$ in the ARIMA(1,1,0) model and parameter $\hat{\theta}_1$ in the ARIMA(0,1,1) model were statistically significant because p-value is greater than level significance. However, none of the parameters in the ARIMA(1,1,1) model were statistically significant. To improve model reliability, ARIMA(1,1,0) and ARIMA(0,1,1) models were re-estimated by excluding the insignificant constant term, results are shown in Table 3.

The results of re-estimation in Table 3 validated the significance of the parameter in both models because p-value is greater than level significance.

4.2.4. Selecting Best ARIMA Model

After estimated parameter and significance test was done, the next step is to select the best model using the Akaike Information Criterion (AIC), as defined in Equation (8). The AIC values for each model were calculated using RStudio, and the results are presented in Table 4.

Table 4: AIC value

Model	AIC
ARIMA(1,1,0)	7491.24
ARIMA(0,1,1)	7491.73

Based on Table 4, the ARIMA(1,1,0) model was selected as the best model with smallest AIC value. So, the equation of ARIMA(1,1,0) is defined as:

$$Z_t = -0.0976 Z_{t-1} \tag{14}$$

4.2.5. Diagnostic Test

The Ljung-Box test was used to evaluate the presence of autocorrelation in the residuals. For the ARIMA(1,1,0) model, the test produced a p-value of 0.1708, which greater than significance level α = 0.05 indicates that the residuals exhibit white noise. The next step, to assess normality of residuals, a Q-Q plot was examined, as shown in Figure 4.

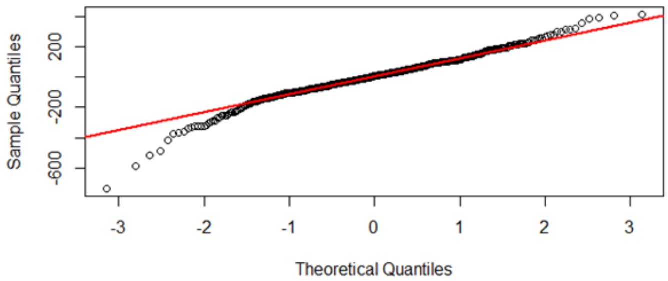

Figure 4: Q-Q plot of residuals

Figure 4 shows that the quantile points were found to align closely with the reference line, indicates that the residuals follow an approximately normal distribution.

4.2.6. Stock Mutual Fund Forecasting with ARIMA Model

The selected ARIMA models were used to forecast mutual fund prices for a seven-day period using RStudio. The forecast results for each issuer are summarized in Table 5.

Table 5: Forecasting results with ARIMA model

Period	Date	RNCN ARIMA(1,1,0)	TRAM ARIMA(0,1,1)	SCHRP ARIMA(0,1,1)	MICB ARIMA(1,1,0)	BNPP ARIMA(1,1,0)
742	01/04/2025	15,284.37	1,591.95	28,509.72	1,958.59	22,412.87
743	02/04/2025	15,284.31	1,591.95	28,509.72	1,958.69	22,412.94
744	03/04/2025	15,284.32	1,591.95	28,509.72	1,958.68	22,412.94
745	04/04/2025	15,284.32	1,591.95	28,509.72	1,958.68	22,412.94
746	07/04/2025	15,284.32	1,591.95	28,509.72	1,958.68	22,412.94
747	08/04/2025	15,284.32	1,591.95	28,509.72	1,958.68	22,412.94
748	09/04/2025	15,284.32	1,591.95	28,509.72	1,958.68	22,412.94

Based on the data from period 741, the actual mutual fund prices were as follows: RNCN at 15,283.75, TRAM at 1,593.02, SCHRP at 28,518.58, MICB at 1,959.45, and BNPP at 22,413.61. Compared to the actual prices, the forecasts in Table 5 shows minimal changes across all five issuers. RNCN, for instance, slightly increases on day one and then stabilizes. MICB and BNPP show small declines before stabilizing, while TRAM and SCHRP remain unchanged throughout. These results suggest that mutual fund prices are expected to stay relatively stable over the next week.

4.3. NNAR Model

4.3.1. Splitting Data

The data splitting process for the NNAR model follows the same training and testing division explained in the previous section.

4.3.2. Data Normalization

Before proceeding to the next step, the training data for RNCN issuer was normalized using equation (12). This normalization is necessary because the sigmoid function in the NNAR model requires input data to be scaled within [0,1]. After normalization, the data was used for designing the neural network structure.

