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OPTIMAL PORTFOLIO FORMATION USING MEAN VARIANCE EFFICIENT PORTFOLIO AND CAPITAL ASSET PRICING MODEL WITH ARTIFICIAL NEURAL NETWORK AS STOCK SELECTION METHOD

Emy Siswanah [1*], Siti Maslihah[2], Agustina Anggraini[3], Muhammad Malik Hakim[4]

[1,2,3]Department of Mathematics, Universitas Islam Negeri Walisongo Semarang
Jln. Prof. Dr. Hamka, Ngaliyan, Semarang, 50185, Indonesia

[4]Department of Informatics, Universitas Diponegoro
Jln. Prof. Sudharto SH, Tembalang, Semarang, 50275, Indonesia

Corresponding author's e-mail: ***emysiswanah@walisongo.ac.id***

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ABSTRACT

There are two main things in forming an optimal stock portfolio: stock selection and stock weight determination. This study aims to determine the performance of an optimal portfolio formed using ANN as a stock selection method and MVEP (Mean-Variance Efficient Portfolio) and CAPM (Capital Asset Pricing Model) to determine stock weights. In addition, it is also necessary to determine the characteristics of the stocks formed in the portfolio. The criteria for stock selection are choosing stocks predicted to have maximum mean returns with minimal risk. This research uses data from 10 stocks listed on the Indonesian Stock Exchange. The forecasting results state that ANN can be used to predict stock prices to get a picture of stock prices in the future. Based on the calculation results, BMRI, TLKM, ASII, TPIA, and BBNI stocks were selected to form a stock portfolio. The MVEP and CAPM methods produce stock weights with different characteristics. The MVEP method gives the most significant weight to stocks that have the largest predicted mean return but experience changes in accuracy categories. The CAPM method gives the most significant weight to stocks with less risk than other stocks and has the smallest MAPE value. Empirically, ANN can be used to select stocks to form a portfolio. Stock price predictions with the most significant mean return and small risk can be used as a reference when forming a portfolio using the MVEP and CAPM methods.

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1. INTRODUCTION

In investing in stocks, investors must uphold the saying, "Do not put all your eggs in one basket." The point is that investors should not invest in just one stock because if the stock loses, then the investment that has been invested will also lose. Therefore, investors must diversify stocks by forming a portfolio to maximize profits and reduce the risk of loss. A stock portfolio is an investment in several stocks. So, if one stock loses, a profit can still be obtained from the other stock.

To form a stock portfolio, investors need to determine the combination of stocks that make up the portfolio and know how much of the funds are invested in each stock. Mathematically, investors need to know what percentage of each stock is weighted to get maximum profits and minimal losses. Investors must form an optimal stock portfolio to maximize returns and minimize risk [1]. Two important things need to be considered when forming a stock portfolio: the method of forming a stock portfolio and selecting shares forming a stock portfolio. Many methods for forming an optimal stock portfolio include MVEP (Mean-Variance Efficient Portfolio) and CAPM (Capital Asset Pricing Model). According to Purba et al. [2] and Sukono et al. [3], CAPM and MVEP are suitable methods to form an optimal portfolio. The principle of the CAPM and MVEP methods is to maximize the expected return with a certain risk tolerance. Stock selection methods, such as fundamental techniques, clustering techniques, or random stock selection, are often used in forming stock portfolios.

This research offers a new method of selecting stocks to form a stock portfolio. The method is the ANN forecasting method. ANN forecasting is artificial intelligence forecasting. The rapid development of technology has made artificial intelligence forecasting widely available for various purposes. Artificial intelligence forecasting, such as artificial neural networks (ANN), is becoming popular and widely used to solve prediction problems in various fields, such as predicting wind waves [4], forecasting the time series of the Electrocardiogram/ECG signal [5], predicting the end of life of an automotive vehicle [6], predicting the number of patients recovered from COVID-19 [7], prediction of international visitors [8], predicting engine performance and emissions [9]. In addition to predicting, ANN is also used to classify students' academic performance [10], classify the incidence of anemia [11], and detect problems in streaming video [12]. ANN is widely used for prediction because it is an effective method [7], [13], suitable for dynamic data [6], has high accuracy [4], [5], [14], and has a small error [15], [16]. ANN is also a stable method [17], has faster convergence [4], and provides superior performance simulations [5].

ANN is an appropriate method for forecasting financial fields, such as stock prices [13], [15], [18], [19] and the index [20]. Based on the advantages of artificial neural networks (ANN), this study used ANN to predict stock prices. Through this prediction, investors can analyze which stocks have a positive or negative trend, which will rise in price, and which stocks will fall. These predictions' results can help investors make the right decisions in choosing which stocks to buy or sell.

Although there have been many studies on the ANN method, in previous studies, no one has used the results of artificial intelligence forecasting (ANN) to select stocks to form a stock portfolio. One of the algorithms in ANN is Backpropagation. ANN with the backpropagation algorithm is used to select stocks to form a stock portfolio because it excels in financial forecasting [21], is effective in forecasting [22], increases computational efficiency [23], produces accurate predictions [24], [25], and produces small errors [26]. A small error shows that the ANN method can predict future stock prices well, so that the results of stock price predictions from ANN can be used to select stocks that will be used to form stock portfolios.

