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Implementation of Simulated Annealing Algorithm for Portfolio Optimization in Jakarta Islamic Index (JII) Stocks with Mean-VaR

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Abstract

One of the challenges for investors in the investment world is to manage the stock portfolio optimally. The main objective of portfolio optimization is to obtain maximum profit with a controlled level of risk. This study aims to find a portfolio combination that provides the best return with a more controllable risk than the conventional method, using Simulated Annealing (SA). This research method applies the Mean-Value at Risk (Mean-VaR) approach in measuring portfolio performance and uses the application of the SA algorithm as an optimization method to determine the optimal investment weight on stocks in the Jakarta Islamic Index (JII), so as to obtain a portfolio with the best performance compared to a simple weighting strategy. The data used in this study is the daily closing price of stocks listed in the JII during the period January 3, 2022 - January 2, 2024. Based on the results and discussion, there are 7 stocks included in the formation of the optimal portfolio of JII index stocks, namely ADRO, ICBP, INKP, ITMG, MIKA, TPIA, and UNTR. The weight allocation of each stock generated by the Simulated Annealing method for the period is for ADRO shares 7.4177%; ICBP 1.7817%; INKP 7.3369%; ITMG 15.0006%; MIKA 2.5894%; TPIA 63.5506%; and UNTR 2.323%. The optimal portfolio of the Mean-VaR model with the Simulated Annealing method is generated when the risk tolerance is 0 ($\tau = 0$), with a return or return of 0.001923 and a VaR risk level of 0.029788. This approach is expected to be an alternative for investors in determining investment strategies based on Islamic stocks in Indonesia.

Keywords: Mean-VaR, Simulated Annealing, portfolio optimization, Jakarta Islamic Index

1. Introduction

Nowadays, one of the investment instruments that is increasingly popular among the public is the capital market, especially in this era of globalization and digitalization. The capital market is generally defined as a place or platform where transactions between buyers and sellers take place through a specific platform. What distinguishes the Islamic capital market from the non-Islamic capital market is the instruments used; the Islamic capital market adheres to Islamic teachings and avoids prohibited transactions (Bahrul et al., 2023). Sharia stocks, as one of the instruments traded in the Islamic capital market, offer attractive investment opportunities for investors who wish to invest while maintaining their religious values. There are two types of Sharia stocks recognized in the Indonesian capital market. First, stocks that meet the criteria for sharia stock selection based on OJK Regulation No. 35/POJK.04/2017. Second, stocks listed as sharia stocks by issuers or sharia public companies based on OJK Regulation No. 17/POJK.04/2015.

One of the indices used as a reference for stock investors in Indonesia is the Jakarta Islamic Index (JII), which consists of the 30 most liquid sharia stocks that comply with Islamic sharia principles and are listed on the Indonesia Stock Exchange (Puspaningsih et al., 2024). The development of the sharia capital market in Indonesia has been rapid. This is evidenced by the large number of sharia-based investment instruments traded in the capital market, such as sukuk, mutual funds, stocks, and so on. The Financial Services Authority (OJK) recorded a 35% increase in the number of sharia stocks in Indonesia in 2019, from 328 stocks to 445 stocks.

When it comes to investing, portfolio management is one of the crucial elements that investors must pay attention to. The main challenge in investment management is optimizing the portfolio to maximize returns while minimizing risk. Quantitative approaches are often used to assist in investment decision-making, such as risk measurement and portfolio optimization. The Mean-Value at Risk (Mean-VaR) approach is a reliable method for measuring risk. When constructing a portfolio, investors must determine the proportion or weighting of the portfolio to allocate their funds across various available stocks (Puspaningsih et al., 2024).

Investment portfolio that considers many variables and risk constraints often difficult to optimize. Metaheuristic algorithms such as Simulated Annealing (SA) have been widely used to address this issue. The Simulated Annealing algorithm mimics the process of crystal formation, which involves heating a solid material to a temperature above its melting point, followed by gradual cooling until a crystal structure with highly ordered atomic arrangement and minimum energy probability is obtained.

