JTAM (Jurnal Teori dan Aplikasi Matematika)
http://journal.ummat.ac.id/index.php/jtam
p-ISSN 2597-7512 | e-ISSN 2614-1175
Vol. 8, No. 2, April 2024, pp. 578-593

Projection of PT Aneka Tambang Tbk Share Risk Value Based on Backpropagation Artificial Neural Network Forecasting Result

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Article History:
Received : 20-11-2023
Revised : 01-04-2024
Accepted : 02-04-2024
Online : 02-04-2024

Keyword:
Backpropagation Neural Network;
Expected shortfall;
Nguyen-Widrow;
PT. Aneka Tambang Tbk.

ABSTRACT

PT Aneka Tambang Tbk (ANTAM) received an award as the most sought-after stock issuer in Indonesia in 2016. That stock continued to attract investors in 2022 due to a 105% increase in net profit and a 19% increase in sales from the previous year. Despite the upward trend, investors still had doubts due to the fluctuating movement of ANTAM's stock prices. The price fluctuations impact the difficulty in determining the actual price movements. Hence, forecasting was needed to understand future stock price movements to assist investors in making informed investment decisions. The Backpropagation Neural Network method had good capabilities for fluctuating data types. However, this method has the disadvantage of a lengthy iteration process. To handle this limitation, The Nguyen-Widrow weighted setting was applied to address this constraint. The expected Shortfall (ES) method used the forecasting results to measure investment risk. This research uses ANTAM stock closing price data from May 2, 2018, to May 31, 2023. Based on the analysis results, the best architecture was obtained with a configuration of 5-11-1, using Nguyen-Widrow weight initialization and a combination of a learning rate of 0.5 and momentum of 0.9. This architecture yielded a prediction error based on the Mean Absolute Percentage Error (MAPE) of 1.9947%, which was classified as a very accurate prediction. Risk measurement with the ES method based on the prediction for the next 60 periods showed that at a 95% confidence level, the risk value was 0.002181; at a 90% confidence level, it was 0.002165; at an 85% confidence level, it was 0.002148, and at an 80% confidence level, it was 0.002132. The probability values of risk were very beneficial for investors to determine how many assets were needed to cover the potential losses incurred from an investment.

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https://doi.org/10.31764/jtam.v8i2.20267
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A. INTRODUCTION

Investment in the stock market increases every year to achieve economic goals and growth (Karatri et al., 2021; Jang & Park, 2019). Stock selection represents a challenging task in determining the factors influencing investor decisions. Evaluating the financial performance of a company has attracted significant attention and interest from various parties, such as managers, creditors, financial experts, investors, and researchers. Modeling financial problems is more complex and sometimes conflicting, not to mention the subjectivity of decision-makers in the evaluation process (Nguyen et al., 2020). Investment was a form of capital placement made by investors in the present to gain profits in the future. It involved elements of risk and uncertainty (Ilyas et al., 2018; Maulidya et al., 2020). One of the types of investments widely chosen and traded in the stock market was stocks. The main factor that investors should pay attention to is the stock price. High price, low price, and close price were three categories that constitute stock prices in the capital market. A company's high revenue or profit will result in a high stock price (Fathi et al., 2021). The fluctuation of stock prices is crucial for investors because if a company's stock price consistently rises, investors or potential investors might perceive the company as successful in managing its business and vice versa (Ardana et al., 2019).

PT Aneka Tambang Tbk, more commonly known as ANTAM, was a vertically integrated mining company focusing on exports. The activities conducted by ANTAM included exploration, excavation, processing, and trading of commodities such as gold, silver, ferronickel, nickel, bauxite, and coal. ANTAM operates in various regions of Indonesia, known for abundant mineral resources, and has secured long-term clients in Asia and Europe. In 2016, ANTAM received the IDX Best Blue 2016 award from the Indonesia Stock Exchange (BEI) for being the most sought-after stock by investors (Indrastiti & Rafie, 2016). ANTAM remains one of the coveted stocks in Indonesia in 2022, evidenced by a 105% increase in net profit from the previous year, reaching IDR 3.82 trillion, supported by a 19% rise in sales to IDR 45.93 trillion (Malik, 2023). Therefore, ANTAM's stock continues to attract the attention of many investors.

The stock market allows investors to put money into businesses to gain profits from purchasing and selling listed stocks (Agustini et al., 2018; Fathi et al., 2021; Utami, Haris, & Wasono, 2023). Besides offering profit potential, such investments also entail significant risks. Therefore, the analysis of stock price movements became a main point for investors because the fluctuations in stock prices did not guarantee the profits or losses incurred (Ardana et al., 2019; Gurav, 2018).