In the previous study, ANN forecasting and MVEP and CAPM stock portfolio formation research were stand-alone (separate) studies. This study combines the two studies, namely the ANN forecasting method as a stock selection method and the MVEP and CAPM methods as stock portfolio formation methods. Furthermore, this merger has never existed before. ANN forecasting selects stocks based on price predictions with the most significant mean return and the least risk. The selected stock combination is then formed into a stock portfolio. MVEP and CAPM methods are used to determine the weighting of each stock. The results of this study are expected to be a preference for investors when analyzing a stock.

2. RESEARCH METHODS

2.1 Materials

Backpropagation is one of the learning techniques used in artificial neural networks (ANN) with supervised learning algorithms. Backpropagation architecture has neurons that are in one or more hidden layers. Backpropagation architecture has n neurons (plus one bias), one hidden layer with p neurons (plus one bias), and m output neurons [27]. There are three training phases in backpropagation, namely the forward phase, the backward phase, and the weight change, so that errors can be minimized [28]. The forward phase is a pattern of forward calculation inputs starting from the input layer to the output layer. The backward phase is the distance or reduction between the output of the network and the expected target. The activation function used in this study is the binary sigmoid function. The binary sigmoid function has a value of 0 to 1. This function is often used because it has a simple derivative and is easy to calculate. The derivative of the binary sigmoid function is used to update the network weights [29].

The use of backpropagation aims to obtain harmony in recognizing learning patterns correctly and good actions for other similar patterns (test data). Mutually exclusive data is the data pattern used for learning and testing [29]. The pattern of data sharing is 80% for the training process and 20% for the testing process. Before conducting the training and testing process, the number of neurons in the input, hidden, and output layers is determined. The training and testing process is carried out to form the best network structure with the least errors. The network structure is used to forecast stock prices over several periods ahead. The results of ANN forecasting form the basis for selecting optimal portfolio-forming stocks.

The portfolio's expected level of profit (mean return) is the expected value of the portfolio return R_p, which is the weighted sum of the returns for each share $R_p = w_1 r_1 + w_2 r_2 + \ldots + w_k r_k$. Meanwhile, the portfolio's expected return is a weighted sum of the expected returns for each stock.

$$E(R_p) = \mathbf{w}^T E(\tilde{\mathbf{r}}) = \mathbf{w}^T \boldsymbol{\mu} \tag{1}$$

where $\mathbf{w}$ is a matrix of size $1 \times k$, $\mathbf{w} = \begin{pmatrix} w_1 \\ w_2 \\ \vdots \\ w_k \end{pmatrix}$ shows the weight/composition of the assets formed in the portfolio and meets the amount equal to 1. $\tilde{\mathbf{r}}$ and $\boldsymbol{\mu}$ are also matrices of size $1 \times k$ [30]. The expected value of the portfolio return $\mathbf{w}^T \boldsymbol{\mu}$ is estimated by

$$E(R_p) = \mathbf{w}^T \bar{\mathbf{r}} \tag{2}$$

The portfolio variants formed are:

$$\sigma_p^2 = \mathbf{w}^T \boldsymbol{\Sigma} \mathbf{w} \tag{3}$$

The $\bar{\boldsymbol{r}}$ is a matrix of size $1 \times k$ that shows the average return of each asset in the portfolio. The variance and covariance of each asset are expressed by the covariance matrix $\boldsymbol{\Sigma}$ of size $k \times k$, whose elements contain the variance of an asset j (σ_{jj}) and the covariance between asset i and asset j (σ_{ij}) [30].

Several methods for forming an optimal portfolio include the MVEP and CAPM methods. The optimal portfolio weighting formula can be completed by defining a mean-variance efficient portfolio (MVEP), namely a portfolio that minimizes the risk of $\frac{1}{2}\mathbf{w}^T \boldsymbol{\Sigma} \mathbf{w}$ with the limit of the sum of the portfolio weights $\mathbf{w}^T \mathbf{1}_k = 1$. $\mathbf{1}_k$ is a vector with one element in k rows. Next, the Lagrange function L can be formed, and we will find $\mathbf{w}$, which minimizes the Lagrange function.

$$L = \frac{1}{2}\mathbf{w}^T \boldsymbol{\Sigma}\, \mathbf{w} - \lambda\,(\mathbf{w}^T \mathbf{1}_k - 1) \tag{4}$$

The Lagrange function in Equation (4) can be solved by finding the partial derivatives of $\mathbf{w}$ and equating them to 0.

$$\frac{\partial L}{\partial w} = \boldsymbol{\Sigma}\mathbf{w} - \lambda \mathbf{1}_k = 0$$

$$\mathbf{w} = \lambda \boldsymbol{\Sigma}^{-1} \mathbf{1}_k$$

Substitute $\mathbf{w} = \lambda\boldsymbol{\Sigma}^{-1}\mathbf{1}_k$ into **Equation (4)** to obtain $\lambda = \frac{1}{\mathbf{1}_k{}^{\mathrm{T}}\boldsymbol{\Sigma}^{-1}\mathbf{1}_k}$

Thus, the mean-variance efficient portfolio (MVEP) weights are

$$\mathbf{w} = \frac{\boldsymbol{\Sigma}^{-1}\mathbf{1}_k}{\mathbf{1}_k{}^{\mathrm{T}}\boldsymbol{\Sigma}^{-1}\mathbf{1}_k} \tag{5}$$

