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HYBRID AUTOREGRESSIVE INTEGRATED MOVING AVERAGE AND NEURAL NETWORK AUTOREGRESSIVE METHODS (CASE STUDY OF INDONESIA SHARIA STOCK DATA)

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Abstract

The Indonesian Sharia Stock Index (ISSI) was first officially introduced on May 12, 2011. ISSI data is a fluctuating time series data which is something that is uncertain and difficult to predict. therefore forecasting is one of the important things to do. Good forecasting indicators produce the right forecasting value, a forecasting method is needed that is in accordance with the characteristics or patterns of the data. In general, there are two types of time series data patterns, namely linear and nonlinear, linear patterns using the ARIMA method and nonlinear using NNAR. The results of the ARIMA-NNAR hybrid are the best model with an RMSE of 1.099 and a MAPE value of 4.375%. The forecasting results of the Indonesian Sharia Stock Index on April 21, 2025 to April 30, 2025 are 206.0341; 207.1324; 208.3564; 210.4519; 212.1144; 213.4942; 215.0161; 216.646, respectively.

Keywords: Forecasting, Time Series, ARIMA, NNAR, Indonesian Sharia Stock Index (ISSI)

1. Introduction

The financial system refers to an economic order in which various financial institutions play a role in providing financial services that support national economic activity. The main function of the financial system is to channel funds from those who have a surplus (savers) to those who need funds (users), in order to support consumption and investment activities, which ultimately encourage the improvement of public welfare and economic growth [1].

Strong economic growth is one of the benefits of the capital market, both in the conventional capital market and the Sharia capital market. The Sharia capital market is a capital market that in its implementation is based on Sharia principles, prohibits the practice of riba (interest) and investment in sectors that are considered haram in Islam, such as gambling, liquor and pornography [2]. The function of the Islamic capital market is to allow the public to participate in business activities in order to make profits, increase the company's capital, and invest in business activities that are reflected in stock price fluctuations [3].

Stock price fluctuations are uncertain and difficult to predict, so investors can make large profits or make losses in a short period of time. Therefore, forecasting is one of the important things to do to estimate the future state of stocks using past data, which can then be a reference in making a decision and knowing the bad situation that may occur in the future [4]. Good forecasting indicators produce accuracy that reflects data patterns historically. So that to produce the right forecasting value, a forecasting method that is in accordance with the characteristics or patterns of the data is needed. In general, there are two known types of time series data patterns, namely, linear patterns and nonlinear patterns. However, it is often found in real life that data patterns are a combination of these two data patterns. Therefore, forecasting using a combination of the two patterns is expected to have better performance [5].

Of the different types of forecasting models in time series, the ARIMA (Autoregressive Intergrated Moving Average) model being one of the very popular approaches that Introduced by George Box and Gwilym Jenkins in 1976. The ARIMA model is a time series data forecasting method that uses the properties and characteristics of historical data to produce future time series data forecasts. The ARIMA model assumes that values in the present tense as well as values in the past as well as errors are white noise, which means that the errors are free with constant averages and varieties [6]. The disadvantage of the ARIMA model is that the residual generated still has nonlinear elements, so the ARIMA model requires a model that can capture nonlinear patterns, one of which is by using the Artificial Neural Network (ANN) model [5]. There are three reasons for the combination or hybrid of the ARIMA model and neural network [5] First, it is often difficult to determine the use of linear models or nonlinear models in a time series problem, so that this combination model becomes a better alternative. Second, in reality time series data is rarely linear or nonlinear but often contains both, so this combination can be used to model time series that contain linear and nonlinear. Third, in some forecasting literature it is stated that no single model is best for every situation. However, the weakness of ANN is that in the process of selecting the number of hidden layers that are determined subjectively, to overcome this weakness, a more specific model, namely the neural network autoregressive (NNAR) model, can be used.

Related research conducted by [7] regarding Stock Price Forecasting with the ARIMA-GARCH Hybrid Model and the Walk Forward Method. Moreover regarding the hybrid method has been carried out by ARIMA (Autoregressive Integrated Moving Average) – ANN (Artificial Neural Network) Hybrid Modeling on Indonesia Inflation Data for 2009 – 2020. The results showed that the MSE value of 0.459152 generated by the ARIMA-ANN hybrid model was smaller than the MSE of 0.566139 generated by the ARIMA model. In addition, the prediction value points of the ARIMA-ANN hybrid model are closer than the predictive values generated by the ARIMA model. This shows that by doing a hybrid on the ARIMA model, it can increase the accuracy of the model. So it can be concluded that the ARIMA-ANN hybrid model is the best model for forecasting Indonesia's inflation data [8].Click or tap here to enter text.

