

## ANALYSIS OF OPTIMAL PORTFOLIO FORMATION ON IDX30 INDEXED STOCK WITH THE MEAN ABSOLUTE DEVIATION METHOD

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### ABSTRACT

#### Article History:

Received: 1<sup>st</sup> February 2024

Revised: 1<sup>st</sup> April 2024

Accepted: 3<sup>rd</sup> July 2024

Published: 1<sup>st</sup> September 2024

#### Keywords:

Factor Analysis;  
IDX30;  
Mean Absolute Deviation  
(MAD)  
Sharpe Index.

In investing in stocks, an investor must be able to form a stock portfolio to obtain optimal results. Factor analysis is one way to select stocks to form a portfolio. Factor analysis with Principal Component Analysis (PCA) extraction is used to summarize many variables into new smaller factors by producing the same information. The new factor formed is called a portfolio. This study aims to form an optimal portfolio using the Mean Absolute Deviation (MAD) method, which is an alternative to Markowitz optimization, and assess the stock portfolio's performance using the Sharpe index. This research uses IDX30-indexed stocks because the stocks in this index have high market capitalization and liquidity. The data used in this study are daily close stock price data on the IDX30 index from September 20, 2022, to September 20, 2023. The data used is secondary data obtained from the official website <https://finance.yahoo.com/>. From the analysis, three stock portfolios were obtained. With MAD optimization, the investment weight of each stock is obtained namely, in the first portfolio, the investment weight of AMRT shares is 21.95%, BBKA shares are 30%, BBNI shares are 18.05%, and BBRI shares are 30%. In the second portfolio, the investment weight of AKRA shares is 34.03%, BRPT shares are 40%, and MEDC shares are 25.97%. In the third portfolio, the investment weight of BMRI shares is 50%, and INDF shares are 50%. By measuring the performance of the Sharpe index, the optimal portfolio is obtained in the second portfolio with an expected return portfolio of 0.155% and a portfolio risk of 1.927%.



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#### How to cite this article:

A. N. Pratama, N. Satyahadewi, and E. Sulistianingsih, "ANALYSIS OF OPTIMAL PORTFOLIO FORMATION ON IDX30 INDEXED STOCK WITH THE MEAN ABSOLUTE DEVIATION METHOD," *BAREKENG: J. Math. & App.*, vol. 18, iss. 3, pp. 1753-1764, September, 2024.

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Journal homepage: <https://ojs3.unpatti.ac.id/index.php/barekeng/>

Journal e-mail: [barekeng.math@yahoo.com](mailto:barekeng.math@yahoo.com); [barekeng.journal@mail.unpatti.ac.id](mailto:barekeng.journal@mail.unpatti.ac.id)

Research Article · Open Access

## 1. INTRODUCTION

The development of the capital market in Indonesia has increased rapidly. Based on data issued by the Indonesian Central Securities Depository (KSEI), the number of capital market investors increased by 92.99% in 2021, and in 2022 it increased by 37.68% [1]. The existence of the capital market is funding for companies from investment activities carried by investors [2]. One of the investment activities that can be carried out is investing in stocks, which are financial instruments on the Indonesia Stock Exchange, also known as the BEI [3].

Stock investment is investing a sum of money in securities, which can be shown as ownership of a company asset to provide profits in the future [4]. Stock investment is an investment that can provide a high level of return and high risk. An investor can form a stock portfolio by investing to maximize return or reduce risk [5].

A stock portfolio is a form of stock investment that consists of two or more stocks of different companies with the hope that if one stock goes down while the other goes up, the investment will not suffer a loss [6]. One strategy that can be used in selecting stocks to form a portfolio is using factor analysis [7]. Factor analysis reduces many variables into new smaller factors with the same information. The new factors formed are called portfolios [8].

Stocks listed on the stock index list on the BEI can be selected to form a stock portfolio. BEI is a securities trading place with several stock indexes, one of them is the IDX30 stock index. The IDX30 index is an index that describes the performance of 30 stocks with high market capitalization and high liquidity [9]. The IDX30 index is expected to be one of the references for investors investing in stocks because the selection of stock membership in the IDX30 index consists of transaction value, transaction frequency, total transaction days, and market capitalization [10].