The CAPM portfolio is formed in such a way that it has a minimum variance based on two constraints, namely the initial specification mean return $\overline{\mu}$ that must be achieved, namely $\mathbf{w}^T\boldsymbol{\mu}$ and the sum of the weights or proportions of the portfolio formed is equal to 1, $\mathbf{w}^T\mathbf{1}_k = \mathbf{1}$. This optimization problem can be solved using the Lagrange Function with two constraints, namely $\mathbf{w}^T\boldsymbol{\mu} = \overline{\mu}$ and $\mathbf{w}_T\mathbf{1}_k = \mathbf{1}$ so that the Lagrange function is as in **Equation (6)**

$$L = \mathbf{w}^T\boldsymbol{\Sigma}\mathbf{w} + \lambda_1(\bar{\mu} - \mathbf{w}^T\boldsymbol{\mu}) + \lambda_2(1 - \mathbf{w}^T\mathbf{1}_k) \tag{6}$$

The Lagrange function solution in **Equation (6)** produces portfolio weights using the CAPM method, namely

$$\mathbf{w} = \frac{1}{\mathbf{1}_k{}^{\mathrm{T}}\boldsymbol{\Sigma}^{-1}(\boldsymbol{\mu} - r\mathbf{1}_k)}\boldsymbol{\Sigma}^{-1}(\boldsymbol{\mu} - r\mathbf{1}_k) \tag{7}$$

$$\boldsymbol{\mu} = r\mathbf{1}_k + \boldsymbol{\beta}(\overline{\mu} - r) \tag{8}$$

$$\boldsymbol{\beta} \equiv \frac{\boldsymbol{\Sigma}\mathbf{w}}{\mathbf{w}^{\mathrm{T}}\boldsymbol{\Sigma}\mathbf{w}} \tag{9}$$

where $\overline{\mu}$ is the mean market return. $\boldsymbol{\Sigma w}$ shows the covariance between the return of each asset and the market return, and $\boldsymbol{w}^T\boldsymbol{\Sigma w}$ shows the variance of the market return. Therefore, **Equation (9)** can be written as

$$\boldsymbol{\beta} \equiv \frac{\sigma_{jm}}{\sigma_{mm}} \tag{9}$$

The β factor reflects the asset's market-based sensitivity. Thus, beta is a measure of the systematic risk of a security or portfolio relative to market risk. Vector μ is a vector of expected profit levels.

2.2 Method

This research data is in the form of stock data listed on the Indonesia Stock Exchange (IDX). The stocks used are the ten stocks of Limited Liability Companies (Perseroan Terbatas (PT)) with the largest capitalization in Indonesia in 2023: PT Bank Central Asia (stock code: BBCA), PT Bayan Resources (stock code: BYAN), PT Bank Mandiri **(**stock code: BMRI)**,** PT Telekomunikasi Indonesia (stock code: TLKM), PT Astra International (stock code: ASII), PT Chandra Asri Pacific (stock code: TPIA), PT Unilever Indonesia (stock code: UNVR), PT Bank Negara Indonesia (stock code: BBNI), PT Bank Rakyat Indonesia (stock code: BBRI), and PT Indofood CBP Sukses Makmur (stock code: ICBP). This research uses secondary data, namely, daily closing stock price data from Yahoo! Finance **[31]** and the Indonesia Stock Exchange **[32]**. This study uses daily closing stock price data for the last three years, from July 1, 2020, to July 10, 2023. BI rate (r) interest rate data is obtained from Badan Pusat Statistik (BPS) **[33]**. The BI rate in July was 5.75%. The flow in this study is presented in **Figure 1**.

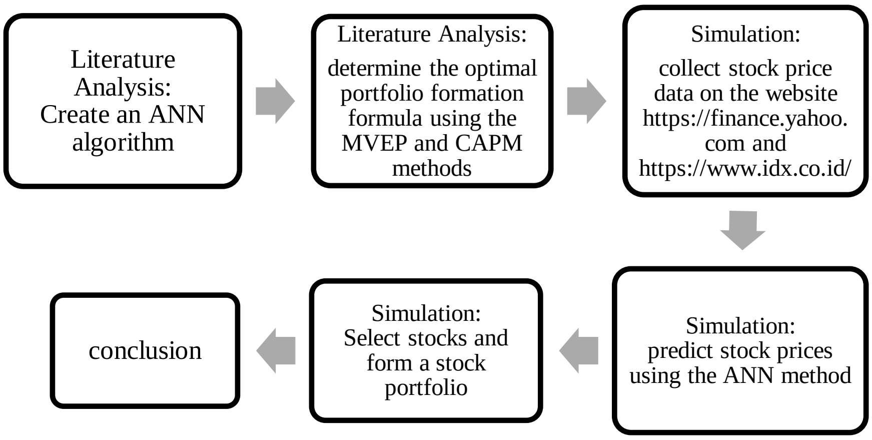

Figure 1. Research Flow

The initial step of the research is to conduct a literature analysis to create an ANN algorithm and determine the optimal portfolio formation formula using the MVEP and CAPM methods. ANN is used as a method in stock selection. The results of stock price predictions from ANN over a certain period are used as a reference to determine the mean return and risk of stocks. The stocks selected to form a portfolio have the most significant predicted mean return and the least risk. The MVEP and CAPM methods are used to determine the weight of the selected stocks so that an optimal stock portfolio is formed.

