Investment Portfolio Optimization in Renewable Energy Stocks in Indonesia Using Mean-Variance Risk Aversion Model

Willen Vimelia[1*], Riaman[2], Sukono[3]

[1]*Mathematics Undergraduate Study Program, Faculty of Mathematics and Natural Science, Universitas Padjadjaran, Sumedang, Indonesia*

[2,3]*Department of Mathematics, Faculty of Mathematics and Natural Science, Universitas Padjadjaran, Sumedang, Indonesia*

*Corresponding author email: willen20001@mail.unpad.ac.id

Abstract

Climate change is a phenomenon that has been occurring for quite some time. However, the increasingly felt impacts of climate change necessitate human action to mitigate these effects. One way to address this issue is by transitioning from conventional or non-renewable energy sources to renewable energy. This step undoubtedly has implications for various aspects, such as investments. Naturally, investors are beginning to turn their attention to the field of renewable energy as a new target. Investments are inherently associated with risks and returns One approach to maximizing returns is through portfolio optimization. One well-known method in portfolio optimization is the Mean-Variance method, also known as the Markowitz method, as it was first introduced by Harry Markowitz. In this research, an optimal portfolio is generated with weights of 0.1470 for ADRO; 0.1939 for MEDC; 0.2143 for ITMG and 0.4449 for RAJA. With this composition of optimal portfolio weights, the expected return is obtained at 0.002252, and the return variance is 0.000496.

Keywords: Portfolio Optimization, investment, Mean-Variance, Renewable Energy.

1. Introduction

Climate change, at present, has become a widely discussed topic due to its felt impacts, affecting various aspects of human life. Climate change is a long-term alteration in the statistical distribution of weather patterns over a period of time (Wandira Priyahita et al., 2016). Climate change is a primary factor posing a threat to sustainable food production (Bantacut, 2014). According to the Unity of Nation and Politics Agency of Kulon Progo, climate change is disrupting food production in Indonesia. Indonesia holds significant potential as a global food source due to its agricultural activities. Climate change is expected to disturb food production due to high temperatures and extreme weather conditions. The Intergovernmental Panel on Climate Change (IPCC) estimates that factors such as droughts, heatwaves, and floods resulting from climate change can harm Indonesia's agriculture. Rice production is projected to decrease by 6% without additional efforts. The Unity of Nation and Politics Agency of Kulon Progo suggests that even with additional efforts, rice production will still decline by 2% (Kesbangpol Kulon Progo, 2022).

The impacts of climate change can be mitigated, and one way to achieve this is by transitioning from non-renewable energy to renewable energy sources. The costs of various forms of renewable energy have decreased, leading to an increasing adoption of renewable energy. In some countries and regions, a significant portion of the electricity grid already relies on renewable energy sources (IPCC, 2022). According to the Ministry of Finance of the Republic of Indonesia, climate change and energy transition have been highlighted as crucial issues during the G20 Indonesia Presidency. The Indonesian Minister of Finance has emphasized the importance of expediting the design of a transition towards cleaner and greener energy sources (Kementrian Keuangan Republik Indonesia, 2022).

The transition to the use of renewable energy can impact the stocks of companies in the renewable energy sector. The stock prices of these companies tend to increase over time, making them potentially attractive to investors looking to invest in the renewable energy field. Investment decision-making is inherently tied to the consideration of two crucial factors: return and risk (Senthilnathan, 2015). The relationship between the expected rate of return and the level of risk is linear. This means that the higher the expected rate of return from an investment, the higher the level of risk faced. Conversely, if the expected rate of return is lower, the level of risk tends to be lower as well (Puspitaningtyas, 2015). One effective method to mitigate risks in investment is through diversification. Investment

diversification is a widely embraced strategy that seeks to minimize investment uncertainty while preserving the anticipated level of return. The evolution of investment diversification aligns with the development of portfolio theory (Leković, 2018). Based on the Markowitz portfolio theory, portfolio diversification is achieved by investing in stocks across multiple locations with different compositions (Rokhmawati, 2021).

Optimizing investment portfolios can serve as a tool for investors to make informed investment decisions. The essence of portfolio construction lies in allocating funds across various investment alternatives to minimize investment risks (Das et al., 2010). Portfolio theory, introduced by Harry M. Markowitz in 1952, originated from the investor's desire to minimize investment risk. The portfolio theory advocates for spreading investments across different assets with varying compositions to avoid losses (portfolio diversification) (Rokhmawati, 2021).