Stock prices tended to be nonlinear and unstable. It was influenced by numerous factors such as political news, corporate policies, economic conditions, investor expectations, and investor psychological conditions (Ardana et al., 2019), among others (Wardhani & Gea, 2022). Therefore, forecasting stock prices involves many processes due to changing conditions and noise. Fluctuating stock prices challenged investors to apply appropriate methods to model historical stock price data and predict future periods. In the last decade, the application of Machine Learning (ML) techniques such as Support Vector Machine (SVM), Artificial Neural Network (ANN), and Reinforcement Learning (RL) has been widely conducted and considered effective in predicting financial data (Fauzi et al., 2023; Gurav, 2018).

Backpropagation Neural Network (BPNN), an extension of Artificial Neural Network (ANN), was a machine learning method that simulated the composition and functionality of the human brain. ANN could accurately forecast and differentiate nonlinear data patterns without previous experience, making it widely accepted and applicable (Gurav, 2018). Moreover, BPNN features efficient learning, generalization, and parallel processing capabilities in solving complex problems. Therefore, BPNN was appropriate for modeling time series data with notable deviations and irregularities (Fathi et al., 2021). The pattern of relationships between neurons and the initialization of weight values determined the processing ability of BPNN. The large number of input and hidden units affected the training duration. Additionally, starting weight values far from the actual weights could slow the training process (Wibowo et al., 2019). Hence, the Nguyen-Widrow algorithm initialized neural network weights to expedite training (Linan et al., 2019).

Stock data forecasting using BPNN was conducted by (Fathi et al., 2021), predicting 20 stock prices. The research finding revealed that BPNN, with ten neurons in the input layer, 21 neurons in the hidden layer, and one neuron in the output layer, could forecast stock prices effectively, as evidenced by the Mean Absolute Percentage Error (MAPE) averaging less than 10%. The optimization of BPNN network training performance with Nguyen-Widrow optimization by (Kartini & Chen, 2017; Mittal et al., 2020), and (Wibowo et al., 2019) demonstrated that the Nguyen-Widrow weight initialization in the BPNN model could enhance training speed and forecasting accuracy.

Stock risk analysis is crucial in stock investment because every investment inevitably involves risks, including stock investment (Mara & Sipahutar, 2020; Putrama & Rizal, 2018). By conducting a stock risk analysis, investors can reduce their investment risks by selecting stocks with lower risks or diversifying their portfolios (Rakhman, 2016). Stock risk analysis also helps investors identify stocks with higher profit potential, enabling them to choose more profitable stocks (Putrama & Rizal, 2018). By understanding the risks associated with a particular stock, investors can avoid stocks with excessively high risks that could lead to losses (Apritchzeki, 2020). Stock risk analysis assists investors in making better and more rational investment decisions (Mara & Sipahutar, 2020). With accurate stock price forecasting results, unwanted risks can be minimized.

The expected shortfall is the average of all losses beyond the risk value. An appropriate distribution model must be assumed for this risk measurement to function optimally. Considering that stock price volatility has several economic implications, it is important to measure the investment risk in the stock market accurately (Afuecheta et al., 2022). The application of the expected shortfall method to measure stock price risk has been carried out by (Lina, 2022; Rizani et al., 2019; Utami et al., 2023) because this method can calculate risk for both normally and non-normally distributed data, accurately reflecting the diversification effect to minimize risk. The expected shortfall method is often considered a development of the Value at Risk (VaR) method and represents a risk measure expectation exceeding the VaR value. Therefore, this research aims to measure the stock risk of PT. Aneka Tambang Tbk. using the expected shortfall method based on forecasting results with the BPNN architecture with Nguyen-Widrow weight initialization.

B. METHODS

The data used in this research is the daily historical stock price data of PT Aneka Tambang Tbk (ANTAM), obtained from the website https://www.investing.com. The analyzed data consists of ANTAM's closing stock prices from January 2, 2018, to July 10, 2023, comprising a total of 1340 observations. The data analysis steps are outlined as follows:

1. Descriptive Analysis

Performing descriptive analysis of PT Aneka Tambang Tbk (ANTAM) closing stock prices from January 2, 2018, to July 10, 2023. This step is conducted to gain an overview or understand the general characteristics of the data to be used.