The ANN method with the Backpropagation algorithm uses the following steps:

1. Determine the structure, build a hidden layer network, and input and output patterns. In this study, the number of input layer neurons is 23, the number of neurons in the hidden layer is 22, 23, 24, and the number of output layer neurons is 1.
2. Transpose data
3. Divide data, namely 80% training data (pattern 1-569) and 20% testing data (pattern 570-711)
4. Set the parameters of the Backpropagation Neural Network architecture: the epoch parameter is 1000, the goal parameter is 0, and the activation function used is binary sigmoid with a range of 0 to 1.
5. Conduct training and testing data.
6. Determine the best model based on the smallest MSE and MAPE
7. Forecast

The next step is to conduct a simulation. The stocks used in this simulation are stocks listed on the Indonesia Stock Exchange. The simulation is carried out by collecting stock price data to predict stock prices and select stocks. Stock selection is based on stock price predictions with the largest mean return and the smallest risk. The selected stocks are then formed into a stock portfolio, and the weight of each stock is determined. The results of the portfolio weights obtained are then analyzed to determine the characteristics of the portfolio formed. The final step is to draw conclusions based on the analysis results carried out in the previous stage.

3. RESULTS AND DISCUSSION

3.1 Stock Price Prediction using ANN

The data used for the training and testing process in stock price forecasting is daily closing stock price data from July 1, 2020, to July 10, 2023. The best network structure is formed from the training and testing process to forecast stock prices from July 11 to August 10, 2023. The network structure is formed for each stock price, and the MAPE (Mean Absolute Percentage Error) value is generated based on test data, as in Table 1.

A small MAPE value indicates that forecasting shows very accurate results. According to Moreno et al., if the MAPE value < 10% means the forecasting result is very accurate; if the MAPE value is between 10% - 20%, then the forecasting result is in a suitable category, and if the MAPE value is between 20% - 50% then the forecasting result is reasonable [34]. Stock price forecasting results for ten stocks are presented in Table 2.

Table 1. Network Structure and MAPE Value of Test Data Generated

No	Stock	Network Structure	MAPE (%)	Forecasting Accuracy
1	BBCA	23-23-1	3.292168	Highly Accurate
2	BYAN	23-17-1	12.62062	Good
3	BMRI	23-1-1	4.967481	Highly Accurate
4	TLKM	23-18-1	3.587856	Highly Accurate
5	ASII	23-21-1	4.932601	Highly Accurate
6	TPIA	23-7-1	4.741085	Highly Accurate
7	UNVR	23-4-1	4.384489	Highly Accurate
8	BBNI	23-21-1	2.567141	Highly Accurate
9	BBRI	23-25-1	6.816606	Highly Accurate
10	ICBP	23-29-1	6.229016	Highly Accurate

Table 2. Stock Price Forecasting Results

No	Time	BBCA	BYAN	BMRI	TLKM	ASII	TPIA	UNVR	BBNI	BBRI	ICBP
1	11-7-23	9005.86	18224.36	4115.47	3980.08	6912.85	2210.39	4270.03	9097.36	5044.03	10236.64
2	12-7-23	9005.86	18224.36	4115.47	3980.08	6912.85	2210.39	4270.03	9097.36	5044.03	10236.64
3	13-7-23	9057.71	20108.57	4123.51	3970.30	6916.37	2208.74	4211.34	9003.33	4993.92	10181.29
4	14-7-23	8977.84	16995.13	4118.34	3981.60	6946.18	2252.20	4341.28	9051.47	4980.61	10291.93
5	17-7-23	9014.85	19695.87	4133.89	3976.84	6971.82	2238.29	4255.42	9035.93	4925.46	10034.42
	…	…	…	…	…	…	…	…	…	…	…
19	04-8-23	8921.97	20268.64	4109.61	3999.39	7008.08	2342.15	4098.88	9055.72	4964.64	9704.91
20	07-8-23	8931.55	14564.57	4113.82	4004.29	7002.78	2368.71	4048.46	9025.68	4930.23	9693.42
21	08-8-23	8906.96	19346.03	4119.87	3986.22	6938.03	2357.41	4047.73	9049.84	4944.61	9679.73
22	09-8-23	8915.92	16941.95	4114.94	4012.93	7023.04	2349.71	4191.42	9038.30	4947.33	9679.11
23	10-8-23	8919.91	17075.47	4117.20	4014.22	6930.92	2360.93	3959.70	9038.22	4900.26	9784.14

3.2 Stock Selection

The next step is determining the stock's mean return and risk from the stock price forecasting results. The mean return and risk calculation results are considered when selecting stocks to form a stock portfolio. Stock selection is based on stock price predictions with the highest mean return and the lowest risk. Five stocks out of 10 were selected to form a portfolio. The mean return and risk results of the stocks are presented in Table 3.