4.3.3. NNAR Model Architecture Design

The NNAR(p, k) model consists of one input layer, one hidden layer, and one output layer. The input layer, denoted by order p, represent significant lag values identified from the Partial Autocorrelation Function (PACF) plot and are selected based on the lowest AIC value. The number of nodes in the hidden layer, denoted by order k, is determined through a trial-and-error process to identify the best performing NNAR model (Maier et al., 2023). The output layer consists of a single node, representing the forecasted value of the stock mutual fund prices.

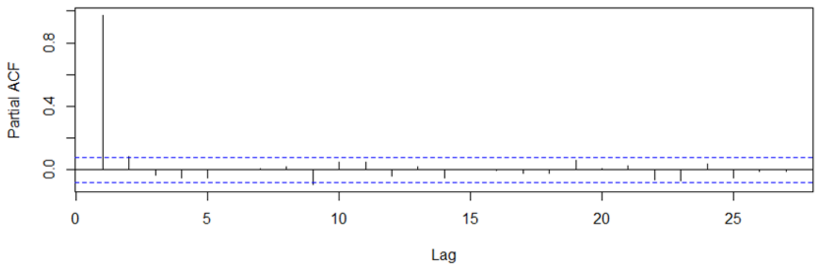

Figure 5: PACF NNAR model

As shown in Figure 5, significant PACF values are observed at lag 1 (p = 1) and lag 2 (p = 2), then selected based on the lowest AIC value, as shown in Table 6.

Table 6: AIC value

Order p	AIC
1	-2019.58
2	-2022.08

Table 6 presents the AIC values for NNAR model. Among the candidates, order p = 2 yields the lowest AIC and is therefore selected for the NNAR model.

4.3.4. Training and Testing

The previously selected order p was used to determine the order k through a trial and error process during training. Model training was conducted using the backpropagation algorithm, implemented the "nnetar()" function in RStudio that automatically handles activation functions, weight updates, and output generation (Hyndman & Athanasopoulos, 2018).

Order k was selected by evaluating several NNAR(p, k) models with varying k values and selecting the one with the lowest Mean Absolute Percentage Error (MAPE) on the testing set, as shown in Table 7.

Table 7: AIC value

Model	Order p	Order k	MAPE
NNAR(2,1)	2	1	6.24%
NNAR(2,2)	2	2	5.49%

NANR(2,5)	2	5	6.47%

Table 7 shows the MAPE values for each tested NNAR model. Although increasing the number of hidden nodes initially reduces the error, performance begins to degrade when $k > 2$. Therefore, NNAR(2,2) is chosen as the optimal model for RNCN.

4.3.5. Data Denormalization

Before evaluating the model performance, the forecasted results for the RNCN issuer were denormalized using equation (12). This step is necessary to convert the predicted values back to their original scale and the results were compared to the actual data for performance evaluation.

4.3.6. Stock Mutual Fund Forecasting with ARIMA Model

The selected NNAR models were used to forecast mutual fund prices for a seven-day period using RStudio. The forecast results for each issuer are summarized in Table 8.

Table 8: Forecasting results with NNAR model

Period	Date	RNCN NNAR(2,2)	TRAM NNAR(4,1)	SCHRP NNAR(4,2)	MICB NNAR(2,2)	BNPP NNAR(5,1)
742	01/04/2025	15,283.48	1,600.86	28,632.04	1,954.85	22,483.55
743	02/04/2025	15,283.27	1,611.24	28,741.69	1,950.55	22,586.98
744	03/04/2025	15,283.09	1,613.85	28,700.55	1,946.87	22,610.05
745	04/04/2025	15,282.92	1,617.36	28,676.18	1,943.76	22,625.23
746	07/04/2025	15,282.77	1,620.75	28,644.03	1,941.15	22,644.67
747	08/04/2025	15,282.64	1,623.07	28,593.66	1,938.98	22,654.92
748	09/04/2025	15,282.51	1,625.43	28,551.72	1,937.19	22,662.38

Based on the data from period 741, the actual mutual fund prices were as follows: RNCN at 15,283.75, TRAM at 1,593.02, SCHRP at 28,518.58, MICB at 1,959.45, and BNPP at 22,413.61. Compared to the actual prices, as shown in Table 8, the forecasted prices for TRAM, SCHRP, and BNPP exhibit an increasing trend from period 742. In contrast, the prices for RNCN and MICB are predicted to decline until period 748.

5. Conclussion

This study successfully applied ARIMA and NNAR models to forecast stock mutual fund prices. The best models found were ARIMA([1],1,0) and NNAR(2,2) for RNCN, ARIMA(0,1,[1]) and NNAR(4,1) for TRAM, ARIMA(0,1,[1]) and NNAR(4,2) for SCHRP, ARIMA([1],1,0) and NNAR(2,2) for MICB, and ARIMA([1],1,0) and NNAR(5,1) for BNPP. The respective MAPE values were 6.83% and 5.49% for RNCN, 6.53% and 5.75% for TRAM, 8.57% and 7.10% for SCHRP, 8.39% and 8.74% for MICB, and 8.51% and 7.30% for BNPP. Overall, NNAR performed better in most cases, showing lower MAPE values than ARIMA.