Based on several previous studies on the hybrid method, the researcher will combine the Autoregressive Intergrated Moving Average method and the Neural Network Autoregressive method in predicting data for future periods. In this research, the time series data used is the Indonesia Sharia Stock Index data. The size of the error used to obtain accurate forecast results was measured using RMSE and MAPE.

2. Methodology

The data used in this study is secondary data on the Indonesia Sharia Stock Index in the daily period starting from January 2, 2025 to April 30, 2025. The data in this study is secondary data obtained from the website of the financial market platform id.investing.com.

The variable used in this study is the daily data of the Indonesia Sharia Stock Index in the period from January 2, 2025 to April 30, 2025 as many as 74 data. For the purpose of analysis, the data was divided into two groups, namely training data used to form a model and testing data used to see the accuracy of the model obtained. The training data used is 90% and the testing data is 10%. The training data from January 2, 2025 to April 17, 2025 is 66 data and the testing data from April 21, 2025 to April 30, 2025 is 8 data.

2.1. Sharia Capital and Stock Markets

The development of the Islamic capital market in Indonesia began with the issuance of Islamic mutual funds by PT Dana Reksa Invesment Management on July 3, 1997, which was then followed by the issuance of Islamic bonds at the end of 2002 [3]. The Islamic capital market is a type of capital market where the entire transaction mechanism related to the securities commodities traded by issuers, as well as the trading procedures (contracts) have complied with sharia principles [9]. The Islamic capital market provides various financial instruments that attract investors, one of which is Islamic stocks.

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Sharia shares are securities that present capital participation in a company in accordance with sharia principles[10]. A form of ownership (participation) that shareholders have a set of rights such as the right to speak in the general meeting of the government [12]. shareholders (GMS), residual claims and the like, business activities and the way they are managed do not conflict with sharia principles. According to DSN Fatwa Number: 40/DSN-MUI/X/2003 concerning the Capital Market and General Guidelines for the Application of Sharia Principles in the Capital Market Sector, it has determined the criteria for investment products that are in accordance with Islamic teachings. In essence, the product must meet the requirements, including:

2.2.1 The type of business, the products of goods and services provided and the way the issuer's company is managed are not businesses that are prohibited by sharia principles [9].

2.2.2 Not to exceed the financial ratios.

2.2. Indonesia Sharia Stock Index (ISSI)

The Indonesia Sharia Stock Index (ISSI) was first officially introduced on May 12, 2011. ISSI is a stock index that reflects all sharia stocks listed on the Indonesia Stock Exchange (IDX) with the number of sharia stocks listed as many as 214 shares. The existence of the ISSI Index complements the existing sharia index, namely the Jakarta Islamic Index (JII). ISSI's constituents are all sharia stocks listed on the IDX and listed on the Sharia Securities List (DES). ISSI constituents are reviewed every 6 months, namely in May and November, the results of the review are published at the beginning of the following month. The adjustment of ISSI constituents is carried out if there is an Initial Public Offering (IPO), which is an initial public offering to the public or delisting, which is the removal of the issuer on the stock exchange so that the shares can no longer be traded from DES.

2.3. Time Series Analysis

Time series analysis was introduced in 1970 by George E. P. Box and Gwilym M. Jenkins in their book Time Series Analysis: Forecasting and Control [11]. Time series analysis is a method of quantitative estimation based on past data from a variable collected on a regular basis with the aim of finding patterns in past data series and extrapolating them to the future [4]. This type of data is often encountered in everyday life because the data is collected through interval times, namely daily, weekly or monthly. From the data collected, it can be seen that there is a pattern in it. In the time series, the pattern is divided into three, namely trend, cyclical and seasonal patterns. Trend is a data series that shows a continuous upward or downward direction. Cyclical is a regular repeating pattern but with changing periods (example: business cycle). while seasonal is a pattern that experiences the same repetition many times at certain intervals [12]. Various methods have been developed to process, model, and produce accurate forecasts in time series analysis. One of the commonly used forecasting methods is ARIMA or Box-jenkins.