Previous research in recent years has employed various methods to optimize investment portfolios. For example, Zhang et al. evaluated optimal investment portfolio strategies implemented by electric companies using real options and portfolio optimization methods. The results indicated that the optimal decision to ensure relatively high value while reducing risk involves increasing the share of solar PV and wind power generation. Stricter carbon reduction standards and higher prices for renewable energy certificates help enhance investment value, reduce the risk of losses, and increase the share of renewable energy power generation (Zhang et al., 2022). Additionally, Mahayani and Suarjaya determined the optimal portfolio based on the Markowitz model for infrastructure companies listed on the Indonesia Stock Exchange. The study produced nominations and fund proportions from stocks included in the optimal portfolio combination, resulting in an optimal expected return accompanied by portfolio risk based on the Markowitz model (Mahayani & Suarjaya, 2019).

Based on the explanations above, this paper discusses the optimization of investment portfolios in renewable energy stocks in Indonesia using the Mean-Variance Risk Aversion model. The aim of this research is to obtain the allocation proportions of capital invested in various renewable energy stocks traded on the Indonesian capital market. The findings of this study can serve as considerations for investment decision-making for investors, particularly concerning the analyzed stocks.

2. Literature Review

2.1. Investment

Investment is any effort related to how to input the value of investors money into assets or objects that will become more valuable in the future compared to its initial value (Firmansyah et al., 2022). investor buys a certain amount of shares at present with the hope of gaining profits from the increase in stock prices or a certain amount of dividends in the future. The profits obtained are a reward for the time and risk associated with the investment (Handini & Astawinetu, 2020).

Investment is inherently tied to both return and risk. The relationship between risk and expected return in an investment is typically linear and direct. Consequently, investors consider not only high returns but also the level of risk they must bear (Handini & Astawinetu, 2020).

2.2. Stock Return

Stocks, as one of the instruments for seeking additional funds and representing ownership in a company, implies that investors who invest in these stocks reflect ownership of the company. Investors gain profits from buying stocks through two means: dividends and capital gains (Samsul, 2015). Dividends are profits distributed by the company to all shareholders. Stock returns can be calculated using equation (1) (Miskolczi, 2017)

$$r_{it} = \ln\left(\frac{P_{it}}{P_{i(t-1)}}\right) \tag{1}$$

where,
r_{it} : return of stock i at time t,
P_{it} : price of stock i at time t,
$P_{i(t-1)}$: price of stock i at time $(t-1)$.

2.3. Stock Risk

Risk represents the possibility of an investment failing to meet the expected return level or expected return as anticipated by the investor (Sari, 2021). Every decision made in investing is strongly associated with risk. Therefore,

the risk of stocks is always considered one of the primary factors when an investor engages in investment activities (Suryani, 2019).

2.4. Normal Distribution

Normal distribution stands out as the most renowned probability model, extensively applicable in addressing real-world issues. Also referred to as the Gaussian distribution, it derives its name from the German mathematician Carl Friedrich Gauss. The probability density function of the Normal distribution is depicted in equation (2) with parameters where μ ranges from negative infinity to positive infinity, and σ is greater than zero (OA, 2018)

$$f(x, \mu, \sigma) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right) \tag{2}$$

Mean of the Normal distribution is obtained by using the expectation formula $E[X] = \int_{-\infty}^{\infty} x \cdot f(x, \mu, \sigma) dx$, resulting equation (3).

$$E[X] = \mu \tag{3}$$

The variance of the Normal distribution is provided in equation (4)

$$E[X^2] - E[X]^2 = \sigma^2 \tag{4}$$

2.5. Burr (4P) Distribution

A non-negative continuous random variable, X, is said to follow a Burr (4P) distribution if it has a probability density function as described in equation (5) (Shakil et al., 2020).

$$f(x) = \frac{\alpha k \left(\frac{x-\gamma}{\beta}\right)^{\alpha-1}}{\beta\left(1 + \left(\frac{x-\gamma}{\beta}\right)^{\alpha}\right)^{k+1}} \tag{5}$$

Mean and variance of the Burr (4P) distribution is provided in equation (6) and (7),

$$E[X] = \gamma + k\beta \cdot B\left(1 + \frac{1}{\alpha}, k - \frac{1}{\alpha}\right) \tag{6}$$

$$E[X^2] - E[X]^2 = k\beta^2 \cdot B\left(1 + \frac{2}{\alpha}, k - \frac{2}{\alpha}\right) - k^2\beta^2\left(B\left(1 + \frac{1}{\alpha}, k - \frac{1}{\alpha}\right)\right)^2 \tag{7}$$