Table 3. Mean Return and Stock Risk Forecasting Results

No	Stock	Mean Return	Risk	Rank	Risk Rank	Total Rank
1	BBCA	-0.000461	0.005998	7	4	11
2	BYAN	0.006555	0.141865	1	10	11
3	**BMRI**	**0.000021**	**0.002185**	**5**	**1**	**6**
4	**TLKM**	**0.000395**	**0.003654**	**3**	**3**	**6**
5	**ASII**	**0.000156**	**0.008790**	**4**	**7**	**11**
6	**TPIA**	**0.003027**	**0.007597**	**2**	**6**	**8**
7	UNVR	-0.003147	0.024033	10	9	19

No	Stock	Mean Return	Risk	Rank	Risk Rank	Total Rank
8	**BBNI**	**-0.000291**	**0.003327**	**6**	**2**	**8**
9	BBRI	-0.001292	0.006683	8	5	13
10	ICBP	-0.001872	0.019442	9	8	17

Based on **Table 3**, the mean return of forecasting results is ranked from largest to smallest, while risk is ranked from smallest to largest. Stock selection uses the most miniature total ranking score. So, the selected stocks are BMRI, TLKM, ASII, TPIA, and BBNI. BBCA, BYAN, and ASII stocks have the same total ranking score. However, in this study, ASII shares were chosen because ASII shares have a mean return and risk ranking that is halfway between BBCA and ASII shares, so the mean return is not too low, and the risk is not too significant. Stocks with the largest mean return and the slightest risk prediction illustrate that these stocks are expected to provide profits in the future, with the expectation of negligible risk.

3.3 Optimal Stock Portfolio Formation with MVEP Method

The stock portfolio comprises BMRI, TLKM, ASII, TPIA, and BBNI stocks. The formation of an optimal stock portfolio aims to determine the weight of each stock in order to obtain a portfolio with maximum expected value and minimal risk. Based on historical data, namely daily stock price closing data from July 1, 2020, to July 10, 2023, the returns of each portfolio-forming stock are presented in **Table 4**.

Table 4. Return Stock

Time	BMRI	TLKM	ASII	TPIA	BBNI
July 10, 2023	0.004854	-0.002525	-0.007326	-0.009569	-0.002755
July 07, 2023	-0.028302	0.000000	0.003676	0.009662	-0.002747
July 06, 2023	0.004739	-0.005025	0.003690	-0.014286	-0.005464
⋮	⋮	⋮	⋮	⋮	⋮
July 06, 2020	0.015000	-0.022436	-0.002062	-0.021818	0.010965
July 03, 2020	0.000000	-0.006369	-0.004107	0.007326	-0.006536
July 02, 2020	0.002004	0.032895	0.012474	0.038023	0.011013
Mean ($\bar{r}_j$)	0.001833	0.000515	0.000655	0.000503	0.001123
Var (σ_{jj})	0.001991	0.000318	0.000377	0.000378	0.000366
Risk (σ_j)	0.044616	0.017831	0.019424	0.019451	0.019131

The stock return data contained in **Table 4** form the mean return vector $\bar{\mathbf{r}}$ and the covariance matrix $\mathbf{\Sigma}$.

$$\bar{\mathbf{r}} = \begin{pmatrix} 0.001833 \\ 0.000515 \\ 0.000655 \\ 0.000503 \\ 0.001123 \end{pmatrix}$$

$$\mathbf{\Sigma} = \begin{pmatrix} 0.001991 & 0.000090 & 0.000128 & 0.000011 & 0.000235 \\ 0.000090 & 0.000318 & 0.000107 & 0.000042 & 0.000121 \\ 0.000128 & 0.000107 & 0.000377 & 0.000042 & 0.000152 \\ 0.000011 & 0.000042 & 0.000042 & 0.000378 & 0.000056 \\ 0.000235 & 0.000121 & 0.000152 & 0.000056 & 0.000366 \end{pmatrix}$$

The weights of each portfolio stock according to **Equation (5)** are:

$$\mathbf{w} = \begin{pmatrix} 0.028242 \\ 0.290871 \\ 0.204506 \\ 0.315733 \\ 0.160648 \end{pmatrix}$$

The weight of each stock forming the optimal portfolio using the MVEP method is BMRI = 2.8242%, TLKM = 29.0871%, ASII = 20.4506%, TPIA = 31.5733%, and BBNI = 16.0648%. The total amount of weight is 100%. The expected value of return $E(R_p)$ and risk σ_p of the portfolio formed by the MVEP method is $E(R_p) = \mathbf{w}^T\bar{\mathbf{r}} = 0.000675$ and $\sigma_p = 0.012231$.

3.4 Optimal Stock Portfolio Formation with CAPM Method

In forming an optimal stock portfolio using the CAPM method, data on the Indonesian central bank's interest rate and the mean and variance of market returns are needed. The mean and variance of market return are obtained from the IDX Composite Stock Price Index data. In July, the Indonesian central bank's interest rate (r) was 5.75%. The mean, variance, and risk of market return based on IDX Composite historical price data for the period July 1, 2020, to July 10, 2023, are mean $(\bar{\mu})$= 0.000467, Var (σ_{mm}) = 0.000076, and Risk (σ_m) = 0.008701. The value of the covariance between $\boldsymbol{\sigma}_{jm}$ the return of each asset and the market return, **β** value, and **μ** can be seen in **Table 5**.