2.4. Autoregressive Integrated Moving Average (ARIMA)

The Autoregressive Integrated Moving Average (ARIMA) method was studied in depth by George Box and Gwillym Jenkins in 1976 and their names are then often synonymized with the ARIMA process applied to time series analysis. In general, the ARIMA model is written with the notation ARIMA (p,d,q), p-order autoregressive (AR), q-order moving average (MA) process or a combination of both. The d-order difference process is performed if the time series data is non-stationary to the mean, while data that is not stationary to the variance is transformed [13]. Stationarity testing is done using the Augmented Dickey Fuller (ADF) hypothesis test with the following equation:

$$\Delta Z_t = \beta_1 + \beta_2 t + \delta Z_{t-1} + \sum_{i=1}^{m} \alpha_i \Delta Z_{t-i} + a_t \tag{1}$$

The value of $\Delta Z_{t-i} = Z_{t-1}\text{-}Z_{t-2}, \Delta Z_{t-2} = Z_{t-2}\text{-}Z_{t-3}$, and so on[14]. The ADF test has the following hypothesis:

$H_0: \delta = 0$ (data is not stationary)
$H_0: \delta \neq 0$ (data stationer)

The test statistics used is as follows:

$$\tau = \frac{\hat{\rho}}{Se(\hat{\rho})} \quad (2)$$

Rejection region, reject H_0 if $|t_{hit}| > t_{table}$ atau $p_{value} < \alpha$, which indicates that the data is stationary in the mean.

The stationer to the variance can be seen If the data structure over time has constant or constant and unchanging data fluctuations. In the test, stationarity in variance can be used with the following equation [15]:

$$W = Z_t^{(\lambda)} = \begin{cases} \frac{Z_t^{\lambda} - 1}{\lambda}, \lambda \neq 0 \\ \ln Z_t, \lambda = 0 \end{cases} \quad (3)$$

With λ referred to as the transformation parameter. In the Box-Cox Transform the value will be obtained λ, which will later determine the transformation that must be carried out. The following are the values λ and the Box-Cox Transform rules are shown in Table 1[16].

Table 2.1 Value of Box-Cox transformations

λ	**Box-Cox Transformation**
-1	Parking
-0.5	$\sqrt{Z_t}$
0	Ln Z_t
0.5	$\frac{1}{\sqrt{Z_t}}$
1	$\frac{1}{Z_t}$

Model specification is carried out to determine tentative model estimates based on sample data to identify the values of p, d, and q through the plot values of the autocorrelation function (ACF) and partial autocorrelation function (PACF). Autocorrelation is a correlation that occurs between a series and itself. ACF plot values are commonly used to identify MA models of order q or commonly written MA (q). While the PACF plot value is used to identify the AR model with order p or commonly written AR (p).

Box and Jenkins have effectively reached an agreement on the relevant information needed to understand and use the ARIMA models for a single variable time series [17]. The elements of the ARIMA method are:

2.4.1 Autoregressive (AR)

The autoregressive model is a process that assumes that the data at the current time is affected by the data at previous times on the order (p).The AR process is written as follows [18]:

$$(1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p) Z_t = \delta + a_t \quad (4)$$

2.4.2 Integrated (I)

The process of stationing data against the average can be overcome by doing differentencing = d (distinction). Keep in mind that differentening is done after the data is stationary against variance. The backward shift operator is very apt to describe the differentencing process as follows [13]:

$$(1 - B)^d Z_t = Z_{t-d} \quad (5)$$

2.4.3 Moving Average (MA)

The moving average process is a process that assumes that the data at this point is affected by residual elements at previous times with the order (q) [19]. The MA process is written as follows[18]:

$$Z_t = \mu + \left(1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q\right)a_t \tag{6}$$

In general, the ARIMA model is written as follows [13]:

$$\phi_p(B)(1-B)^d Z_t = \theta_q(B)a_t \tag{7}$$

2.5. Neural Network Autoregressive/NNAR

Artificial neural networks (ANNs) are the most widely used neural network models for time series modeling and forecasting [5] . One of the advantages of ANN compared to other models is that it has a universal zero estimator that is able to estimate large class functions with a high degree of accuracy [5].