2.6. Stock Covariance

The covariance of returns is a measure that indicates the extent to which the returns of two stocks tend to move together. The covariance of returns between two stocks can be calculated by involving the correlation coefficient. Correlation is a standardized form of covariance obtained by dividing covariance by the standard deviation of each variable. The formula for covariance can be obtained by modifying the formula for the correlation coefficient in equation (8) (Kim, 2018).

$$Cov(X, Y) = Cor \cdot \sigma_X \cdot \sigma_Y \tag{8}$$

where,
$Cov(X, Y)$: covariance of stock X and Y,
σ_X : standard deviation of stock X,
σ_Y : standard deviation of stock Y.

2.7. Expectation, Variance, and Covariance of Portfolio Return

Let's assume an investment portfolio consists of N risky stocks, where the return of each stock is denoted as $r_{1.t}, r_{2.t}, \ldots, r_{N.t}$. If we denote **r** as the vector of stock returns, then **r** can be expressed in the following equation (Stoilov et al., 2021).

$$\mathbf{r} = \begin{pmatrix} r_{1.t} \\ r_{2.t} \\ \vdots \\ r_{N.t} \end{pmatrix}$$

Assuming that the first and second moments of the stock returns exist. Let **μ**, **w**, and **e**, represent the vector of mean, vector of weights, and the unit vector, respectively, defined as:

$$\boldsymbol{\mu} = \begin{pmatrix} \mu_1 \\ \mu_2 \\ \vdots \\ \mu_N \end{pmatrix}; \mathbf{w} = \begin{pmatrix} w_1 \\ w_2 \\ \vdots \\ w_N \end{pmatrix}; \text{ and } \mathbf{e} = \begin{pmatrix} 1 \\ 1 \\ \vdots \\ 1 \end{pmatrix}$$

where $\mu_i = E[r_{i.t}]$, $(i = 1, 2, \ldots, N)$. The weight or proportion of funds allocated to stock i represented by w_i ($i = 1, 2, \ldots, N$) and **e** is a vector with elements consisting of the number 1, repeated N times. The return of the investment portfolio, r_p is expressed as stated in equation (9)

$$r_p = \sum_{i=1}^{N} w_i r_{i.t} \text{ where } \sum_{i=1}^{N} w_i = 1 \tag{9}$$

Using mathematical notation, the investment portfolio return in equation (9) can be expressed as shown in equation (10)

$$r_p = \mathbf{w}^T \mathbf{r} \tag{10}$$

Based on equation (9), the expected return of the investment portfolio μ_p can be expressed as shown in equation (11)

$$\mu_p = E[r_p] = \sum_{i=1}^{N} w_i E[r_{i.t}] = \sum_{i=1}^{N} w_i \mu_i \tag{11}$$

Meanwhile, based on equation (10), the expected return of the investment portfolio μ_p can be expressed in equation (12)

$$\mu_p = E[r_p] = \mathbf{w}^T E[\mathbf{r}] = \mathbf{w}^T \boldsymbol{\mu} \tag{12}$$

Furthermore, let **Σ** and **I** represent the covariance matrix and identity matrix, respectively, as stated in equation (13)

$$\boldsymbol{\Sigma} = \begin{pmatrix} \sigma_1^2 & \sigma_{12} & \cdots & \sigma_{1N} \\ \sigma_{21} & \sigma_2^2 & \cdots & \sigma_{2N} \\ \vdots & \vdots & \vdots & \vdots \\ \sigma_{N1} & \sigma_{N2} & \cdots & \sigma_N^2 \end{pmatrix} \text{ and } \mathbf{I} = \begin{pmatrix} 1 & 0 & \cdots & 0 \\ 0 & 1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & \cdots & 1 \end{pmatrix} \tag{13}$$

Referring to equation (9), the algebraic expression for the variance of the investment portfolio return can be stated in equation (14)

$$\sigma_p^2 = Var(r_p) = \sum_{i=1}^{N}\sum_{j=1}^{N} w_i w_j \sigma_{ij} = \sum_{i=1}^{N}\sum_{j=1}^{N} w_i w_j \sigma_i \sigma_j \rho_{ij} \tag{14}$$