2. Data Preprocessing

Data preprocessing is carried out to prepare the data for analysis using the BPNN method with Nguyen-Widrow optimization. The closing stock prices of ANTAM are normalized using equation (1)(Soenandi & Hayat, 2019);

$$x' = \frac{0{,}8\ (x_i - x_{min})}{(x_{max} - x_{min})} + 0{,}1 \tag{1}$$

Normalized data can be consistent with the activation function and will be stable. Since the sigmoid activation function will be used for the data, the data will be converted using the formula to a narrower interval or a number that falls between 0 and 1. The goal of this transformation process, known as data normalization, is to make the calculating process simpler (Christyaditama et al., 2020). The normalized data is then divided into training and testing data, with an 80% proportion for training and 20% for testing. Subsequently, the training and testing data are arranged with a pattern of stock prices for a 5-day trading period, used as input data to forecast the stock price for the next 1 day.

3. Backpropagation Neural Network Architecture (BPNN)

BPNN is a supervised learning algorithm commonly used to train perceptrons capable of addressing the weight adjustment issues of continuous nonlinear functions in multi-layered feedforward neural networks (Wang et al., 2020; Xu et al., 2019). Through the use of backpropagation, the network is trained to reach convergence between its capacity to identify patterns from training and its ability to correctly respond to input patterns that resemble the model from movement. The three primary steps of backpropagation, which involves a multilayer perceptron as the neural network structure, are transmission between the input and output layers, calculating errors, and updating weights from the output layer to the input layer. The backpropagation learning algorithm consists of the following steps (Wibowo et al., 2019):

a. Initially assigning weights w_{kj} for every hidden unit $(z_i, i = 1, 2, \dots, p)$ to every output unit $(y_i, i = 1, 2, \dots, m)$ and weights v_{ji} for every input $(x_i, i = 1, 2, \dots, n)$ to every hidden unit.
b. Calculating the value of each neuron in the hidden layer z_j using equations (2) and (3),

$$z_{net_j} = v_{j0} + \sum_{j=1}^{n} x_i v_{ji} \tag{2}$$

$$z_j = f\left(z_{net_j}\right) = \frac{1}{1 + e^{-z_{net_j}}} \tag{3}$$

c. Calculating the output values in each output layer using equations (4) and (5),

$$y_{net_k} = w_{k0} + \sum_{j=1}^{p} z_j w_{jk} \tag{4}$$

$$y_k = f(y_{net_k}) = \frac{1}{1 + e^{-y_{net_k}}} \tag{5}$$

d. Calculating th δ e factor in each output unit and calculating the rate of change of weights for each hidden unit (Δw_{jk}) using equations (6) and (7),

$$\delta_k = (t_k - y_k)\, f'(y_{net_k}) = (t_k - y_k)\, y_k(1 - y_k) \tag{6}$$

$$\Delta w_{jk} = \alpha\, \delta_k\, z_j \quad ;\ k = 1, 2, \dots, m\ ;\ j = 0, 1, \dots, p \tag{7}$$

e. Calculating the δ factor in each hidden layer unit and calculating the rate of change of weights for each hidden unit (Δv_{jk}) using equations (8), (9), and (10),

$$\delta_{net_j} = \sum_{k=1}^{m} \delta_k\, w_{jk} \tag{8}$$

$$\delta_j = \delta_{net_j}\, f'\left(z_{net_j}\right) = \delta_{net_j}\, z_j(1 - z_j) \tag{9}$$

$$\Delta v_{ji} = \alpha\, \delta_j x_i \quad ;\ j = 1, 2, \dots, p\ ;\ i = 0, 1, \dots, n \tag{10}$$

f. Calculating all the new weight changes using equations (11) and (12),

$$w_{jk}(baru) = w_{jk}(lama) + (\mu \times \Delta w_{jk}) \tag{11}$$

$$v_{ji}(baru) = v_{ji}(lama) + (\mu \times \Delta v_{ji}) \tag{12}$$

g. Updating the epoch value and evaluating the model's goodness accuracy with the Mean Square Error (MSE) using equation (13),

$$MSE = \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n} \tag{13}$$

The general architecture of BPNN can be shown in Figure 1.