Along with the growing interest in sharia-based investment in Indonesia, there is a need to develop more adaptive and efficient portfolio optimization methods, especially for stocks listed on the JII. This study aims to integrate the Mean-VaR approach with the Simulated Annealing algorithm in constructing an optimal portfolio of stocks on the JII. This approach is expected to help investors select a combination of stocks that provide optimal returns with manageable risk.

There are several previous studies relevant to this research, including Puspaningsih et al. (2024), who studied the formation of the Jakarta Islamic Index stock portfolio with optimization using the K-Medoids Clustering method and the Mean-VaR model. Additionally, Dogan et al. (2024) developed an optimal portfolio solution using Simulated Annealing on BIST30 data, concluding that the optimal number of assets in a portfolio is 10 to minimize risk and maximize return.

Based on the descriptions above, this research examines the optimization of investment portfolios that can minimize risk and maximize returns by applying the Simulated Annealing algorithm to stocks on the JII based on the Mean-VaR model. The results of this study are expected to provide consideration for decision-making by investors, especially those investing in stocks on the JII.

2. Literature Review

2.1. Capital Markets and Investment

The capital market functions as a bridge connecting investors with entities that need funds (companies). The capital market facilitates the flow of funds from investors to companies by providing various financial instruments such as stocks and bonds. The existence of the capital market can strengthen economic activity by providing additional financing options for business actors, enabling them to grow on a larger scale.

Investing is a personal decision that involves placing funds with the expectation of future profits. Calculating returns alone is never enough in the context of investing. Risk also needs to be included in the calculation, because the consideration of an investment is a trade-off between these two factors (Fareva et al., 2021). Investors often use various analytical tools such as fundamental and technical analysis to maximize returns and minimize risk.

2.2. Stocks

Stocks represent partial ownership of a company. An investor who owns shares indirectly becomes an owner of the company. In terms of claim rights, shares are divided into two types: common stock and preferred stock (Brabenec et al., 2020). Stock prices in the market tend to be volatile and are influenced by various factors, including the company's overall performance, general economic conditions, and prevailing market sentiment.

2.3. Stock Return

Return can be defined as the rate of return or the results obtained from investment activities (Puspaningsih et al., 2024). Expected stock returns are estimates of the returns that investors expect to earn in the future. Many factors influence stock returns, including internal and external factors (Rudianto & Sutawidjaya, 2012). Return can be calculated using the following formula,

$$R_{i,t} = \frac{P_{i,t} - P_{i(t-1)}}{P_{i(t-1)}}, \tag{1}$$

with

$R_{i,t}$: return of the i-th stock in t-th period,
$P_{i,t}$: price of the i-th stock in t-th period,
$P_{i(t-1)}$: price of the i-th stock in $(t-1)$-th period.

Furthermore, the expected value of return can be determined from the stock return using the following formula,

$$\mu_i = \frac{\sum_{t=1}^{n} R_{i,t}}{n}, \tag{2}$$

with
μ_i : expected return of of the i-th stock,
n : the number of periods used.

Covariance measures the strength of the relationship between the returns of two stocks, calculated as

$$\sigma_{i,j} = \frac{\sum_{t=1}^{n} \left(R_{i,t} - \mu_i\right).\left(R_{j,t} - \mu_j\right)}{n}, \tag{3}$$

with
$\sigma_{i,j}$: covariance between the i-th stock and the j-th stock,
$R_{j,t}$: return of the j-th stock in t-th period,
μ_j : expected value return of the j-th stock.