The Autoregressive Neural Network (NNAR) model is a specific model of the ANN model, where the input layer is in the form of a single variable input with a lag model of 1, lag 2, and so on until the lag to p is called NNAR. The mathematical form of NNAR is as follows [20]:

$$Z_t = w_0 + \sum_{j=1}^{h} w_j \times g\left(w_{0,j} + \sum_{i=1}^{p} w_{i,j} \times Z_{t-1}\right) + \varepsilon_i \tag{8}$$

Where Z_t is the output, $Z_{t-1}; \dots; Z_{t-p}$ is the input, $w_{i,j}$ $(i = 0,1,2,\dots,p, j = 1,2,\dots,h)$ dan w_j $(j = 1,2,\dots,h)$ are model parameters or connection weights, n is the number of inputs, g is the activation function and h is the number of hidden layers.

These layers involve a linear combination function that connects each neuron between the layers, followed by an activation function that gives non-linear to the network. Using this combination, the NNAR model can learn from the input data and produce outputs that forecast time series with a high degree of accuracy.

2.6. Model Hybrid ARIMA-NNAR

The ARIMA-NNAR hybrid model is used as an alternative model to solve the problem of time series data. There are several models that can be used, but by using a hybrid model, the accuracy of the prediction results can be improved. Because by combining models, it is hoped that it can overcome the shortcomings of one model with the advantages of another. A hybrid model is a method of combining one or more models in the functioning of a system. According to [5] In general, the combination of time series models that have a linear and nonlinear structure can be written as follows:

$$Z_t = L_t + N_t \tag{9}$$

The ARIMA model is used to solve linear cases, where linear residual still contains nonlinear information. Mathematically, it can be written as follows:

$$e_t = Z_t - \hat{L}_t^{ARIMA} \tag{10}$$

The next step is to model the residuals from the ARIMA model as the NNAR input, since the ARIMA model has identified a linear trend so the residue is assumed to include nonlinearly. The predictions from the NNAR method were then combined with the predictions of the AREMA method. Mathematically, the overall prediction results obtained are as follows:

$$\hat{Z}_t^{HYBRID} = \hat{L}_t^{ARIMA} + \hat{N}_t^{NNAR} \tag{11}$$

2.7. Best Model Selection

There is no universally applicable best model because, the effectiveness of a model depends largely on the specifics of the data to be analyzed. The data used in this study is time series data to find out the value of the forecast, according to [16] forecasting is a technique to estimate a value in the future by paying attention to past data and current data. Some of the error measurement approaches used in this study are:

2.7.1 Information Intelligence Criterion (AIC)

The Akaike Information Criterion (AIC) is a measure used in the selection of statistical models. AIC can help compare different potential models and determine which one best fits the data and avoid overfitting. The AIC mathematical equations are written as follows:

$$\mathrm{AIC} = 2\mathrm{k} + 2\ln(\mathrm{L}) \tag{12}$$

2.7.2 Root Mean Square Error (RMSE)

Root Mean Square Error (RMSE) is a residual deviation (prediction error). Residual is a measure of how far away the data point of the regression line is; RMSE is a measure of how dispersed this residue is. In other words, it tells how the data is concentrated around the most suitable line [21]. Value RMSE written in equations [22]:

$$\mathrm{RMSE} = \sqrt{\sum_{i=1}^{n} \frac{(\hat{Z}_t - Z_t)^2}{n}} \tag{13}$$

2.7.3 Mean Absolute Percentage Error (MAPE)

The MAPE value is used to measure the accuracy of a model written in the percentage where the best model is marked with the smallest MAPE value [23]. The MAPE evaluation is calculated using the absolute error of each period divided by the actual observation value for that period. The MAPE value is written in the equation:

$$\mathrm{MAPE} = \frac{\sum_{t=1}^{n} |(\frac{Z_t - \hat{Z}_t}{y_t}) X 100\%|}{n} \tag{14}$$

3. Results and Discussion

3.1 Descriptive Analysis

Descmutriptive data is carried out with the aim of providing an overview of the initial information on the data of the Indonesia Sharia Sharia Stock Index. The daily data of the Indonesia Sharia Stock Index for the period from January 2, 2025 to April 30, 2025 is 74 data.