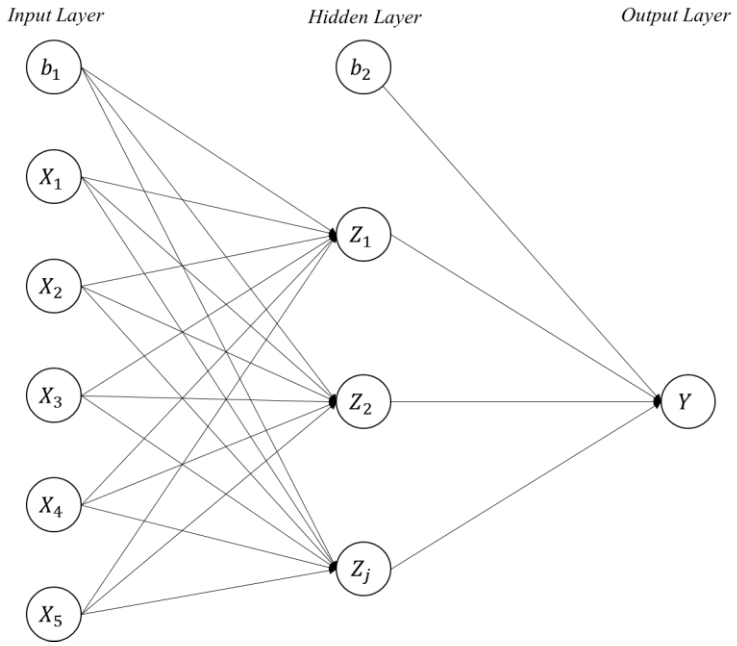

Figure 1. Architecture of BPNN

4. The Nguyen-Widrow Algorithm

The initial values of weights can affect how quickly the network converges. The common procedure used in backpropagation to initialize weight values is random initialization. If the weights are initially too small, it can result in the net input to hidden or output neurons approaching zero, leading to very slow learning (Christyaditama et al., 2020; Linan et al., 2019). Compared to random initialization, the Nguyen-Widrow approach of initializing initial weights can speed up the learning process. The consequences from input units to hidden units are initialized via the Nguyen-Widrow optimization. A range is chosen for the initialization of the weight values, taking the number of concealed units into account. The Nguyen-Widrow scale factor (β) is calculated using equation (14), and then the weight initialization is calculated using equations (15) and (16) (Christyaditama et al., 2020).

$$\beta = 0{,}7(p)^{1/n} = 0{,}7\sqrt[n]{p} \tag{14}$$

$$\left\|v_j(old)\right\| = \sqrt{v_{j1}(old)^2 + v_{j2}(old)^2 + \cdots + v_{jn}(old)^2} \tag{15}$$

$$v_{ji} = \frac{\beta v_{ji}(old)}{\left\|v_j(old)\right\|} \tag{16}$$

5. Mean Absolute Percentage Error (MAPE)

The accuracy of the forecasting results is evaluated by calculating the MAPE value. The MAPE value is a percentage calculated from the absolute Error values in each period, divided by the total number of actual data in that period (Haris et al., 2023; Kharisudin et al., 2023; Yunitasari et al., 2023). The calculation formula for MAPE is shown by equation (17), where y_i is the actual data value, $\hat{y}_i$ is the forecasted data value, and n is the number of observations used.

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \times 100\% \tag{17}$$

According to (Yulisa et al., 2023), there is a range of values that can be used as an assessment for evaluating the performance of a forecasting model. This range of values is indicated in Table 1.

Table 1. Category of MAPE Value

Value Ranges of MAPE	Category
$< 10\%$	Very good
$10 - 20\%$	Good
$20 - 50\%$	Fairly good
$> 50\%$	Bad

6. Risk Analysis using the Expected Shortfall Method

The expected shortfall is a risk measurement method that considers every maximum loss and can estimate risk in both normally and non-normally distributed data (Azmi et al., 2022; Setiawan & Rosadi, 2020; Syuhada et al., 2021). The expected shortfall method can be illustrated as shown in Figure 2.