Table 5. Covariance Value and Value β

Stock	σ_{jm}	β	μ
BMRI	0.000103	1.356504	-0.019865
TLKM	0.000076	1.006732	0.000083
ASII	0.000090	1.184074	-0.010031
TPIA	0.000047	0.619133	0.022189
BBNI	0.000112	1.474842	-0.026614

The **w** vector is a stock weight vector formed through the CAPM method.

$$\mathbf{w} = \frac{1}{\mathbf{1}_p^T\boldsymbol{\Sigma}^{-1}(\boldsymbol{\mu} - r\mathbf{1}_p)}\boldsymbol{\Sigma}^{-1}(\boldsymbol{\mu} - r\mathbf{1}_p) = \begin{pmatrix} 0.064806 \\ 0.219387 \\ 0.21275 \\ 0.135736 \\ 0.367321 \end{pmatrix}$$

The weight of each optimal portfolio-forming stock using the CAPM method is BMRI = 6.4806%, TLKM = 21.9387%, ASII = 21.275%, TPIA = 13.5736%, and BBNI = 36.7321%. The total amount of weight is 100%. The weight of each stock that has been formed results portfolio's expected return value $E(R_p) = \mathbf{w}^T\bar{\mathbf{r}} = 0.000852$ and risk value $\sigma_p = 0.013192$. The optimal portfolio that is formed has a maximum expected return value with the same risk or minimal risk with the same expected value compared to other portfolios.

3.5 Discussion

The stock portfolio is formed according to investors' preferences. In this study, the selection of stocks forming a portfolio is based on forecasting stock prices with the largest mean return (expected profit) with the least risk. This preference is chosen with the expectation that the portfolio will provide future returns with little risk. Considering these preferences, based on the results in **Table 3**, BMRI, TLKM, ASII, TPIA, and BBNI stocks were selected to form a portfolio.

The optimal portfolio is formed through the MVEP and CAPM methods. MVEP and CAPM methods are used to determine the weight of each stock so that an optimal portfolio is formed that is expected to provide profits. The MVEP method focuses on avoiding risk or looking for stocks with little risk. The expected profit (mean) and risk calculated for each stock in the MVEP method uses historical stock price data from July 1, 2020, to July 10, 2023. The results of the **w** weight calculation show that BMRI shares have the least significant weight, which is 2.8242%, because BMRI shares have the most significant risk. The risk of

BMRI shares is far above that of other stocks. TPIA and TLKM shares have almost the same weight because they have almost the same return.

In the CAPM method, the covariance value between the return of each stock and the return of the IDX Composite Stock Price Index (market return) is positive. A positive covariance indicates that if the IDX Composite Index's price increases, each stock's price also increases. BMRI, TLKM, ASII, and BBNI stocks are all stocks with considerable systematic risk and are sensitive to market changes because they have a value of $\beta > 1$, meaning that changes in market returns significantly affect changes in stock prices. BBNI shares have the most considerable β value, so BBNI shares are classified as aggressive stocks and have a sizable systematic risk of market changes. The order of stocks that have a systematic risk of market changes, from smallest to most significant, based on β value in **Table 5** are TPIA, TLKM, ASII, BMRI, and BBNI stocks. The expected rate of return of stocks (μ) based on the results in **Table 5**, the most profitable expected stock orders are TPIA, TLKM, ASII, BMRI, and BBNI. Empirically, the CAPM method gives the most significant weight to BBNI stocks with greater systematic risk and smaller expected stock returns. This result seems to be contrary to the principle of optimal portfolio, which emphasizes choosing stocks with greater expected returns and lower levels of risk. Based on the average expected return ($\bar{r}_j$) and risk (σ_j) of historical data in **Table 4**, BBNI is a stock with a smaller risk and a larger mean than several other stocks. So, based on historical stock data, BBNI shares are shares with good prospects. **Figure 2** compares portfolio weights using the MVEP and CAPM methods.

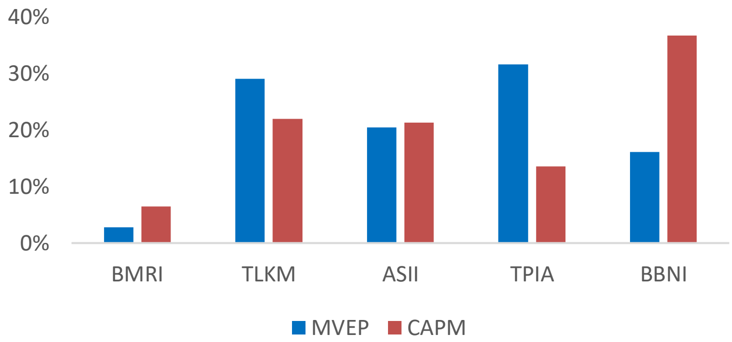

Figure 2. Comparison of Portfolio Weights with MVEP and CAPM Methods

Determination of forecasting accuracy is carried out after the optimal portfolio is formed. Forecasting accuracy is obtained by comparing forecasting result data with actual data. This accuracy determination is to determine the accuracy of stock price forecasting that has been done and also to find out whether the stocks forming the portfolio come from stocks with accurate price forecasting. Based on stock forecasting in **Table 2**, the results of forecasting accuracy using the ANN backpropagation method for five portfolio-forming stocks are presented in **Table 6**. The forecasting accuracy of the five stocks has different results. The greatest accuracy is found in BBNI's stock price forecasting with a MAPE of 1.236991%, while the smallest accuracy is found in BMRI's stock forecasting with a MAPE of 26.44636%. Furthermore, an analysis of the MAPE category was carried out, which was derived from the comparison of test data with forecasting results. Comparison of MAPE test data with forecasting data is shown in **Table 6** and **Figure 3**.