The optimal portfolio using IDX30 indexed stock can be found using the Markowitz method [11]. However, this method has shortcomings in nonlinear mathematics due to complex computation if large-scale data is used. Variance is used as a level of risk measure, and the return data must be normally distributed. Therefore, an alternative portfolio optimization method, Mean Absolute Deviation (MAD), was introduced by Konno and Yamazaki in 1991 [12].

In [12] conducted portfolio optimization by comparing the MAD and Single Index Model (SIM) methods on stocks in the LQ-45 index. The results show that the portfolio formed using the MAD method provides a risk value of 0.05524, while the portfolio formed using the SIM method provides a risk value of 0.05757. The portfolio formed by the MAD method produces a smaller risk value compared to the portfolio formed by the SIM method. The MAD method was also applied in Rachmawati et al. research in 2020 to form an optimal portfolio of stocks indexed by the Jakarta Islamic Index (JII) [8]. This research produces an optimal portfolio that provides an expected return value of 0.00389 and a risk of 0.021213.

The MAD method portfolio optimization does not require normally distributed stock return data like the Markowitz method and it does not require a covariance matrix in its calculation. Like the Markowitz method, the MAD method also minimizes the risk measure by determining the average of the absolute value of the deviation of the stock return from the expected stock return [12]. The portfolio formation problem using the MAD method is a linear programming problem, so the calculation is faster than the quadratic programming in the Markowitz method [13].

In previous research, no one has discussed the formation of optimal portfolios using the MAD method on IDX 30 indexed stocks, where the stocks used are stocks that produce positive expected return values. Therefore, in this research, an optimal portfolio is formed on IDX30 indexed stocks, where the stocks used have been selected first. After the portfolio is formed, the optimal portfolio performance assessment is carried out using the Sharpe index to get the optimal portfolio.

## 2. RESEARCH METHODS

### 2.1 Stock Return and Expected Return Stock

Stock return is the rate of refund obtained from buying and selling stocks [14]. Stock return can be calculated by using **Equation (1)**:

$$R_{i(t)} = \ln \left[ \frac{P_{i(t)}}{P_{i(t-1)}} \right] \quad (1)$$

where:

- $R_{i(t)}$  :  $i$ -th stock return at time  $t$
- $P_{i(t)}$  : The closing price of the  $i$ -th stock at the time  $t$
- $P_{i(t-1)}$  : The closing price of the  $i$ -th stock at the time  $t - 1$

Meanwhile, the expected return of a stock is expected in the future and is uncertain. Calculating the expected return of each stock can use **Equation (2)**:

$$E(R_i) = \frac{\sum_{t=1}^T R_{i(t)}}{T} \quad (2)$$

where:

- $E(R_i)$  : Expected return of the  $i$ -th stock
- $T$  : Number of stock return

### 2.2 Factor Analysis

In this study, factor analysis with extraction of the Principal Component Analysis (PCA) method is used in selecting stock to form a portfolio. PCA is a multivariate statistical technique that reshapes a group of original variables into a smaller set of uncorrelated variables that can represent the information of the original variables [15]. The steps in the formation of stock using factor analysis with extraction PCA method are:

- a. Calculating the Kaiser Meyer Olkin (KMO) and Measure of Sampling Adequacy (MSA) Values.

KMO value testing is used to see the data's adequacy. Data is sufficient to factorize if the KMO value is greater than 0.5. There is an **Equation (3)** for calculating the KMO value [16]:

$$KMO = \frac{\sum_{i=1}^p \sum_{j=1}^p r_{ij}^2}{\sum_{i=1}^p \sum_{j=1}^p r_{ij}^2 + \sum_{i=1}^p \sum_{j=1}^p a_{ij}^2}, \text{ for } i \neq j \quad (3)$$

with

$$r_{ij} = \frac{T \sum_{t=1}^T R_{i(t)} R_{j(t)} - (\sum_{t=1}^T R_{i(t)}) (\sum_{t=1}^T R_{j(t)})}{\sqrt{(T \sum_{t=1}^T R_{i(t)}^2 - (\sum_{t=1}^T R_{i(t)})^2) (T \sum_{t=1}^T R_{j(t)}^2 - (\sum_{t=1}^T R_{j(t)})^2)}} \quad (4)$$

and

$$a_{ij} = \frac{-r_{ij}^{-1}}{\sqrt{\text{diag. } r_{ii}^{-1} \times \text{diag. } r_{jj}^{-1}}} \quad (5)$$

where:

- $p$  : The number of stock return data variables
- $r_{ij}$  : Correlation coefficient of stock return data variables  $i$  and  $j$
- $a_{ij}$  : Partial correlation between stock return data variables  $i$  and  $j$
- $r_{ij}^{-1}$  : Inverse coefficient of the correlation matrix of stock return data variable  $i$  and  $j$
- $\text{diag. } r_{ii}^{-1}$  : Diagonal value of inverse correlation matrix of return variable of stock  $i$
- $\text{diag. } r_{jj}^{-1}$  : Diagonal value of inverse correlation matrix of return variable of stock  $j$ .

After the KMO test, the MSA test was continued. MSA testing is used to measure homogeneity and filter between stock return data variables so that the stock return data variables can be analyzed further. To calculate the MSA value on the stock return data variable, the following **Equation (6)** can be used [16].

$$MSA_i = \frac{\sum_{j=1}^p r_{ij}^2}{\sum_{j=1}^p r_{ij}^2 + \sum_{j=1}^p a_{ij}^2}, i \neq j \quad (6)$$

The MSA value of each stock return data must be greater than 0.5 to be analyzed further. Suppose the MSA value of the stock return data variable is less than 0.5. In that case, the stock return data variable must be eliminated one by one from the smallest value until all MSA values of the stock return data variable are more than 0.5 [17].

#### b. Bartlett Test of Sphericity

This test is used to see whether there is a correlation between the stock return data variables being analyzed [18]. This research uses a correlation matrix (**R**) between stock return data. The stock return data variable passes this test if the  $\chi_{count}^2 \geq \chi_{table}^2$ . The  $\chi_{count}^2$  can be calculated using Equation (7) and  $\chi_{table}^2$  can be calculated using Equation (8) [19].

$$\chi_{count}^2 = - \left( (b-1) - \frac{2p+5}{6} \right) \ln |\mathbf{R}| \quad (7)$$

$$\chi_{table}^2 = \chi_{\frac{1}{2}(p(p-1))}^2 \quad (8)$$

where:

- $b$  : Number of observations
- $|\mathbf{R}|$  : Determinant of the correlation matrix

#### c. Factor Extraction

The method commonly used in extracting factors is looking at eigenvalues greater than or equal to one. Factors with eigenvalues greater than one are retained, but if they are smaller than one, the factor is excluded. In this research, the matrix used in the calculation of eigenvalues is the correlation matrix (**R**) of stock return data. To calculate the eigenvalue, it can be utilized Equation (9) [20].

$$\text{Det}(\lambda \mathbf{I} - \mathbf{R}) = 0 \quad (9)$$

where:

- $\lambda$  : Eigenvalue
- $\mathbf{I}$  : Identity matrix

### 2.3 Mean Absolute Deviation Portfolio

The basic concept of portfolio MAD is the absolute value of the difference between the return and the expected return of each stock over a certain period, where the equation to find it is as follows:

$$m_{it} = |R_{i(t)} - E(R_i)| \quad (10)$$

where  $m_{it}$  is an absolute value of the difference between return and expected return. The average of  $m_{it}$  is the MAD value of each stock that can be quantified by Equation (11).

$$MAD_i = \sum_{t=1}^T \frac{m_{it}}{T} \quad (11)$$

According to [12], solving linear program optimization on the MAD Portfolio to determine the investment weight of each stock can use the simplex method, the equation is written as:

$$\text{Minimize: } \sigma(W) = (MAD)_1 w_1 + (MAD)_2 w_2 + \dots + (MAD)_n w_n \quad (12)$$

with constraint

$$E(R_1)w_1 + E(R_2)w_2 + \dots + E(R_n)w_n \geq R_{min} \quad (13)$$

$$w_1 + w_2 + \dots + w_n = 1 \quad (14)$$

$$0 \leq w_i \leq u_i, \text{ by } i = 1, 2, \dots, n \quad (15)$$

where:

- $\sigma(W)$  : Portfolio risk
- $R_{min}$  : Minimum return rate portfolio
- $w_i$  : The amount of investment weight of the  $i$ -th stock
- $u_i$  : Maximum weight of  $i$ -th stock

A stock portfolio has an expected return portfolio that can provide an overview of the expected return on stock investment. To calculate the stock expected return, it can be utilized **Equation (16) [12]**.

$$E(R_p) = \sum_{i=1}^n w_i \cdot E(R_i) \quad (16)$$

where  $E(R_p)$  is the expected return portfolio.

## 2.4 Simplex Method

The simplex method solves linear program problems with two or more decision variables until the optimum value is obtained in the optimization problem. The simplex method has maximization and minimization problems with a set of equation and inequalities constraint [21]. Reference [22] states the general form of a linear program.

1. Minimize

$$Z = \sum_{j=1}^n C_j x_j \quad (17)$$

with constraint

$$\sum_{j=1}^n d_{ij} x_j \geq b_i \quad (18)$$

and

$$x_j \geq 0$$

2. Maximize

$$Z = \sum_{j=1}^n C_j x_j \quad (19)$$

with constraint

$$\sum_{j=1}^n d_{ij} x_j \leq b_i \quad (20)$$

and

$$x_j \geq 0$$

where  $i = 1, 2, \dots, m$ ,  $j = 1, 2, \dots, n$ ,  $Z$  is a destination function,  $C_j$  is objective function coefficient,  $x_j$  is a decision variable,  $d_{ij}$  is a constraint variable, and  $b_i$  is a right-hand side constant of each constraint.

In solving the linear problems with the simplex method, program problems must be converted to standard form with the provisions, namely [8]:

- For constraints that have an inequality sign smaller than or equal to ( $\leq$ ), a non-negative slack variable ( $s$ ) is added on the left side of the constraint.
- For constraints that have an inequality sign greater than or equal to ( $\geq$ ), subtract the non-negative surplus variable ( $t$ ) on the left side of the constraint and add an artificial variable ( $A$ ).
- For constraints with an equal constraint ( $=$ ), add an artificial variable ( $A$ ) on the left side of the constraint.

## 2.5 Sharpe Index

The Sharpe index evaluates an investment that has provided a return at a certain level of risk taken. The higher the Sharpe index of a portfolio, the better the portfolio's performance [23]. To calculate the Sharpe index, we can use **Equation (21) [24]** :

$$S_{p_i} = \frac{E(R_{p_i})}{\sigma(W_{p_i})} \quad (21)$$

where:

- $S_{p_i}$  :  $i$ -th portfolio Sharpe index  
 $E(R_{p_i})$  : Expected return portfolio  $i$ -th  
 $\sigma(W_{p_i})$  :  $i$ -th portfolio risk

### 3. RESULTS AND DISCUSSION

The data used in this study are daily close stock price data on the IDX30 index from September 20, 2022, to September 20, 2023. The data used is secondary data obtained from the official website <https://finance.yahoo.com/>. The IDX30 index is a stock index consisting of 30 stocks that have good performance liquidity and large market capitalization. The analyzed close price data are stocks with a positive expected return value on the IDX30 index. The first step in this study is to calculate stock returns and expected stock returns. The calculation of the stock return value uses the **Equation (1)**. After getting the return value of each stock, then calculate the expected return value of each stock using **Equation (2)**. Based on **Equation (2)**, it is found that there are nine stocks indexed by IDX30 that generate positive expected returns. The stocks are shown in **Table 1**.