2.4. Stock Risk

Stock price volatility is a significant indicator of risk. Stocks with high volatility tend to have greater risk, so investors need to consider their risk profile before investing (Bodie et al., 2014). The amount of stock risk can be determined using the following equation,

$$\sigma_i^2 = \frac{\sum_{t=1}^{n} (R_{i,t} - \mu_i)^2}{n}, \tag{3}$$

or

$$\sigma_i = \sqrt{\frac{\sum_{t=1}^{n} (R_{i,t} - \mu_i)^2}{n}}, \tag{4}$$

with
σ_i^2 : variance of the i-th stock,
σ_i : standard deviation of the i-th stock in t-th period,
$R_{i,t}$: return of the i-th stock in t-th period,
μ_i : expected return of the i-th stock.

2.5. Jakarta Islamic Index (JII)

The Jakarta Islamic Index (JII) is an index of 30 sharia stocks with good financial performance and high transaction liquidity on the Indonesia Stock Exchange (Puspaningsih et al., 2024). PT Bursa Efek Indonesia (BEI) introduced the Jakarta Islamic Index (JII) on July 3, 2000, as an effort to develop the sharia capital market in Indonesia. The establishment of the JII was made possible through collaboration between the Indonesian Capital Market and PT. Danareksa Investment Management (PT. DIM). The selection of stocks included in the JII is highly selective, based on sharia criteria set by the National Sharia Council, so that stocks included in the JII must meet two main criteria: sharia criteria and liquidity. A study conducted by Al Ghifari et al., (2021) revealed that macroeconomic factors such as the SBIS (Bank Indonesia Sharia Certificate) yield rate, the rupiah exchange rate, and the inflation rate have a significant effect on the performance of the Jakarta Islamic Index (JII).

2.6. Investment Portfolio

Investment portfolio is a combination of financial assets selected by investors as investment targets under certain conditions and for a specific period of time, with the aim of maximizing returns and minimizing risk (Puspaningsih et al., 2024). Portfolio formation (diversification) is carried out by selecting several combinations of minimized investment risks without reducing the expected return. Portfolio performance is then measured to determine whether the investor's objectives can be achieved (Rahayu et al., 2024). A well-diversified portfolio can provide more stable returns and reduce the total risk faced by investors. Through a deep understanding of diversification and risk management, investors can make better decisions and increase their chances of achieving success in investing. Therefore, it is important for investors to conduct careful analysis in selecting assets to include in their portfolios.

2.6.1. Portfolio Return

Portfolio return is an indicator of the performance of an investment portfolio. The size of the portfolio return indicates changes in the value of the portfolio over time, as well as the income generated from the assets within it. The return on a stock portfolio can be calculated using the following equation,

$$R_{p,t} = \sum_{i=1}^{N} w_i R_{i,t}, \tag{5}$$

with
$R_{p,t}$: return of the p-th portfolio in t-th period,
w_i : weight of the i-th stock,
$R_{i,t}$: return of the i-th stock in t-th period,
N : the number of stocks in the portfolio.

Furthermore, the expected value of return can be determined from the portfolio return using the following formula,

$$\mu_p = \sum_{i=1}^{N} w_i \mu_i, \tag{6}$$

with
μ_p : expected value return of the portfolio,
μ_i : expected value return of the i-th stock.

2.6.2. Portfolio Risk

Portfolio risk is a measure used to evaluate the level of uncertainty in the returns of a portfolio. The portfolio risk formula using the portfolio variance metric is given by the following equation,

$$\sigma_p^2 = \sum_{i=1}^{N} \sum_{j=1}^{N} w_i w_j \, \sigma_{i,j}, \tag{7}$$

with
σ_p^2 : variance of the portfolio,
w_i : weight of the i-th stock,
w_j : weight of the j-th stock.

Value at Risk (VaR) can also be used in portfolio risk measurement. Referring to Sukono et al. (2020), to calculate VaR using the weight vector **w** and the normal distribution approach, the following equation can be used as,

$$VaR_p = -W_0(Z_\alpha . \sigma_p + \mu_p), \tag{8}$$

or

$$VaR_p = -W_0(Z_\alpha . (\mathbf{w}^T \mathbf{\Sigma} \mathbf{w})^{\frac{1}{2}} + \mathbf{w}^T \boldsymbol{\mu}), \tag{9}$$

with
VaR_p : portfolio value at risk,
W_0 : initial weight,
Z_α : percentile value of normal distribution,
α : significance level ($\alpha = 0.05$).