The term σ_{ij} in equation (14) can be expressed in the form of equation (15)

$$\sigma_{ij} = Cov(r_i, r_j) = E\left[(r_i - \mu_i)(r_j - \mu_j)\right] = \rho_{ij}\sigma_i\sigma_j \tag{15}$$

where σ_{ij} represents the covariance between stocks i and j where $\sigma_i = \sqrt{\sigma_i^2}$ $(i = 1, 2, \ldots, N)$ is called the standard deviation. By using matrix-vector notation, the variance of the portfolio return in equation (14) can be expressed as in equation (16)

$$\sigma_p^2 = \mathbf{w}^T \boldsymbol{\Sigma} \mathbf{w} \tag{16}$$

After determining the expected return, variance, and covariance of the portfolio return, the next issue is how to choose an efficient portfolio, namely a portfolio that has a high expected return μ_p with low risk measured by the variance (σ_p^2).

2.8. Mean Variance Model

The portfolio theory was introduced by Harry M. Markowitz in 1952. Markowitz's portfolio theory was motivated by investors' desire to minimize investment risks. The theory suggests that investors should diversify their investments across different assets to mitigate losses (portfolio diversification) (Rokhmawati, 2021). Portfolio theory establishes a direct relationship between return and risk (Maf'ula et al., 2018). Furthermore, investment decisions are made by identifying securities with the highest return and low risk, and including them in the investment portfolio (Ivanova & Dospatliev, 2018).
To obtain an efficient portfolio, the objective function is typically to maximize equation (17),

$$\mu_P - \frac{\rho}{2}\sigma_P^2, \rho \geq 0 \tag{17}$$

where the investor's risk aversion is expressed by the parameter ρ . This means that for an investor with *risk aversion* ρ ($\rho \geq 0$), they need to solve the portfolio problem:

$$\text{Maximize } \left\{\mu_p - \frac{\rho}{2}\sigma_p^2\right\}$$

$$\text{with the condition } \sum_{i=1}^{N} w_i = 1$$

$$w_i \geq 0$$

or

$$\text{Maximize } \left\{\mathbf{w}^T\boldsymbol{\mu} - \frac{\rho}{2}\mathbf{w}^T\boldsymbol{\Sigma}\mathbf{w}\right\}$$

$$\text{with the condition } \boldsymbol{w}^T\mathbf{e} = 1 \tag{18}$$

$$w_i \geq 0$$

where $\boldsymbol{e}^T = (1, 1, \ldots, 1) \in \mathfrak{R}^N$ (Ivanova & Dospatliev, 2018). The solution to the Markowitz portfolio model in equation (18) is given in equation (19).

$$\mathbf{w} = \frac{2}{\rho}\boldsymbol{\Sigma}^{-1}(\boldsymbol{\mu} + \lambda\mathbf{e}) \tag{19}$$

where,

$$\lambda = \frac{\frac{\rho}{2} - \mu^T \Sigma^{-1} e}{e^T \Sigma^{-1} e} \tag{20}$$

The solutions to (18), for all $\rho \in [0, \infty)$, form a complete set of efficient portfolios. The set of all points in the (μ_p, σ_p^2) diagram associated with efficient portfolios is called the efficient frontier, as illustrated in Figure 1, for example.
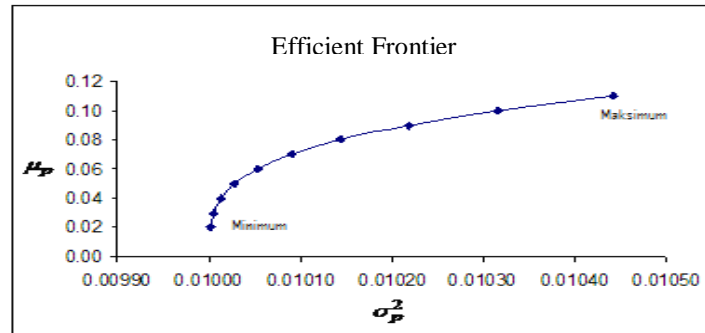

Figure 1: Efficient Frontier

3. Materials and Methods

3.1. Materials

In this paper, the subject under investigation is stocks of companies in Indonesia that operate in the field of renewable energy. Closing stock price data is collected from www.finance.yahoo.com for the period from 1 December 2021 to 30 November 2023. The data utilized comprises 6 (six) stocks, namely ADRO, MEDC, ITMG, RAJA, TOBA, and INDY.