**Table 1. List of Nine Selected Stocks**

No	Company Name	Stock Code	Expected Return
1	PT AKR Corporindo Tbk	AKRA	0.00017
2	PT Sumber Alfaria Trijaya Tbk	AMRT	0.00105
3	PT Bank Central Asia Tbk	BBCA	0.00027
4	PT Bank Negara Indonesia (Persero) Tbk	BBNI	0.00028
5	PT Bank Rakyat Indonesia (Persero) Tbk	BBRI	0.00076
6	PT Bank Mandiri (Persero) Tbk	BMRI	0.00118
7	PT Barito Pacific Tbk	BRPT	0.00238
8	PT Indofood Sukses Makmur Tbk	INDF	0.00041
9	PT Medco Energi Internasional	MEDC	0.00208

Based on **Table 1**, nine stock return data will be tested for KMO. Stock return data is considered feasible and sufficient for factor analysis if the KMO value is greater than 0.5. Based on **Equation (3)**, the KMO value is 0.54565. It means that the nine stock return data variables are feasible and sufficient for further analysis because the KMO value is greater than 0.5. The next step is the MSA test. The test criteria for stock return data variables are suitable for further analysis if the MSA value of each stock return data variable is greater than 0.5. If an MSA value is less than 0.5 on the stock return data variable, elimination will occur. Elimination of stock return variables is done one by one by looking at the smallest MSA value. Based on **Equation (6)**, the MSA value of each stock is presented in **Table 2**.

**Table 2. MSA Testing Of Stock Return Data**

Stock	MSA
AKRA	0.59324
AMRT	0.60192
BBCA	0.64363
BBNI	0.69279
BBRI	0.69679
BMRI	0.63660
BRPT	0.57235
INDF	0.65045

MEDC    0.56369

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Based on **Table 2**, nine stocks pass the MSA test because all MSA values of nine stock return data variables are greater than 0.5. Therefore, the nine stock return variables can proceed with a correlation test using the Bartlett Test of Sphericity. The nine stock return variables pass this test if the  $\chi^2_{count} \geq \chi^2_{table}$ . Based on **Equation (7)**, the value  $\chi^2_{count}$  is 183.24850 and according to **Equation (8)**, the value  $\chi^2_{count}$  is 50.99846. Therefore, it can be interpreted that there is a correlation between stock return variables because the value of  $\chi^2_{count} \geq \chi^2_{table}$ . Because all assumptions have been met, the nine stock return variables can proceed to the factor analysis process.

### 3.1 Factor Analysis

Stock return data that has met the assumptions of factor analysis, then factor extraction is carried out. Factor extraction processing uses the PCA method to determine the new factors formed in this analysis. The new factors formed are called portfolios. Based on **Equation (9)**, the eigenvalues are presented in **Table 3**.

**Table 3. Eigenvalue**

Component	Eigenvalue
1	<b>2.03147</b>
2	<b>1.35604</b>
3	<b>1.11964</b>
4	0.95231
5	0.92187
6	0.80587
7	0.71990
8	0.60724
9	0.48566

Based on **Table 3**, three new factors are formed with eigenvalues greater than one, or it can be said that three portfolios are used for portfolio optimization using MAD. After knowing the number of portfolios formed, then compare the correlation between portfolios and the stock return data variable based on the loading factor value, where this process will group which stocks will enter into portfolio 1, portfolio 2, and portfolio 3. The loading factor values are shown in **Table 4**.

**Table 4. Loading Factor Value Of Stock Return Data**

	Portfolio		
	1	2	3
AKRA	0.35743	<b>0.59662</b>	-0.02394
AMRT	<b>0.30572</b>	-0.29387	-0.36081
BBCA	<b>0.80161</b>	-0.16461	-0.09759
BBNI	<b>0.73806</b>	-0.10527	0.01592
BBRI	<b>0.61615</b>	-0.22302	-0.26337
BMRI	0.30264	-0.03788	<b>0.69603</b>
BRPT	0.09800	<b>0.56208</b>	-0.08481
INDF	0.25714	-0.06137	<b>0.64256</b>
MEDC	0.27564	<b>0.71042</b>	-0.07235

Based on **Table 4**, the stock return coded AKRA has largest loading factor value in portfolio 2, so AKRA code stock are entered into Portfolio 2. In stock coded AMRT, the largest loading factor value is in Portfolio 1, so AMRT stock entered in Portfolio 1. BMRI coded stock are included in Portfolio 3 because the largest loading factor value is in Portfolio 3. Meanwhile, **Table 5** contains stocks constructing the portfolio based on the most considerable loading factor value.