2.6.3. Optimal Portfolio Based on Mean-Value at Risk

An optimal portfolio can be defined as a portfolio located on the "efficient frontier," which is a curve showing the portfolio combinations that provide the highest returns for each level of risk. Mean-VaR is used in the optimization process by minimizing the VaR risk value. Using Mean-VaR, investors can better identify and manage risk, as well as make more informed investment decisions. Mathematically, this optimization problem can be formulated as the following equation,

$$\text{Maximize: } z = \left(2\tau \boldsymbol{\mu}^T \mathbf{w} + \left(\boldsymbol{\mu}^T \mathbf{w} + z_\alpha (\mathbf{w}^T \textstyle\sum \mathbf{w})^{\frac{1}{2}}\right)\right), \tag{10}$$

with constraint $\mathbf{e}^T\mathbf{w} = 1$.

2.7. Simulated Annealing

Simulated Annealing algorithm is based on the principles of solid annealing, which is a thermodynamic process; a solid object is heated until it melts, and then slowly cooled until it solidifies into a regular crystal. The correlation between the Simulated Annealing method and stock portfolio optimization is a mathematical analogy of the physical process (annealing) with the search for optimal stock weight solutions in a complex search space. The temperature in the Simulated Annealing method acts as a control parameter that regulates the level of search and refinement of random solutions. The initial stage of the annealing process, in which the metal is heated to a high temperature, is analogous to an investment portfolio that is explored with highly random stock weight solutions. When the temperature in the algorithm is still high, the system intentionally considers solutions that seem less optimal, akin to an investor daring to try various combinations of risky assets to uncover rare investment opportunities. Next, the molten metal is slowly cooled, analogous to an investment portfolio being gradually refined by selecting stock weight allocation combinations that can optimize the objective function. Over time, as the temperature slowly decreases, the atoms in the metal will freeze in stable positions, analogous to an investment portfolio narrowing down to the optimal combination where risk is minimized and returns are maximized. As the temperature continues to drop, the process becomes more selective, akin to an investor beginning to filter options and refine their portfolio by balancing risk (Mean-VaR) and potential returns.

This algorithm is a powerful method for solving many optimization problems, and its flexibility and ability to approach global optimality are higher than other local search methods (Dogan et al., 2024). This algorithm allows investors to explore various asset combinations and determine allocations that minimize Mean-VaR while still meeting return targets. The steps of the Simulated Annealing algorithm are as follows:

a) Parameter initialization.
Initiate the number of stocks, initial temperature (C_0) and final temperature (C_t), the number of iterations (IN), and cooling rate (α).

b) Initial solution generation.
Generate random values for the allocation weights of each stock using the following equation,

$$x_i^k = lb_i + rand(0,1) * (ub_i - lb_i), \tag{11}$$

with

x_i^k : weight of stock i in portfolio k,
lb_i : lower bound of weight of stock i,
ub_i : upper bound of weight of stock i,
$rand(0,1)$: random number between 0 and 1.

The weights are then normalized so that their total sum remains 1, using the following equation

$$x_i^{k\prime} = \frac{x_i^k}{\sum_{i=1}^{N} x_i^k}. \tag{12}$$

c) Random solution modification.
The solutions were randomly altered using the same steps as in stage 2.

d) Evaluation stage.
At this stage, the old energy value ($E_{(m)}$) and the new energy value ($E_{(m+1)}$) are calculated based on the weights obtained. The energy value/objective value is obtained using equation (11).