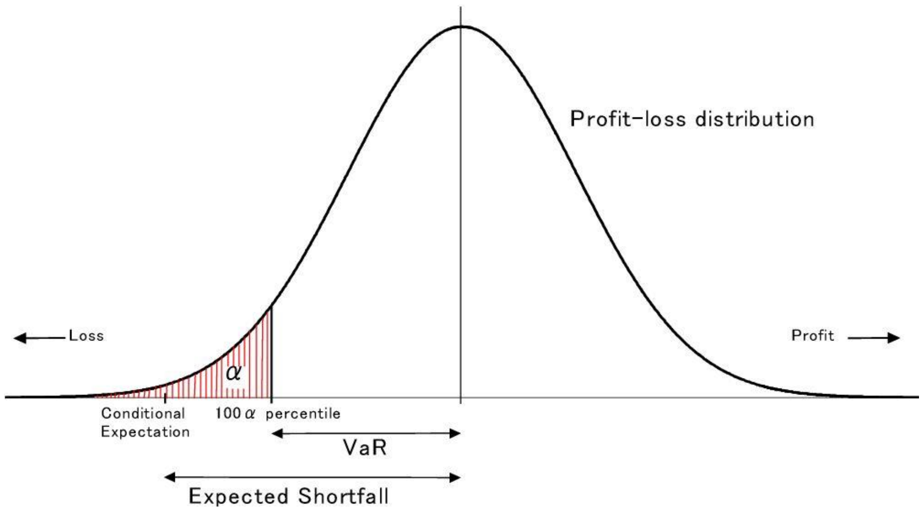

Figure 2. Illustration of the Expected Shortfall Method

The expected shortfall method is a non-parametric method that can be used to measure risk based on historical data by sorting the predicted data return values from lowest to highest. The equation for the expected shortfall method is formulated by equation (18), with N being the number of stock price data, $N\alpha$ as an integer value $\leq N\alpha$, and X_i as the sorted price value.

C. RESULT AND DISCUSSION

1. Descriptive Analysis

The stock price graph of PT Aneka Tambang Tbk (ANTAM) from January 2, 2018, to July 10, 2023, is examined in order to perform a descriptive analysis. The time series plot of PT Aneka Tambang Tbk (ANTAM)'s stock price, as shown in Figure 3.

Figure 3. Stock Price Chart of ANTAM from January 2, 2018, to July 10, 2023

Based on Figure 3, ANTAM's stock price experienced a drastic increase towards the end of 2020 until the early part of 2021. This surge was attributed to driving factors such as the sentiment of rising nickel commodity prices, especially Class I nickel used in electric vehicle batteries (Dwi, 2021). The highest stock price occurred on January 20, 2021, due to the global commodity price increase euphoria and the establishment of an electric battery factory in Indonesia (Ihsan, 2021). When viewed overall, the stock price exhibits fluctuations and tends to be nonlinear. Therefore, a nonlinear method will be employed using the BPNN method. The stock data plot for ANTAM from January 2, 2018, to July 10, 2023.

2. Data Analysis

Data preprocessing is carried out to prepare the data for analysis using the BPNN method with Nguyen-Widrow weight initialization. The initial step involves organizing the actual stock price data patterns up to 4 days prior, which are used to forecast the stock price for the following day. The arranged data patterns are then divided into training and testing data, with proportions of 20% for testing and 80% for training. After forming the data patterns, normalization is applied using equation (1). The results of the organized and normalized data patterns are presented in Table 2.

Table 2. The Arrangement of Data Patterns that have been Normalized

Data Category	Data Patterns	X_1	X_2	X_3	X_4	X_5	Y
Training	1	0.181	0.179	0.182	0.186	0.185	0.186
	2	0.179	0.182	0.186	0.185	0.186	0.185
	3	0.182	0.186	0.185	0.186	0.185	0.185
	⋮	⋮	⋮	⋮	⋮	⋮	⋮
	1067	0.697	0.723	0.709	0.709	0.706	0.692
	1068	0.723	0.709	0.709	0.706	0.692	0.683
Testing	1069	0.900	0.900	0.892	0.851	0.826	0.826
	1070	0.900	0.892	0.851	0.826	0.826	0.809
	1071	0.892	0.851	0.826	0.826	0.809	0.719
	⋮	⋮	⋮	⋮	⋮	⋮	⋮
	1334	0.438	0.451	0.455	0.467	0.496	0.459
	1335	0.451	0.455	0.467	0.496	0.459	0.463

The training data is then used to train the BPNN architecture, either with random weight initialization or Nguyen-Widrow weight initialization. At the same time, the testing data is utilized to evaluate the accuracy of the forecasting results. The training of the BPNN network is performed using 5 inputs, 1 output, and a combination of the number of neurons in the hidden layer ranging from 1 to 20. The set parameters include the number of epochs set to 1000, the target error defined as 0.0001, the learning rate with a combination of 5 experiments (0.5, 0.1, 0.05, 0.01, and 0.001), and momentum values with a combination of 5 experiments (0.9, 0.7, 0.5, 0.3, and 0.1). The results of the training process with random initial weight initialization are shown in Table 3.