**Table 5. Interpretation of Principal Component Analysis Result**

Portfolio	Stock	Loading Factor
1	AMRT	0.30572
	BBCA	0.80161
	BBNI	0.73806
	BBRI	0.61615
2	AKRA	0.59662
	BRPT	0.56208
	MEDC	0.71042
3	BMRI	0.69603
	INDF	0.64256

Based on **Table 5**, the first portfolio consists of four stocks coded AMRT, BBCA, BBNI, and BBRI. The second portfolio consists of three stocks coded AKRA, BRPT, and MEDC. The third portfolio consists of two stocks coded BMRI and INDF.

### 3.2 Mean Absolute Deviation Portfolio

The first step in MAD portfolio optimization is to calculate the minimum return of each portfolio. The minimum return is obtained from the average expected return of the stock (**Table 1**). The minimum return value of each stock portfolio is obtained as shown in **Table 6**.

**Table 6. Minimum Return Portfolio**

Portfolio	Minimum Return
1	0.00059
2	0.00155
3	0.00079

Next, calculate the MAD value of each stock using **Equation (11)**. The MAD value of each stock is presented in **Table 7**.

**Table 7. MAD Value of Each Stock**

Stock	MAD
AKRA	0.01750
AMRT	0.01584
BBCA	0.00855
BBNI	0.00924
BBRI	0.01014
BMRI	0.01716
BRPT	0.01693
INDF	0.00940
MEDC	0.02520

To obtain the investment weight of each stock using the MAD method portfolio, one can use the simplex method by creating an equation consisting of an objective function and a constraint function. The risk of the portfolio of stocks and also the objective function can be calculated using **Equation (12)**, while the constraint function uses **Equation (13)**, **Equation (14)**, and **Equation (15)**.



Portfolio 1  
 minimize :  $\sigma(W_1) = 0.01584w_2 + 0.00855w_3 + 0.00924w_4 + 0.01014w_5$   
 with constraint  
 $0.00105w_2 + 0.00027w_3 + 0.00028w_4 + 0.00076w_5 \geq 0.00059$   
 $w_2 + w_3 + w_4 + w_5 = 1$   
 $w_i \leq 30\%, i = 2,3,4,5$

Portfolio 2  
 minimize :  $\sigma(W_2) = 0.01750w_1 + 0.01693w_7 + 0.02520w_9$   
 with constraint  
 $0.00017w_1 + 0.00238w_7 + 0.00208w_9 \geq 0.00155$   
 $w_1 + w_7 + w_9 = 1$   
 $w_i \leq 40\%, i = 1,7,9$

Portfolio 3  
 minimize :  $\sigma(W_3) = 0.01716w_6 + 0.00940w_8$   
 with constraint  
 $0.00118w_6 + 0.00041w_8 \geq 0.00079$   
 $w_6 + w_8 = 1$   
 $w_i \leq 50\%, i = 6,8$

From the above problems, the solution to getting the investment weight of each stock is done using the simplex method. **Table 8** shows the investment weights of each stock as follows.

**Table 8. Stock Investment Weight**

Portfolio	Stock	Investment Weight
1	AMRT	0.21950
	BBCA	0.30000
	BBNI	0.18050
	BBRI	0.30000
2	AKRA	0.34030
	BRPT	0.40000
	MEDC	0.25970
3	BMRI	0.50000
	INDF	0.50000

After getting the stock investment weight, calculate the portfolio's expected return using **Equation (16)** and portfolio risk using **Equation (12)**. Furthermore, portfolio performance assessment is carried out using the Sharpe index to determine which portfolio has the best performance using **Equation (20)**. The expected return portfolio value, portfolio risk, and portfolio performance assessment can be seen in **Table 9**.

**Table 9. Expected Return Portfolio, Risk Portfolio, and Portfolio Performance Assessment**

Portfolio	Expected Return Portfolio	Risk Portfolio	Performance Assessment
1	0.00059	0.01075	0.05488
2	<b>0.00155</b>	<b>0.01927</b>	<b>0.08043</b>
3	0.00079	0.01328	0.05948

Based on **Table 9**, the expected return and the risk of the largest stock portfolio are in the second portfolio, which consists of three stocks: AKRA, BRPT, and MEDC. The expected return value of the portfolio and the risk of the smallest stock portfolio are in the first portfolio, which consists of stocks coded AMRT, BBCA, BBNI, and BBRI. **Table 9** reveals that Portfolio 2 owns the largest Sharpe index. As a result, Portfolio 2 outperforms the other two portfolios. So, among the three portfolios formed, stock investing using Portfolio 2 is more optimal.