e) Calculation of energy change/ change in objective function.
Energy changes are calculated using the following equation,

$$\Delta E = E_{(m+1)} - E_{(m)} = f(x_{m+1}) - f(x_m), \tag{13}$$

with

$f(x_{m+1})$: objective function value at iteration $(m + 1)$,
$f(x_m)$: objective function value at iteration m.

f) Acceptance or rejection of candidate solutions.
New solutions will be accepted if they fulfil the following criteria:

(a) $$\Delta E < 0, \tag{14}$$

(b) $$(P > rand(0,1)), \text{ with } P = e^{-\frac{\Delta E}{C}}. \tag{15}$$

g) Temperature decrease.
After the iteration at a certain temperature is complete, the temperature is lowered using the following equation,

$$C_m = \alpha \,.\, C_{m-1}, \tag{16}$$

with
C_m : new temperature,
α : temperature reduction factor$(0 < \alpha < 1)$,
C_{m-1}: previous iteration temperature.

h) Repetition stage and iteration termination.
The iterations will continue to repeat until meet the following criteria:
a. The maximum number of iterations has been reached.
b. The iteration temperature is equal to the final temperature.
c. There have been no significant changes in the solution for several consecutive iterations.

i) Selection of the best solution.
The best solution has the lowest (optimal) energy/objective function value found during the iteration.

3. Materials and Methods

3.1. Materials

The object used in this research is the daily closing price of stocks which is listed on the JII (Jakarta Islamic Index). Stock data was obtained from https://id.investing.com. The period used is from January 3, 2022, to January 2, 2024. Data processing was carried out using Microsoft Excel and Python.

3.2. Methods

a) Calculate stock returns $(R_{i,t})$ using equation (1), expected returns and stock variances using equations (2) and (4).
b) Select stocks to include in the portfolio based on positive expected returns and above-average return-to-risk ratios.
c) Formulate the objective function using equation (11).
d) Initialize parameters; IN=100, $C_0 = 95$, $C_t = 0,\ \alpha = 0.95.$
e) Form the initial solution using equation (12), then calculate its energy using equation (11), expected return of portfolio using equation (7), and VaR using equation (10).
f) Randomly modify the solution and calculate its energy/objective function value, portfolio expected return, and VaR.
g) Calculate the change in energy using equation (14).
h) Check if the new candidate solution is accepted by meeting the criteria in equations (15) or (16).
i) Calculate the temperature decrease using equation (17).
j) Perform iteration and termination.
k) After all iterations are complete, the optimal stock portfolio is obtained from the largest objective function result for each risk tolerance value.
l) The portfolio with the highest return-to-risk ratio becomes the most optimal stock investment portfolio.

4. Results and Discussion

4.1. Calculating Return, Expected Return, and Variance Covariance of Stocks

The first step is calculate the stock return using equation (1) for all stocks. After obtaining the stock returns, calculate the expected return of each stock using equation (2), the risk of each stock using variance with equation (2), and the return-to-risk ratio for each stock. Then select stocks that have a positive expected return and a ratio above average to become the constituent stocks of the investment portfolio. The stocks that form the investment portfolio can be seen in the following table.

Table 1: Optimal Portfolio Constituent Stocks

Num	Stocks Code	μ_i	σ_i	$\frac{\mu_i}{\sigma_i}$
1.	ADRO	0.000455975	0.026717	0.017067
2.	ICBP	0.000562442	0.016013	0.0351233
3.	INKP	0.000315706	0.012511	0.0252333
4.	ITMG	0.000911671	0.024664	0.0369642
5.	MIKA	0.000687268	0.03536	0.0194366
6.	TPIA	0.000595944	0.031798	0.0187418
7.	UNTR	0.00037712	0.021318	0.0176899

Next, calculate the covariance value between two stocks using equation (3). The results of the covariance value calculation are presented in the following table.