Table 3. 1

Maximum Value	Minimum Score	Average (Mean)	Standard Deviation
216.38	185.66	206.23	7.057

Descriptive Statistics of Indonesia Sharia Stock Index Data

Based on Table 3.1, it is known that the data of the Indonesia Sharia Stock Index with the largest value is on January 2, 2025 of 216.38 and the minimum index value on April 9, 2025 is 185.66. The average Indonesia Sharia Stock Index is 206.23 with a standard deviation of 7.057.

Initial identification through a time series plot description was carried out with the aim of evaluating the diversity of data. The results of the plot output obtained, it appears that the data has a pattern that tends to always experience an increase and decrease. Likewise, the diversity or deviation of data does not look constant because the value of the data tends to be very low.

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Figure 3.1 Data Plot of Indonesia Sharia Stock Index (2 January 2025 – 30 April 2025)

Figure 3.1 shows the fluctuations of the Indonesia Sharia Stock Index (ISSI) from early January 2025 to March 2025 with a relative index in the range of 194-216. However, in early April there was a decline to around 185-186. Despite the fact that market movements are quite dynamic, in mid-April the index continues to rise until the end of the month.

In the plot, Figure 3.1 shows that the data is not yet stationary in variance and also stationary in mean. To further ensure that the data is stationary can be seen from the Dickey Fuller Statistical Test, the hypothesis used is:

H_0 : $\rho = 0$, there is a root of a non-stationary unit or time series

H_1 : $\rho \neq 0$, there is no unit root or the time series is stationary

where the test criterion are reject H_0 if p-value < α so it can be concluded that the data has not met the assumption of stationary with a significant level of 5% because the obtained p-value $= 0.53 > \alpha = 0,05$ which means that it fails to reject H_0 or the data is not yet stationary so it is necessary to transform or differencing the data.

3.2 ARIMA Modeling

Modeling the Indonesia Sharia Stock Index data there are several processes that must be done. Starting with plotting Time Series data to identify data patterns, then identifying data stationarity. However, because the data is not stationary, it is necessary to transform or differencing the data twice, so that a p-value $0.01 < 0,05$ α is obtained, which means that the data is stationary.

Once it is known that the data has been stationary, the next step is identification to obtain the AREMA model. Identification is performed by looking at the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots of the data.

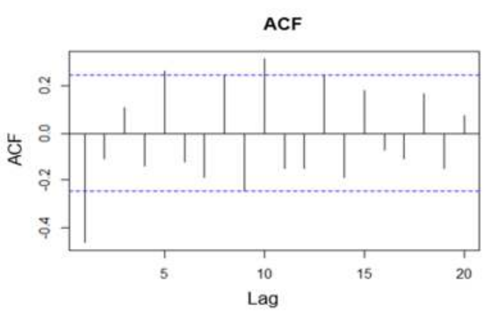

Figure 3.2 Plot Autocorrelation Function (ACF) of Indonesian Sharia Stock Indices

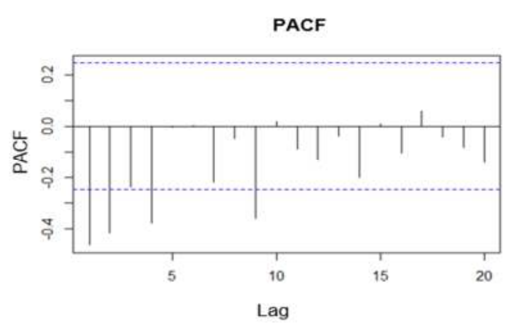

Figure 3.3 Plot Partial Autocorrelation Function (PACF) of Indonesian Sharia Stock Indices

In Figure 3.2 the ACF plot of the Indonesia Sharia Stock Index is known that the lag is significant at lag 1 so that the order q is obtained which may be q = 1. Figure 3.3, PACF can be seen that the PACF plot is identified cut off at the 1st and 2nd lags, so that the order p = 1 and p = 2 is obtained while the order value for differencing is d = 2 because differencing has been done twice.

The identification results show several ARIMA models that can be formed which are denoted p,d,q, namely AR, differencing, and MA orders. ARIMA (0,2,1), ARIMA (1,2,0), ARIMA (1,2,1), ARIMA (2,2,0), ARIMA (2,2,1). However, it does not rule out the possibility of other ARIMA models being formed.