Table 6. Comparison of Mean Return and Risk from Historical Data and Forecasting Data as Well as MAPE of Testing and Forecasting

No	Stock	Mean Return		Risk		MAPE of Testing data		MAPE of Forecasting data	
		Historical Data	Forecasting Data	Historical Data	Forecasting Data	%	Accuracy category	%	Accuracy category
1	BMRI	0.001833	0.000021	0.044616	0.002185	4.967481	Highly Accurate	26.44636	Reasonable
2	TLKM	0.000515	0.000395	0.017831	0.003654	3.587856	Highly Accurate	4.406574	Highly Accurate
3	ASII	0.000655	0.000156	0.019424	0.008790	4.932601	Highly Accurate	3.860954	Highly Accurate
4	TPIA	0.000503	0.003027	0.019451	0.007597	4.741085	Highly Accurate	11.30266	Good
5	BBNI	0.001123	-0.000291	0.019131	0.003327	2.567141	Highly Accurate	1.236991	Highly Accurate

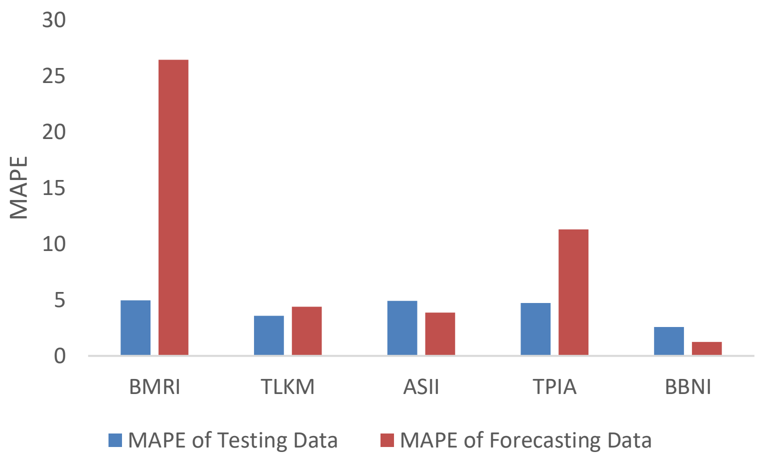

Figure 3. Comparison of MAPE Between Testing Data Results and Forecasting Data

Stocks that do not have differences in the MAPE category are TLKM, ASII, and BBNI stocks, which have very accurate forecasting categories. TPIA shares experienced a change in the MAPE category from very accurate forecasting of testing data to good results forecasting. MAPE on BMRI stock test result data is 4.967481% (very accurate), but MAPE on forecasting result is 26.44636% (reasonable). Although the MAPE obtained by the test results is in an accurate and good category, it does not guarantee that the MAPE forecasting results will also be accurate and good. The difference in MAPE between test results and forecasting results is that stock prices always move (change) according to market conditions, where some factors cannot be predicted mathematically.

A comparative analysis of portfolio-forming stocks' mean return and risk between historical data and forecasting results yields several differences. **Table 6** compares the mean return of stock between historical and forecasting data, and the difference can be clearly seen in **Figure 4** and **Figure 5**.