3.2. Methods

a). Input daily closing price data of renewable energy stocks in Indonesia from 1 December 2021 to 30 November 2023.

b). Calculate the stock return values using equation (1). Then estimate the parameters and perform a model distribution test of stock return using EasyFit.

c). Calculate the expected return values using equations (3) and (6), variance of return using equations (4) and (7), and covariance of return using equation (8). Then form the μ, e, and Σ.

d). Set the initial value of $\rho = 0$ and then calculate the composition of the allocation weights of stocks using equation (19). If there are still negative stock weights and the total composition weight is not equal to 1, then a new rho value is sought.

e). Calculate the expected return and variance of the portfolio return using (12) and (16), as well as the portfolio ratio which is the comparison between return and variance of the portfolio.

f). Determine the optimal portfolio by identifying the portfolio with the highest portfolio ratio.

4. Results and Discussion

The first step is to calculate the return of each stock to determine the type of distribution by estimating the distribution parameters and then testing it with the Anderson-Darling test. The confidence level used is 0,01. With the assistance of EasyFit, it is found that the return of ADRO follows a Normal distribution, while the return of MEDC, ITMG, RAJA, TOBA, and INDY follows a Burr (4P) distribution. The results can be seen in Table 1.

Table 1. expected return, metrix of identity, and covariance matrix

	Distribution	A	A_{table}	Result	Final Result
ADRO	Normal	2.7845	3.9074	$A < A_{table}$	Normal
MEDC	Burr (4P)	0.51454	3.9074	$A < A_{table}$	Burr (4P)
ITMG	Burr (4P)	1.0597	3.9074	$A < A_{table}$	Burr (4P)
RAJA	Burr (4P)	1.9520	3.9074	$A < A_{table}$	Burr (4P)
TOBA	Burr (4P)	1.557	3.9074	$A < A_{table}$	Burr (4P)
INDY	Burr (4P)	1.1121	3.9074	$A < A_{table}$	Burr (4P)

Next, calculate the expected return and variance of return for each stock according to its distribution. The same applies to the covariance of return. Value of expected return, vector **e**, and covariance of return can be seen in Table 2. Based on Table 2, it can be observed that the expected return of TOBA and INDY stocks is negative, indicating a high likelihood of significant risk for investors. Therefore, both stocks are eliminated or not included in the portfolio.

Table 2. Anderson-Darling test result

	μ	e	Σ			
			ADRO	ITMG	MEDC	RAJA
ADRO	0.00082280	1	0.00070925	0.00040547	0.00037863	0.00016653
MEDC	0.00188000	1	0.00040547	0.00057726	0.00027321	0.00014972
ITMG	0.00049827	1	0.00037863	0.00027321	0.00121000	0.00023904
RAJA	0.00373000	1	0.00016653	0.00014972	0.00023904	0.00125000
TOBA	-0.0025200					
INDY	-0.0000813					

The portfolio optimization process commences with the computation of the allocation weights of portfolio stocks when risk aversion value or $\rho = 0$. During this computation, negative weight allocations for portfolio stocks may be encountered. An optimal portfolio at a given ρ value is achieved when all weight allocations for portfolio stocks are positive, summing up to one. Therefore, ρ_B is determined by adding ρ_L or the previous risk avoidance value with a specific value until the condition of positive weight allocations and a total of one is fulfilled. Subsequently, the expected return and variance of the portfolio return are calculated. Additionally, the portfolio ratio, representing the ratio of expected return to the variance of the portfolio return, is computed. The results of these computations, including the composition of capital allocation weights, expected return, variance of return, and portfolio ratio, are presented in Table 3. Based on Table 3, efficient portfolios are obtained when the value of ρ falls within the interval $[9,52; \infty)$. The composition of the weight allocation of the portfolio when $\rho < 9,52$ results in entries with negative values, thus it is not included in the efficient portfolio set, even though the total composition weights are equal to 1. Additionally, the efficient surface plot is depicted in Figure 2.