To find out the best model among the 5 conjecture models, it is necessary to test the hypothesis on the conjecture model.

H_0 : θ = 0, Parameter is insignificant

H_1 : θ ≠ 0, Significant parameter

With the test criterion, reject H_0 if $|t_{count}| > t_{table}$atau p-value < α with a significant level α of 0.05, which means that the parameter is significant. The parameter estimation results of the 3 initial estimation models can be seen in Table 3.2.

Table 3.2 Estimation and Testing of ARIMA Model Parameters

Models ARIMA		**Parameter estimation**	**Standard errors**	**t-Statistic**	**p-value**	**Decision**
ARIMA (0,2,1)	MA1	-0.9999	0.0458	-21.788	2.2×10^{-16}	Significant
ARIMA (1,2,0)	AR1	-0.4591	0.1098	-4.1793	2.9×10^{-5}	Significant
ARIMA (2,2,0)	AR1	-0.6468	0.1131	-5.7190	1.1×10^{-8}	Significant
	AR1	-0.4053	0.1123	-3.6077	0.0003	Significant

Based on Table 3.2, it can be seen 3 significant tentative models with rejection test criteria. Furthermore, after the parameter significance test, then the H_0. Akaike Information Criterion (AIC) value in table 3.3 is seen as follows:

Table 3.3 Akaike Information Criterion (AIC) Value ARIMA tentative model

Models ARIMA	**AIC**
ARIMA (0,2,1)	356.41
ARIMA (1,2,0)	384.83
ARIMA (2,2,0)	375.13

Based on Table 3.3, it can be seen that the ARIMA model (0,2,1) has the smallest Akaike Information Criterion (AIC) value of 356.41 compared to the ARIMA (1,2,0) and ARIMA (2,2,0) models. However, to find out the comparison of the predicted results of the three models, the three models will be continued to the next stage of testing. After diagnostics on the ARIMA model, the next stage is the Ljung-Box test to ensure that the residual is white noise (random and without patterns).

Table 3.4 Ljung-Box Test

Models ARIMA	**Lag**	**p-value**	**Decision**
ARIMA(0,2,1)	12	0.0651	No Autocorrelation
	24	0.0893	No Autocorrelation
	36	0.2439	No Autocorrelation
ARIMA(1,2,0)	12	0.0008	Autocorrelation
	24	0.0022	Autocorrelation

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	36	0.0225	Autocorrelation
ARIMA(2,2,0)	12	0.0041	Autocorrelation
	24	0.0116	Autocorrelation
	36	0.0946	No Autocorrelation

Residual independence test, autocorrelation was carried out White noise test by looking at $p - value > \alpha$ with a significant level of α of 0.05 on the Ljung-Box. A model is considered to meet when the residue exhibits white noise properties (no significant serial patterns or dependencies), where autocorrelation indicates that the model has not managed to capture all the patterns in the data, and that there is still information left. The hypothesis formulation used is:

H_0 : $\rho_1 = \rho_2 = \cdots = \rho_n = 0$, Data white noise (no autocorrelation on all lag)

H_1 : $\rho_k \neq 0$ for k=1,2, …, n Data is not white noise (there is autocorrelation on one or more lags).

With the decision criteria used, namely failing to reject if H_0 the $p - value > \alpha$ with a significant level of α of 0.05.

The results of the Ljung-Box test in table 3.4 show that the residual of the ARIMA model for the ARIMA (0,2,1) model is white noise, meaning that there is no significant autocorrelation pattern, so the ARIMA model is good enough for forecasting. However, for ARIMA(1,2,0) and ARIMA(2,2,0) the Ljung Box test showed that the residual still had autocorrelation (not white noise), which means that the ARIMA model itself was still less than optimal in capturing patterns in the data because it still had non-linear patterns. So to improve accuracy, a hybrid ARIMA-NNAR approach is applied, where ARIMA residue is used as an NNAR input to capture non-linear patterns that are not detected by ARIMA.