#### 4. CONCLUSIONS

Using factor analysis with the Principal Component Analysis (PCA) extraction method, portfolio identification obtained three new factors or three stock portfolios. The first portfolio consists of four stocks, the second one consists of three stocks and the third consists of two stocks where these stocks are IDX30 index. Using the portfolio optimization Mean Absolute Deviation (MAD) method, the investment weight for each stock is obtained as follows: namely, in the first portfolio, the investment weight of AMRT shares is 21.95%, BBKA shares are 30%, BBNI shares are 18.05%, and BBRI shares are 30%. In the second portfolio, the investment weight of AKRA shares is 34.03%, BRPT shares are 40%, and MEDC shares are 25.97%. While the third portfolio investment weighted BMRI shares by 50% and INDF shares by 50%.

The optimal portfolio with portfolio performance measurement using the Sharpe index is in the second portfolio because it has the highest Sharpe index value with an expected return portfolio of 0.155% and a risk portfolio of 1.927%. Thus, the second portfolio has better or more optimal performance than the first and third portfolios.

#### REFERENCES

- [1] Kustodian Sentral Efek Indonesia, "Statistik Pasar Modal Indonesia," PT Kustodian Sentral Efek Indonesia, 2023. [Online]. Address: [https://www.ksei.co.id/files/Statistik\\_Publik\\_-\\_Januari\\_2023\\_v2\\_\(3\).pdf](https://www.ksei.co.id/files/Statistik_Publik_-_Januari_2023_v2_(3).pdf) [access : 28 December 2023].
- [2] A. Maharani and Farhan Saputra, "Relationship of Investment Motivation, Investment Knowledge and Minimum Capital to Investment Interest," *Journal of Law, Politic and Humanities*, vol. 2, no. 1, pp. 23–32, 2021.
- [3] D. Septiani, A. Martono, Ferdiansyah, and L. Karlina, "Pengenalan Manajemen Investasi Dan Pasar Modal Bagi Siswa/i Dan Guru Akuntansi SMK Bintang Nusantara," *KUAT : Keuangan Umum dan Akuntansi Terapan*, vol. 2, no. 1, pp. 58–63, Mar. 2020.
- [4] A. F. Ridwan, Subiyanto, and S. Supian, "IDX30 Stocks Clustering with K-Means Algorithm based on Expected Return and Value at Risk," *IJORM*, vol. 2, no. 4, pp. 201–208, 2021.
- [5] I. N. Safitri, Sudrajat, and E. Lesmana, "Stock Portfolio Analysis Using Markowitz Model," *IJORM*, vol. 1, no. 1, pp. 47–58, 2020.
- [6] N. Zarkan, "Kinerja Portofolio Saham pada Perusahaan Makanan, Properti dan Pertambangan di Bursa Efek Indonesia," *Esensi: Jurnal Bisnis dan Manajemen*, vol. 7, no. 2, pp. 247–260, Oct. 2017.
- [7] L. I. Wijaya and Zunairoh, "Factor Analysis of Investor Behavior in Indonesian Stock Exchange during COVID-19 Pandemic," *Journal Of Hunan University*, vol. 48, no. 8, pp. 244–254, 2021.
- [8] A. H. L. Rachmawati, Mustafid, and D. A. I. Maruddani, "Pembentukan Portofolio Saham Optimal Dengan Mean Absolute Deviation Pada Data Saham Jakarta Islamic Index," *JURNAL GAUSSIAN*, vol. 11, no. 2, pp. 237–247, 2022.
- [9] H. K. Alfredo, "Analysis of Expected Stock Returns in 2020 - 2022 Using Arbitrage Pricing Theory (Study on Stocks Incorporated with The IDX-30 Index on The Indonesia Stock Exchange)," *Eduvest*, vol. 3, no. 3, pp. 626–646, 2023.