Table 3. The Results of the Training Process for the BPNN Architecture with Random Initial Weights

Architecture	Momentum	MSE Value				
		Learning Rate				
		0.5	0.1	0.05	0.01	0.001
5-1-1	0.9	**0.0005482**	0.0005522	0.0005574	0.0005584	0.0005953
	0.7	0.0006293	0.0006333	0.0006315	0.0006637	0.0006584
	0.5	0.0006989	0.0007074	0.0007123	0.0007279	0.0007409
	0.3	0.0007697	0.0007778	0.0007821	0.0007911	0.0008030
	0.1	0.0008534	0.0008682	0.0008610	0.0008716	0.0008812
5-2-1	0.9	**0.0005338**	0.0005336	0.0005373	0.0005460	0.0005584
	0.7	0.0005769	0.0005770	0.0005894	0.0005882	0.0006005
	0.5	0.0006134	0.0006221	0.0006253	0.0006322	0.0006450
	0.3	0.0006638	0.0006701	0.0006729	0.0006789	0.0006877
	0.1	0.0007245	0.0007300	0.0007330	0.0007398	0.0007497
…	…	…	…	…	…	…
5-20-1	0.9	**0.0004758**	0.0004741	0.0004757	0.0004779	0.0004870
	0.7	0.0005055	0.0005030	0.0005086	0.0005114	0.0005202
	0.5	0.0005353	0.0005393	0.0005413	0.0005469	0.0005540
	0.3	0.0005761	0.0005801	0.0005835	0.0005869	0.0005953
	0.1	0.0006393	0.0006403	0.0006402	0.0006464	0.0006556

Table 3 shows the results of the training process with random initial weight initialization. The results indicate that smaller learning rates and smaller momentum tend to result in larger MSE values. An architecture consisting of 5 input layers, 8 hidden layers, and one output layer yields the best-performing BPNN architecture with random weights at 0.5 learning rate and 0.9 momentum (5-8-1). At 0.00042492, this architecture produces the lowest MSE value. Next, Nguyen-Widrow initial weight initialization is used to train the network. The outcomes of the Nguyen-Widrow initial weight initialization training procedure are displayed in Table 4.

Table 4. The Results of the Training Process for the BPNN Architecture with Nguyen-Widrow Initial Weights

Architecture	Momentum	MSE Value				
		Learning Rate				
		0,5	0,1	0,05	0,01	0,001
5-1-1	0,9	**0,0003757**	0,0003808	0,0003803	0,0003824	0,0003904
	0,7	0,0003998	0,0004047	0,0004102	0,0004063	0,0004153
	0,5	0,0004248	0,0004257	0,0004302	0,0004344	0,0004418
	0,3	0,0004586	0,0004644	0,0004675	0,0004734	0,0004798
	0,1	0,0005105	0,0005199	0,0005195	0,0005234	0,0005329
5-2-1	0,9	**0,0003772**	0,0003740	0,0003805	0,0003845	0,0003971
	0,7	0,0004086	0,0004183	0,0004182	0,0004265	0,0004398
	0,5	0,0004489	0,0004571	0,0004609	0,0004645	0,0004727
	0,3	0,0004964	0,0005024	0,0005051	0,0005114	0,0005206
	0,1	0,0005527	0,0005582	0,0005626	0,0005659	0,0005730
…	…	…	…	…	…	…
5-20-1	0,9	**0,0004321**	0,0004315	0,0004332	0,0004347	0,0004458
	0,7	0,0004551	0,0004608	0,0004656	0,0004607	0,0004712
	0,5	0,0004768	0,0004771	0,0004800	0,0004819	0,0004867
	0,3	0,0004953	0,0004969	0,0004984	0,0005005	0,0005039
	0,1	0,0005164	0,0005178	0,0005192	0,0005211	0,0005233

Table 4 shows the results of the training process with Nguyen-Widrow initial weight initialization. Similar to random weights, smaller learning rates and smaller momentum tend to result in larger MSE values. Using an architecture consisting of 5 input layers, 11 hidden layers, and one output layer (5-11-1), the training results with Nguyen-Widrow initial weight initialization produce a BPNN architecture with a learning rate of 0.5 and a momentum of 0.9. At 0.00042492, this architecture yields the lowest MSE value. The selection of the best model is determined by looking at the smallest MSE value among the training processes of the BPNN architecture using both random initial weights and Nguyen-Widrow initial weights. A comparison of the best training results for the BPNN architecture from both weight initialization methods is shown in Table 5.

Table 5. Comparison of BPNN Architecture Training Results based on Random and Nguyen-Widrow Initial Weights

Initial Weights	Neuron Hidden Layer	Learning Rate	Momentum	MSE
Random	8	0,5	0,9	0,00042492
Nguyen-Widrow	11	0,5	0,9	0,00035443

Table 5 shows that the smallest MSE value is 0.00035443, obtained from using Nguyen-Widrow initial weights with the architecture 5-11-1 and a combination of learning rate 0.5 and momentum 0.9. Therefore, Nguyen-Widrow initial weight initialization yields better results compared to random initial weight initialization. The best network architecture obtained from the training process is illustrated in Figure 4, which provides the weight values. X represents neurons in the input layer, totalling 5 with 1 bias; Z represents neurons in the hidden layer, totalling 11 with 1 bias; and Y represents neurons in the output layer. The final weights include$v_{10} = -0.42$, $v_{20} = -0.48$, and so on, until $w_{11\,1} = 1.04$. This optimal architecture is then used for the testing process.