3.3 Autoregressive Neural Network Modeling (NNAR)

Neural Network Autoregressive (NNAR) modeling using input data of the Indonesia Sharia Sharia Stock Index begins with creating a PACF plot to see a significant lag as shown in Figure 3.4 because the lag from the data will be used as an input variable. The plot of the PACF can be seen in figure 3.4

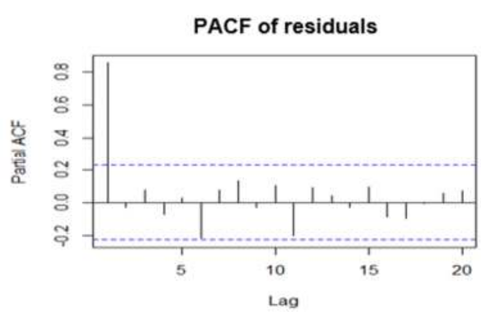

Figure 3.4 PACF Plot of Indonesia Sharia Stock Index

From the PACF plot, Figure 3.4 shows that there are two lags that are significant, namely lag 1 and lag 6. Significant data lag will be included as input. The NNAR model (p,k) means network input on the order (p) with as many neurons as (p+1)/2. Significant lag values on the order (p) will then be combined with possible neurons to produce model combinations with the smallest MAPE. The combination of the NNAR model (p,k) can be seen in the following table 3.5.

Table 3.5 Model NNAR

Model (p,k)	Neurons	RMSE	MAPE
NNAR (1,1)	1	9.999	43.377 %
NNAR (1,2)	2	10.974	48.704 %
NNAR (6,2)	2	1.789	7.119 %
NNAR (6,3)	3	2.478	11.067 %
NNAR (6,4)	4	3.914	16.461 %
NNAR (6.5)	5	3.381	14.229 %

The NNAR model in table 3.5 can be seen that out of 6 models with a combination (p.k), the NNAR model (6.2) is the best model that can be used to forecast because it has an RMSE value of 1.789 and a MAPE of 7.119%, which means that the percentage of absolute error average value of the Indonesia Sharia Stock Index data is actually 7.119%.

3.4 ARIMA-NNAR Hybrid Modeling

NNAR hybrid modeling was carried out using residual data from the ARIMA (1,2,0) and ARIMA (2,2,0) Models, then PACF plots were carried out to see significant lags as shown in Figure 3.4 because the lag from the data would be used as input variables.

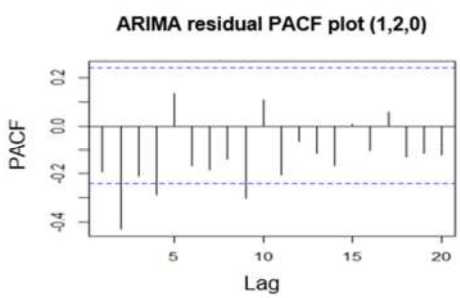

Figure 3.5 ARIMA residual PACF plot (1,2,0)

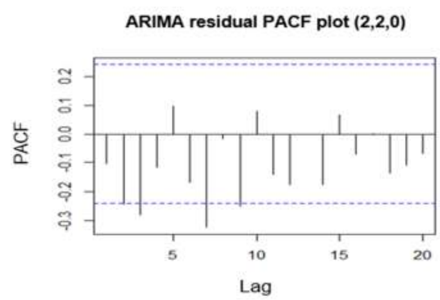

Figure 3.6 Plot of ARIMA residual PACF (2,2,0)

The PACF plot of ARIMA (1,2,0) residuals in Figure 3.5 shows significant lags at lags 2. Meanwhile, the PACF plot of ARIMA (2,2,0) residuals in Figure 3.6 shows significant lags at lags 2, 3 and 7. Significant lag data from each model will be included as input.

NNAR (p,k) model which means network input at order (p) with (p+1)/2 neurons. The significant lag value at order (p) will then be combined with possible neurons to produce a combination of models with the smallest MAPE. The combination of the NNAR (p,k) model can be seen in table 3.6 below.