- [10] E. D. Astawinetu, Istiano, and E. Yuliaty, "Analysis of the Effect of Covid-19 on Stock Prices in IDX30," *JEFMS*, vol. 4, no. 12, pp. 2593–2599, 2021.
- [11] E. P. Sirait, Y. Salih, and R. A. Hidayana, "Investment Portfolio Optimization Model Using The Markowitz Model," *IJORM*, vol. 3, no. 3, pp. 124–132, 2022.
- [12] D. Wulandari, D. Ispriyanti, and A. Hoyyi, "Optimalisasi Portofolio Saham Menggunakan Metode Mean Absolute Deviation Dan Single Index Model Pada Saham Indeks LQ-45," *JURNAL GAUSSIAN*, vol. 7, no. 2, pp. 118–131, 2018.
- [13] N. K. N. S. Suyasa, K. Dharmawan, and K. Sari, "Perhitungan Portofolio Optimal Dengan Metode Mean-Semivariance Dan Mean Absolute Devition (Studi Kasus: Indeks Harga Saham LQ45 Periode Februari 2017-Juli 2019)," *E-Jurnal Matematika*, vol. 10, no. 2, pp. 65–69, May 2021.
- [14] A. Rahmayanti, A. L. Safitri, F. Minata, and Sugiyanto, "Pengaruh Risiko, Return, dan Perekonomian Indonesia Terhadap Keputusan Berinvestasi Saham Saat Covid-19," in *Proc. HUMANIS*, Banten: Universitas Pamulang, 2021, pp. 26–45, Okt. 14–15, 2021.
- [15] S. Manullang, D. Aryani, and H. Rusydah, "Analisis Principal Component Analysis (PCA) dalam Penentuan Faktor Kepuasan Pengunjung terhadap Layanan Perpustakaan Digilib," *Edumatic: Jurnal Pendidikan Informatika*, vol. 7, no. 1, pp. 123–130, 2023.
- [16] C. C. David and J. Jacobs, "Principal Component Analysis: A Method for Determining the Essential Dynamics of Proteins," in *Methods in molecular biology*, vol. 1084, New Jersey: Humana Press, 2014.
- [17] J. F. Hair, W. C. Black, B. J. Babin, and R. E. Anderson, *Multivariate Data Analysis*, 8th ed. Cengage, 2019.
- [18] M. S. Daud, S. Osman, A. H. Hashim, and H. A. Rahim, "Internal Consistency Reliability and Construct Validity of the Safety Questionnaire for Ride-Hailing Car," *International Journal of Academic Research in Business & Social Sciences*, vol. 13, no. 4, pp. 755–768, 2023.
- [19] M. Susilawati, I. W. Sumarjaya, Srinadi IGAM, D. Nilakusmawati, and N. Suciptawati, "Analysis of Socio-Economic Impacts of The Covid-19 Pandemic Using Factor Analysis," *Barekeng*, vol. 17, no. 3, pp. 1235–1244, 2023.
- [20] S. P. Mishra et al., "Multivariate Statistical Data Analysis- Principal Component Analysis (PCA)," *IJLR*, vol. 70, no. 5, pp. 60–78, 2017.
- [21] M. R. Hussain, M. Qayyum, and M. E. Hussain, "Effect of Seven Steps Approach on Simplex Method to Optimize the Mathematical Manipulation," *IJRTE*, vol. 7, no. 5, pp. 34–43, 2019.

- [22] R. Rumahorbo and A. Mansyur, "Konsistensi Metode Simpleks Dalam Menentukan Nilai Optimum," *KARISMATIKA*, vol. 3, no. 1, pp. 36–46, 2017.
- [23] B. Benjljel and H. Mansali, "The expected sharpe ratio of efficient portfolios under estimation errors," *Cogent Economics & Finance*, vol. 9, no. 1, pp. 1–16, 2021.
- [24] F. Melta and D. Murni, "Pembentukan Portofolio Optimal Model Markowitz Menggunakan Metode Sharpe(Studi Kasus pada Saham Jakarta Islamic Index)," *Journal Of Mathematics UNP*, vol. 6, no. 3, pp. 45–52, Sep. 2021.