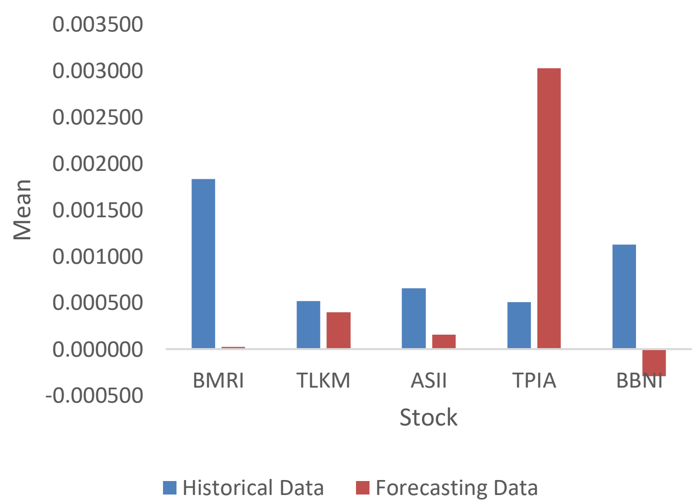

Figure 4. Comparison of Mean Return between Historical Data and Forecasting Data

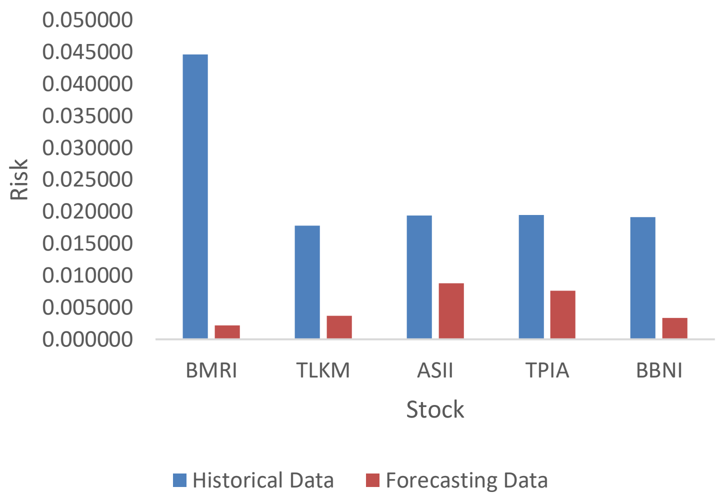

Figure 5. Comparison of Stock Risk between Historical Data and Forecasting Data

The portfolio formed using the MVEP and the CAPM methods is then compared to determine the empirical characteristics of stock weighting. The stock weight characteristics of MVEP and CAPM methods are analyzed based on the mean return and risk of forecasting results, along with MAPE categories, test data, and forecasting results. The optimal portfolio formed through the MVEP and CAPM methods results in different weights. The MVEP method gives the largest weight to TPIA shares and the smallest weight to BMRI shares. TPIA shares and TLKM shares have similar weights. TPIA shares based on historical data have the smallest mean return, but based on forecasting data, have the largest mean return. According to historical data, the risk of TPIA shares is almost the same as ASII and BBNI shares. Still, according to the forecasting results, the risk of TPIA shares is lower than ASII shares. If analyzed, the MAPE value obtained from testing data and forecasting data, TPIA shares experienced changes in the forecasting accuracy category. The TPIA stock forecasting category on the test data is very accurate, but on the forecasting data, the category is good. The forecasting accuracy category changes because the actual data is lower than the forecasting data.

The CAPM method gives the most significant weight to BBNI shares and the smallest to BMRI shares. BBNI shares, based on historical data, have a greater mean return than several other stocks, but based on forecasting results, BBNI shares have a negative mean return. The risk of BBNI shares based on historical data is not much different from ASII and TPIA stocks, while based on forecasting results, BBNI shares have a relatively small risk compared to other stocks. Analysis of the MAPE value on the test data and forecasting results found that BBNI shares have an unchanged forecasting accuracy category, where the MAPE value of forecasting results is smaller than that of the test data. The MAPE value of BBNI shares is the smallest for test data and forecasting results.

The similarity of the two methods in this study is to give the smallest weight to BMRI stocks. Based on historical data, BMRI shares have the greatest risk, and based on forecasting data, BMRI shares have the least risk. According to historical data, BMRI shares have the largest returns, but relatively small returns according to forecasting results. The MAPE value of BMRI shares also experienced significant changes between the MAPE of the test data and the MAPE of forecasting results. The MAPE of the test data result is 4.967481%, while the MAPE of the forecasting result is 26.44636%.

Stock portfolios are formed based on forecasting stock prices with the largest mean return with the least risk. Suppose we analyze based on the mean and risk results of stock price forecasting, as well as a comparison of MAPE testing data and forecasting results, portfolios formed through MVEP and CAPM methods provide different characteristics. Empirically, the MVEP method gives the greatest weight to stocks with the largest predicted mean return. However, when comparing MAPE values, the greatest weight of the MVEP method is given to stocks that experience changes in accuracy categories. The CAPM method gives the largest weight to stocks with less risk than others, has an unchanged accuracy category, and has the smallest MAPE value for testing and forecasting data. The MVEP and CAPM methods give the smallest weight to stocks with a relatively small mean return prediction compared to other stocks. Both methods give the smallest weight to stocks that experience significant MAPE category changes between test data and forecasting results.

The CAPM method has the largest portfolio expectation value and a large risk value. The MVEP method produces a smaller portfolio expectation value with less risk. The MVEP and CAPM methods have a positive mean return, meaning the portfolio formed is expected to provide profitable stock returns. The portfolio risk of the MVEP and CAPM methods is not much different and is classified as a small risk. So, the stock portfolio formed is expected to have a favorable rate of return with little risk. Thus, empirically, ANN forecasting can be used as a tool to select portfolio-forming stocks. Stock price predictions with the most significant mean return and small risk can be used as a reference in forming a portfolio using MVEP and CAPM methods.

4. CONCLUSIONS

Forecasting using ANN yielded nine stocks with accurate categories and one with good categories. Based on the criteria for predicting the stock price with the largest mean return with little risk, BMRI, TLKM, ASII, TPIA, and BBNI stocks were selected to form a stock portfolio. Optimal portfolios formed using MVEP and CAPM methods have different characteristics. The MVEP method gives the most significant weight to stocks with the largest predicted mean return. Meanwhile, the largest weight of the CAPM method is given to stocks with a relatively small risk prediction compared to other stocks with an unchanged accuracy category and the smallest MAPE value for both test data and forecasting data. The smallest weight in the MVEP and CAPM methods is given to stocks with relatively small mean return prediction and MAPE value, and that experience significant changes between test data and forecasting results. The MVEP and CAPM methods have a positive mean return, meaning the portfolio formed is expected to provide profitable stock returns. The portfolio risk of the MVEP and CAPM methods is not much different and is classified as a small risk. So, the stock portfolio formed is expected to have a favorable rate of return with little risk. Thus, empirically, ANN forecasting can be used as a tool to select portfolio-forming stocks. Stock price predictions with the largest mean return and small risk can be used as a reference in forming a portfolio using MVEP and CAPM methods.

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