References

Anjuita, A., Rahayu, W., & Siregar, D. (2023). Intervention Analysis for Modeling and Forecasting Exchange Rates Rupiah Against Yen. *Sainmatika: Jurnal Ilmiah Matematika Dan Ilmu Pengetahuan Alam*, *20*(1), 47–57. https://doi.org/10.31851/sainmatika.v20i1.9209

As'ad, M., Sujito, & Setyowibowo, S. (2020). Neural Network Autoregressive For Predicting Daily Gold Price. *Jurnal INFORM*, *5*(2), 69. https://doi.org/10.25139/inform.v0i1.2715

Bhardwaj, N., Jaslam, P. K. M., Bhatia, J. K., Parashar, B., & Salinder. (2021). Neural Network Autoregression and Classical Time Series Approaches for Rice ield forecasting. *Journal of Animal and Plant Sciences*, *31*(4). https://doi.org/10.36899/JAPS.2021.4.0310

Box, G. E. P., & Jenkins, G. M. (1977). Time Series Analysis: Forecasting and Control. In *Journal of Marketing Research* (Vol. 14, Issue 2). https://doi.org/10.2307/3150485

Daru, A. F., Susanto, S., & Adhiwibowo, W. (2024). Arowana cultivation water quality monitoring and prediction using autoregressive integrated moving average. International Journal of Reconfigurable and Embedded Systems, 13(3), 665.

Fausett, L. V. (1994). *Fundamentals of Neural Networks: Architectures, Algorithms, and Applications*.

Gedeck, P., Bruce, A., & Bruce, P. (2020). *Practical Statistics for Data Scientists: 50+ Essential Concepts Using R and Python*. O'Reilly Media.

Hapsari, R. K., Salim, A. H., Meilani, B. D., Indriyani, T., & Rachman, A. (2023). Comparison of the Normalization Method of Data in Classifying Brain Tumors with the k-NN Algorithm. *Atlantis Press*, *May*, 21–29. https://doi.org/10.2991/978-94-6463-174-6_3

Hyndman, R. J., & Athanasopoulos, G. (2018). *Forecasting: Principles and Practice* (2nd ed.). https://otexts.com/fpp2/buy-a-print-or-downloadable-version.html

Maier, H. R., Galelli, S., Razavi, S., Castelletti, A., Rizzoli, A., Athanasiadis, I. N., Sànchez-Marrè, M., Acutis, M., Wu, W., & Humphrey, G. B. (2023). Exploding The Myths: An introduction to Artificial Neural Networks For Prediction and Forecasting. *International Environmental Modelling & Software Society*, *167*(June). https://doi.org/10.1016/j.envsoft.2023.105776

Melina, Sukono, Napitupulu, H., Mohamed, N., Chrisnanto, Y. H., Hadiana, A. I. D., Kusumaningtyas, V. A., & Nabilla, U. (2024). Comparative Analysis of Time Series Forecasting Models Using ARIMA and Neural Network Autoregression Methods. *Barekeng*, *18*(4), 2563–2576. https://doi.org/10.30598/barekengvol18iss4pp2563-2576

Prihandi, I., Wijono, S., Sembiring, I., & Maria, E. (2024, August). Comparative Analysis of ARIMA and LSTM Algorithms for Predicting Chilli Prices in Bali. In 2024 3rd International Conference on Creative Communication and Innovative Technology (ICCIT) (pp. 1-7). IEEE.

Shmueli, G., Bruce, P. C., Yahav, I., Patel, N. R., & Lichtendahl Jr, K. C. (2018). Data Mining for Business Analytics. In *John Wiley & Sons, Inc*.

Tong, H., & Chatfield, C. (1996). The Analysis of Time Series: An Introduction. In *Journal of the Royal Statistical Society. Series A (General)* (5th ed.). Chapman and Hall CRC, London.

Tsay, R. S. (2005). *Analysis of Financial Time Series* (2nd ed.). John Wiley & Sons, Inc., Hoboken, New Jersey.

Wei, W. W. S., Lynch, D., Hampton, R., Manley, K. A., Hubbard, P., Atkinson, B., Beaton, E., & Mclaughlin, J. (2006). *Time Series Analysis Univariate and Multivariate Methods* (2nd ed.). Greg Tobin.