Table 3. portfolio optimization result

ρ	ADRO	MEDC	ITMG	RAJA	$w^T e$	μ_P	σ_P^2	Ratio
9.51	0.1015	0.2513	-0.0002	0.6475	1	0.002971	0.000727	4.08868
9.52	0.1016	0.2512	0.0002	0.6470	1	0.002969	0.000726	4.09026
9.60	0.1024	0.2502	0.0040	0.6435	1	0.002957	0.000721	4.10267
9.80	0.1043	0.2477	0.0131	0.6349	1	0.002926	0.000708	4.13253
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
17.00	0.1436	0.1981	0.1983	0.4599	1	0.002305	0.000508	4.53520
17.20	0.1442	0.1974	0.2012	0.4572	1	0.002295	0.000506	4.53638
17.40	0.1448	0.1966	0.2041	0.4545	1	0.002286	0.000504	4.53732
17.60	0.1454	0.1958	0.2069	0.4518	1	0.002276	0.000502	4.53801
17.80	0.1460	0.1951	0.2096	0.4492	1	0.002267	0.000500	4.53848
18.00	0.1466	0.1944	0.2123	0.4467	1	0.002258	0.000498	4.53874
18.15	0.1470	0.1939	0.2143	0.4449	1	0.002252	0.000496	4.53880
18.20	0.1471	0.1937	0.2149	0.4442	1	0.002249	0.000496	4.53879
18.40	0.1477	0.1930	0.2175	0.4418	1	0.002241	0.000494	4.53865
18.60	0.1482	0.1923	0.2200	0.4395	1	0.002232	0.000492	4.53834
18.80	0.1487	0.1917	0.2224	0.4371	1	0.002224	0.000490	4.53785
19.00	0.1492	0.1910	0.2248	0.4349	1	0.002216	0.000488	4.53719
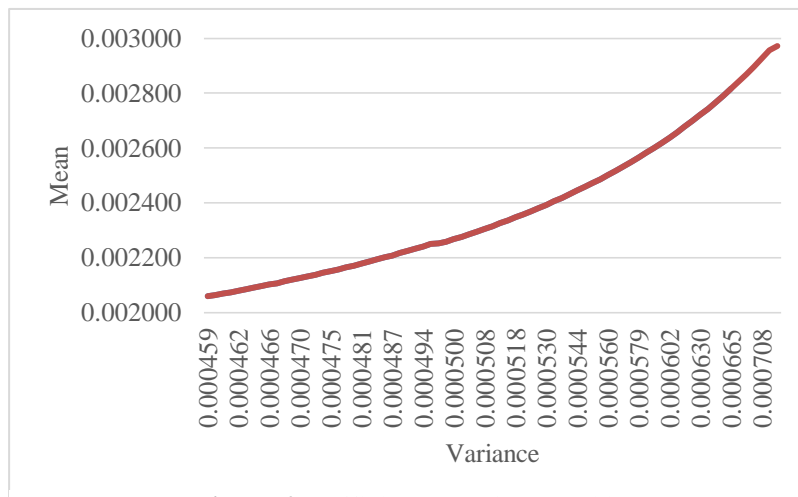
**Figure 2** : Efficient Frontier Graphic

In Figure 2, efficient portfolios are depicted, obtained with the highest expected return value of 0,002971 and the highest variance value of 0,000727. Additionally, it can be observed that as the portfolio variance (σ_P^2) increases, the expected return of the portfolio (μ_P) also increases. This implies that when an investor has a high level of risk aversion, the expected return or the anticipated return will be high. This is because a higher level of risk aversion
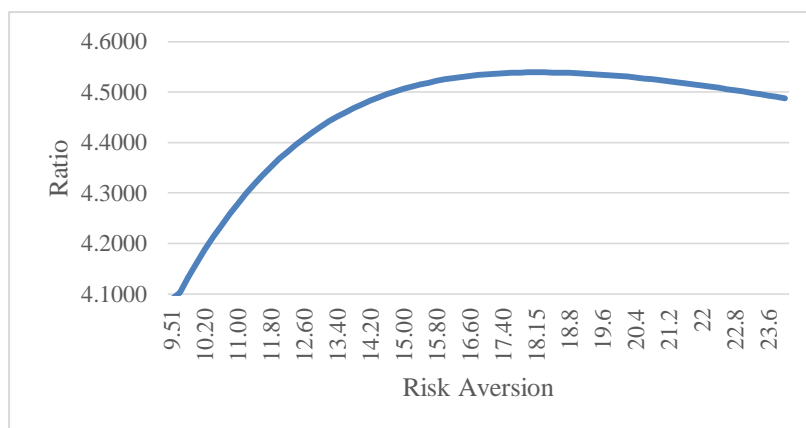
Figure 3: Comparison ratio with risk aversion graph

results in higher risks faced by the investor.