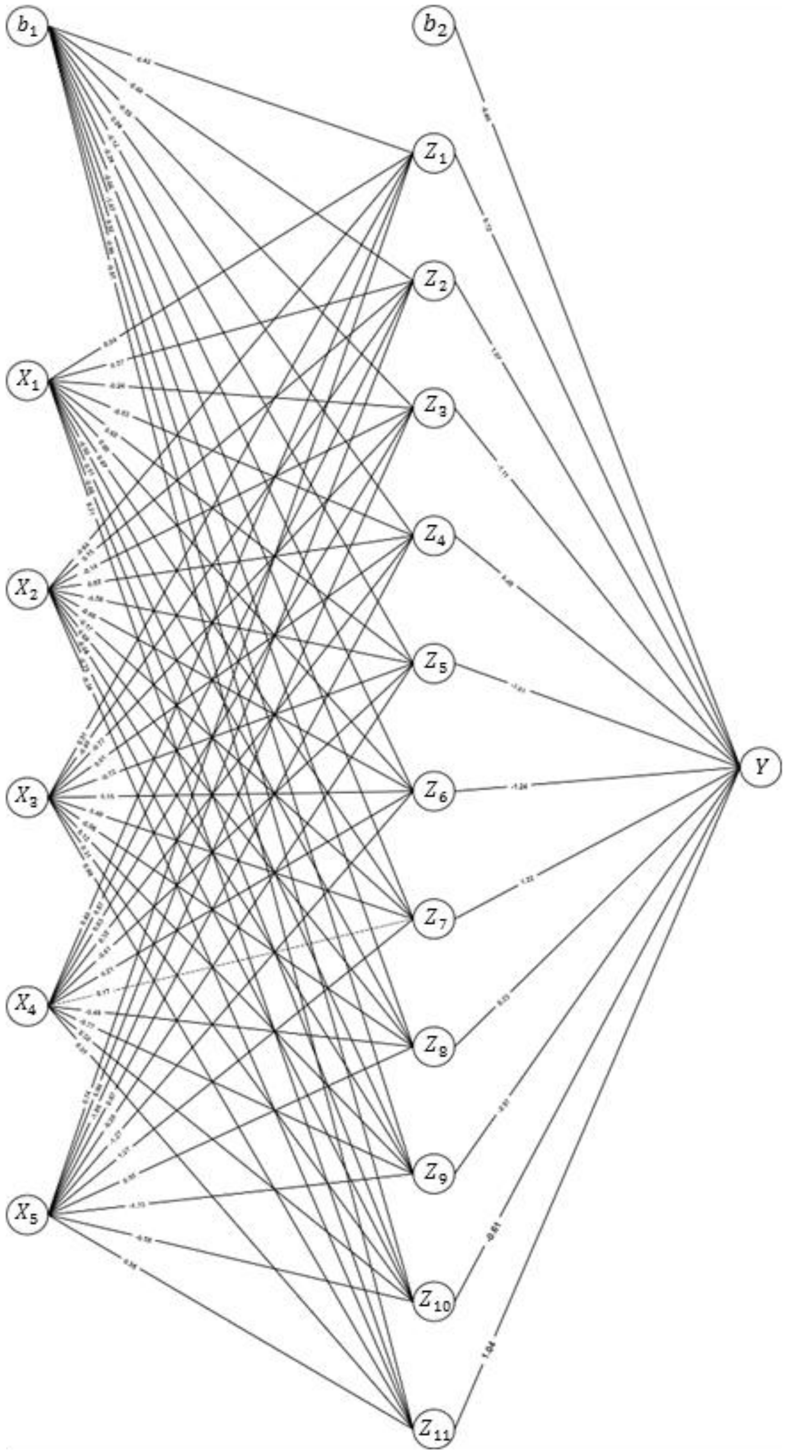

Figure 4. The BPNN Architecture (5-11-1) with Nguyen-Widrow Initial Weights

The best BPNN architecture of (5-11-1) with Nguyen-Widrow initial weights is then used to evaluate the accuracy of forecasting results using testing data. The performance results of the best architecture based on testing data yield an MSE value of 0.0014177. In addition to the MSE value, model goodness is also evaluated using MAPE. The calculated MAPE value is 1.9947%. According to Table 2.1, the resulting MAPE value falls within the range of <10%, indicating that the model's forecasting accuracy is very good. The performance of the best architecture on testing data is presented in Figure 5.