Table 3.6 Best Model Selection

Residual	Lag	Model NNAR	MAPE
ARIMA (1,2,0)	2	NNAR (2,1)	1.0955
		NNAR (2,2)	1.0993
		NNAR (2,3)	1.1143
ARIMA (2,2,0)	2	NNAR (2,1)	2.4749
		NNAR (2,2)	2.4915
		NNAR (2,3)	2.4924
	3	NNAR (3.1)	2.6589
		NNAR (3,2)	2.6709
		NNAR (3,3)	2.6592
	7	NNAR (7.3)	3.8428
		NNAR (7.4)	3.8883
		NNAR (7.5)	4.0996

From table 3.6 it can be seen that the NNAR (2,1) model is best for forecasting the residuals of the ARIMA (1,2,0) model with an RMSE of 1.0955. The NNAR (2,1) model means the NNAR model with AR input lag 1 to lag-2 with a single hidden layer with a neuron count of 1. Meanwhile, to forecast the residuals from the ARIMA (2,2,0) model, the best model is NNAR (2,1) with an RMSE of 2.4749. The NNAR (2,1) model means the NNAR model with AR input lag 1 to lag-2 with a single hidden layer with a neuron count of 1. The following is the residual data from the forecast results using the best model.

The best NNAR model used to forecast the residuals of ARIMA (1,2,0) and ARIMA (2,2,0) which are non-linear values that remain in the residuals and cannot be captured by linear methods. The residual forecast results will then be summed with the ARIMA forecast results for a more optimal prediction of the Indonesia Sharia Stock Index using equation (9). The comparison of the forecast results using the ARIMA, NNAR, and hybrid ARIMA-NNAR methods is presented in the following Table 3.7 and Figure 3.7.

Table 3.7 Comparison actual data, ARIMA, NNAR, and Hybrid

Time	Actual	ARIMA	NNAR	Hybrid ARIMA-NNAR
April 21, 2025	206.16	205.8039	206.9912	207.0339
April 22, 2025	208.67	207.4946	209.9696	208.8701
April 23, 2025	210.09	208.9986	211.6150	209.5448
April 24, 2025	210.22	210.5883	212.0124	210.4272
April 25, 2025	212.02	212.1386	212.8155	212.0674
April 28, 2025	212.97	213.7070	213.0124	213.4764
April 29, 2025	214.23	215.2671	211.7346	215.0089
April 30, 2025	215.04	216.8311	211.7482	216.6224
RMSE		**0.979**	**1.789**	**0.755**
MAPE		**3.938 %**	**7.119 %**	**2.857 %**

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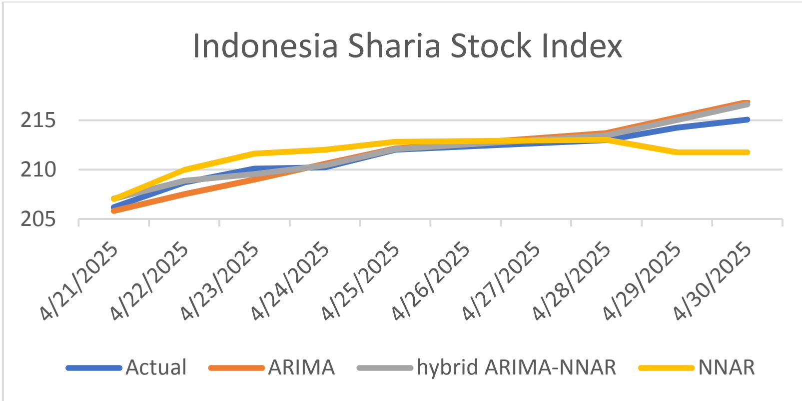

Figure 3.7 Comparison plot of actual data, ARIMA, hybrid ARIMA-NNAR and NNAR

CONCLUSIONS AND SUGGESTIONS

4.1 Conclusion

Based on the analysis and discussion that has been carried out, it can be concluded.

1. The ARIMA-NNAR hybrid model using ARIMA (1,2,0) NNAR (2,1) residuals is the best model for predicting the Indonesian Sharia Stock Index with an RMSE value of 0.755 and a MAPE value of 2.857% which indicates the model has very good prediction accuracy compared to using the ARIMA or NNAR method.
2. Forecasting the Indonesian Sharia Stock Index for the next 8 days on April 21, 2025 to April 30, 2025 is 207.0339; 208.8701; 209.5448; 210.4272; 212.0674; 213.4764; 215.0089; 216.6224 respectively.

4.2 Suggestions

Suggestions given for further research are that you should compare the hybrid ARIMA method with other machine learning methods, besides that it is advisable to identify the data used whether there is a trend or seational in the data.

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