After obtaining efficient portfolios, the optimal portfolio is then determined by selecting the efficient portfolio with the highest ratio. Based on Figure 3, the ratio value continues to increase when $9.52 \leq \rho < 18.15$ and decreases when $\rho > 18.15$. The highest ratio is obtained when $\rho = 18.15$, which is 4.53880.
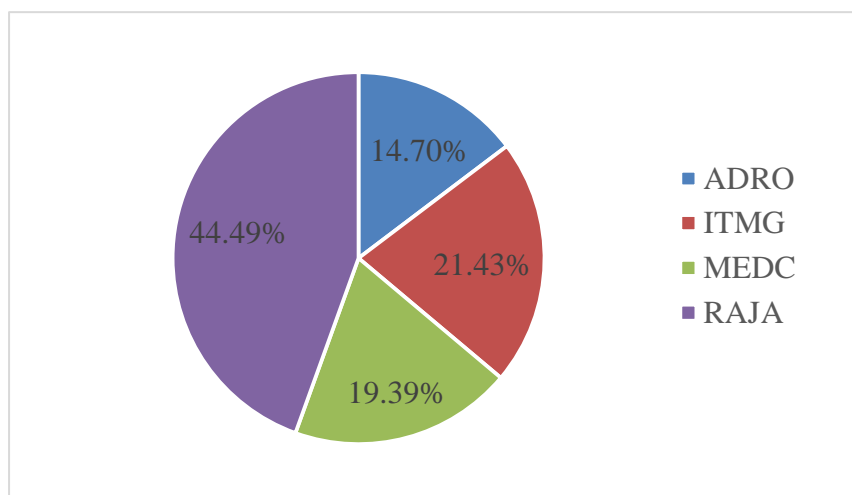
Figure 4: The composition of optimal portfolio weights

In Figure 4, the percentage composition of optimal portfolio weights for four stocks is shown: 14.70% for ADRO; 19.39% for MEDC; 21.43% for ITMG; and 44.49% for RAJA. The optimal portfolio with these weight compositions has an expected return value of 0.002252 and a portfolio variance of 0.000496.

5. Conclussion

The results of the investment portfolio optimization for stocks of companies in the renewable energy sector in Indonesia, using the Mean-Variance Risk-Aversion method, are presented in the form of stock weight compositions. Based on the analysis, the composition of the optimal portfolio weights obtained is as follows: ADRO at 0.1470; MEDC at 0.1939; ITMG at 0.2143; and RAJA at 0.4449. The expected return value is 0.002252 and the portfolio variance is 0.000496. The optimal portfolio is achieved when the portfolio ratio is 4.53880 at $\rho = 18.15$.

References

Bantacut, T. (2014). Indonesian staple food adaptations for sustainability in continuously changing climates. *Journal of Environment and Earth Science*, *4*(21), 202–216.

Das, S., Markowitz, H., Scheid, J., & Statman, M. (2010). Portfolio Optimization with Mental Accounts. *The Journal of Financial and Quantitative Analysis*, *45*(2), 311–334.

Firmansyah, H., Aswanto, Kartini, E., Syaiful, M., Wardhana, (Cand) Aditya, Pratiwi, R., Musdalifah, Hariyani, D. S., Ahdiyat, M., Sukmadewi, R., Nuha, M. U., & Ladjin, N. (2022). Pengantar Ilmu Investasi. In *Pengantar Ilmu Perekonomian, Investasi dan Keuangan* (Issue March, pp. 93–107).

Handini, S., & Astawinetu, E. D. (2020). *Teori Portofolio dan Pasar Modal Indonesia*. Scopindo Media Pustaka.

IPCC. (2022). Climate Change 2022 - Mitigation of Climate Change - Full Report. In *Cambridge University Press* (Issue 1).

Ivanova, M., & Dospatliev, L. (2018). APPLICATION OF MARKOWITZ PORTFOLIO OPTIMIZATION ON BULGARIAN STOCK MARKET FROM 2013 TO 2016. *International Journal of Pure and Apllied Mathematics*, *117*(2). https://doi.org/10.12732/ijpam.v117i2.5

Kementrian Keuangan RI. (2022). *Menkeu: Indonesia Rentan terhadap Dampak Perubahan Iklim*. https://www.kemenkeu.go.id/informasi-publik/publikasi/berita-utama/Indonesia-Rentan-terhadap-Dampak-Perubahan-Iklim