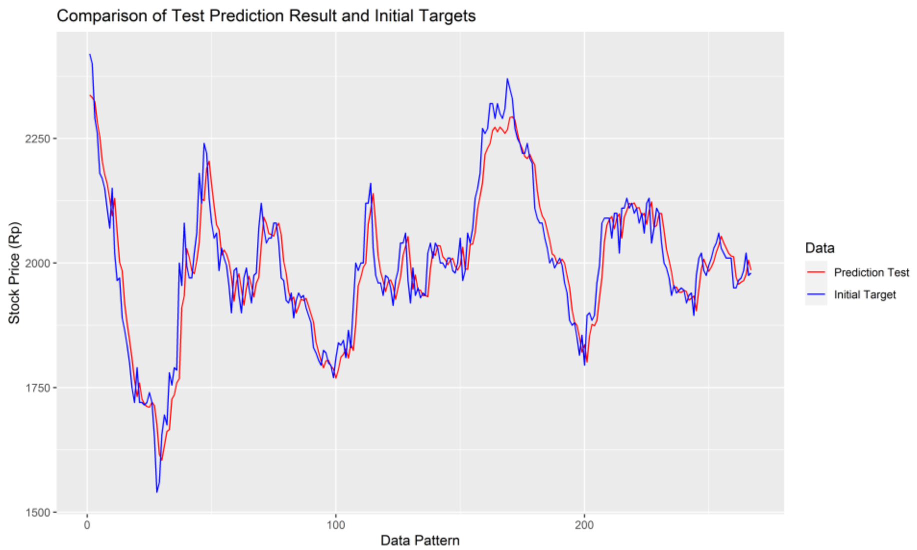

Figure 5. Comparison of Actual Data with the Predicted Results of the BPNN Architecture (5-11-1) using Nguyen-Widrow Initial Weights

The BPNN architecture 5-11-1 with Nguyen-Widrow initial weights can achieve excellent forecasting performance. The application of the Nguyen-Widrow Initialization algorithm has been proven to improve prediction accuracy, as shown in previous research (Aisyah et al., 2019; Rosmaliati et al., 2018). This architecture is subsequently utilized for forecasting for the next 60 days, specifically from July 11, 2023, to October 5, 2023. The forecasted results are then used to estimate the risk of ANTAM stock using the expected shortfall method. The risk calculation results with the expected shortfall method, based on equation (15) at various confidence levels, are presented in Table 6.

Table 6. Estimation of Risk Value using the Expected Shortfall Method

Risk Projection	**Confidence Level (1-α)**			
	80%	**85%**	**90%**	**95%**
ANTAM	0.002132	0.002148	0.002165	0.002181

Table 6 shows that at a confidence level of 95%, the maximum risk value obtained is 0.002181. It implies that there is a 5% chance that the losses incurred by investors in ANTAM could exceed 0.002181. For example, if an investor has an initial investment of Rp 10,000,000, the estimated maximum loss for that investor is projected to be Rp 10,000,000 $\times$ 0.002181 = Rp 21,810 within a 1-day timeframe. This explanation holds for other confidence levels.

D. CONCLUSION AND SUGGESTIONS

The BPNN network architecture with Nguyen-Widrow initial weights is highly effective for daily stock price forecasting of ANTAM, as the network has demonstrated superior predictive capabilities compared to randomly initialized weights. Based on data analysis, the optimal architecture with Nguyen-Widrow initial weights is (5-11-1) with a learning rate of 0.5 and momentum of 0.9. This architecture achieves a prediction error, measured by MAPE, of 1.9947% or a prediction accuracy of 98.0053%. The results of estimating the risk value of ANTAM's stock price over 60 periods using the expected shortfall method indicate that as the confidence level increases, the level of risk also rises. The maximum risk value that an investor may incur each day at a 95% confidence level is estimated at Rp21,810. Reliable prediction methods and risk measurements can provide insights and decision-making for investors in investment. Future research could apply this architecture to evaluate the risk of stock prices or commodities that show investment potential, both on a daily or monthly basis.

ACKNOWLEDGEMENT

The Budget of Universitas Muhammadiyah Semarang funded this research for the fiscal year 2023 through the scheme of Penelitian Dosen Pratama along with Contract Number 046/UNIMUS.L/PG/PJ.INT/2023. Therefore, the research team and authors would like to thank the appropriate parties for their help with this research.

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