Kesbangpol Kulon Progo. (2022). *Bahaya Riil Perubahan Iklim*. https://kesbangpol.kulonprogokab.go.id/detil/620/bahaya-riil-perubahan-iklim

Kim, H.-Y. (2018). Statistical notes for clinical researchers: analysis of covariance (ANCOVA). *Restorative Dentistry & Endodontics*, *43*(4), 1–7. https://doi.org/10.5395/rde.2018.43.e43

Leković, M. (2018). Investment diversification as a strategy for reducing investment risk. *Ekonomski Horizonti*, *20*(2), 173–187. https://doi.org/10.5937/ekonhor1802173L

Maf'ula, Z., Handayani, S. R., & A., Z. Z. (2018). PORTOFOLIO OPTIMAL DENGAN PENERAPAN MODEL MARKOWITZ SEBAGAI DASAR KEPUTUSAN INVESTASI (Studi Pada Perusahaan Yang Tergabung Dalam Indeks LQ-45 Tahun 2014). In *Jurnal Administrasi Bisnis (JAB)/Vol* (Vol. 63, Issue 1).

Mahayani, N. P. M., & Suarjaya, A. A. G. (2019). PENENTUAN PORTOFOLIO OPTIMAL BERDASARKAN MODEL MARKOWITZ PADA PERUSAHAAN INFRASTRUKTUR DI BURSA EFEK INDONESIA. *E-Jurnal Manajemen Universitas Udayana*, *8*(5), 3057. https://doi.org/10.24843/ejmunud.2019.v08.i05.p17

Miskolczi, P. (2017). Note on simple and logarithmic return. *Applied Studies in Agribusiness and Commerce*, *11*(1–2), 127–136. https://doi.org/10.19041/apstract/2017/1-2/16

OA, A. (2018). Statistical Hybridization of Normal and Weibull Distributions with its Properties and Applications. *Journal of Applied & Computational Mathematics*, *07*(04). https://doi.org/10.4172/2168-9679.1000424

Puspitaningtyas, Z. (2015). *Prediksi Risiko Investasi Saham*. Griya Pandiva.

Rokhmawati, A. (2021). Comparison of power plant portfolios under the no energy mix target and national energy mix target using the mean–variance model. *Energy Reports*, *7*. https://doi.org/10.1016/j.egyr.2021.07.137

Samsul, M. (2015). Pasar Modal dan Manajemen Portofolio, penerbit Erlangga. In *Surabaya. P*.

Sari, R. T. R. (2021). Pengaruh Ekspektasi Return, Presepsi Terhadadap Risiko, dan Self Efficacy Terhadap Minat Investasi Generasi Milenial. *Jurnal Ilmu Ekonomi Dan Sosial*, *10*(1), 6–18. http://dx.doi.org/10.22441/jies.2021

Senthilnathan, S. (2015). Risk, Return and Portfolio Theory A Contextual Note. *SSRN Electronic Journal*, *October*. https://doi.org/10.2139/ssrn.2627423

Shakil, M., Kibria, B. M. G., Singh, J. N., & Ahsanullah, M. (2020). on Burr (4P) Distribution: Application of Breaking Stress Data. *Jnanabha*, *50*(02), 190–199. https://doi.org/10.58250/jnanabha.2020.50223

Stoilov, T., Stoilova, K., & Vladimirov, M. (2021). The Probabilistic Risk Measure VaR as Constraint in Portfolio Optimization Problem. *Cybernetics and Information Technologies*, *21*(1), 19–31. https://doi.org/10.2478/cait-2021-0002

Suryani, A. (2019). Analisis Risiko Investasi dan Return Saham pada Industri Telekomunikasi yang Terdaftar di Bursa Efek Indonesia. *J-MAS (Jurnal Manajemen Dan Sains)*, *4*(1), 111. https://doi.org/10.33087/jmas.v4i1.78

Wandira Priyahita, F., Sugianti, N., & Aliah, H. (2016). ANALISIS TAMAN ALAT CUACA KOTA BANDUNG DAN SUMEDANG MENGGUNAKAN SATELIT TERRA BERBASIS PYTHON. *ALHAZEN Journal of Physics*, *II*(2).

Zhang, M., Tang, Y., Liu, L., & Zhou, D. (2022). Optimal investment portfolio strategies for power enterprises under multi-policy scenarios of renewable energy. *Renewable and Sustainable Energy Reviews*, *154*. https://doi.org/10.1016/j.rser.2021.111879