Table 2: Variance-Covariance of Stocks

	ADRO	ICBP	INKP	ITMG	MIKA	TPIA	UNTR
ADRO	0.000714	−0.000014	0.000126	0.000422	−0.000004	−0.000112	0.000306
ICBP	−0.000014	0.000256	0.000014	−0.000041	0.000055	0.000004	−0.000017
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
UNTR	0.000306	−0.000017	0.000109	0.000262	0.000007	−0.000067	0.000454

4.2. Build Vector μ and Matrix Σ

The expected values are formed into vector form as follows,

$$\mu = \begin{bmatrix} 0.000455 \\ 0.000562 \\ 0.000315 \\ 0.000911 \\ 0.000687 \\ 0.000595 \\ 0.000377 \end{bmatrix},$$

and covariances are formed into vector form as follows,

$$\boldsymbol{\Sigma} = \begin{bmatrix} 0.000714 & -0.000014 & 0.000126 & 0.000422 & -0.000004 & -0.000112 & 0.000306 \\ -0.000014 & 0.000256 & 0.000014 & -0.000041 & 0.000055 & 0.000004 & -0.000017 \\ 0.000126 & 0.000014 & 0.000157 & 0.000080 & 0.000004 & 0.000030 & 0.000109 \\ 0.000422 & -0.000041 & 0.000080 & 0.000607 & -0.000016 & -0.000079 & 0.000262 \\ -0.000004 & 0.00005 & 0.000004 & -0.000016 & 0.000125 & 0.000114 & 0.000007 \\ -0.000112 & 0.000004 & 0.000030 & -0.000079 & 0.000114 & 0.001011 & -0.000067 \\ 0.000306 & -0.000017 & 0.000109 & 0.000262 & 0.000007 & -0.000067 & 0.000454 \end{bmatrix}.$$

4.3. Mean-VaR Portfolio Optimization Process with Simulated Annealing

Table 3: Portfolio Composition Result with *Simulated Annealing*

τ	m	Weight w_i for stocks							Σw_i	$f(x_m)$	μ_p	VaR_p	$\frac{\mu_p}{VaR_p}$
		S_1	S_2	S_3	S_4	S_5	S_6	S_7					
	1	0.1378	0.1473	0.1243	0.1462	0.1142	0.1759	0.1543	1	0.0200	0.0009	0.0200	0.0463
0	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
	100	0.1526	0.1746	0.0948	0.1433	0.0571	0.1941	0.1834	1	0.0207	0.0010	0.0207	0.0462
	1	0.1785	0.2862	0.1134	0.1962	0.0893	0.0704	0.0659	1	0.0202	0.0007	0.0199	0.0368
0.2	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
	100	0.3388	0.1732	0.0301	0.0874	0.0939	0.1281	0.1485	1	0.0237	0.0008	0.0234	0.0344
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
	1	0.2864	0.1189	0.2103	0.0517	0.1719	0.1101	0.0507	1	0.0230	0.0007	0.0215	0.0345
1	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
	100	0.0273	0.2697	0.1651	0.1349	0.1060	0.2421	0.0549	1	0.0204	0.0011	0.0182	0.0592

The Mean-VaR portfolio optimization process using Simulated Annealing was performed at several risk tolerance values, namely $\tau = [0 \quad 0.2 \quad 0.4 \quad 0.6 \quad 0.8 \quad 1]$, where the maximum number of iterations for each τ was 100 iterations. The confidence level used in the Mean-VaR model is 95%, with $z_{0.05} = -1.645$. Using the Python programming language, the portfolio composition results for each iteration are presented in Table 3 above.

Based on Table 3, several selected stock weight allocations with the highest objective function values are presented in the following table.

Table 4: Candidates for Optimal Portfolio

τ	Stocks Weight							$f(x_m)$	μ_p	VaR_p	$\frac{\mu_p}{VaR_p}$
	ADRO	ICBP	INKP	ITMG	MIKA	TPIA	UNTR				
0	0.074	0.018	0.073	0.150	0.026	0.636	0.023	0.029789	0.001923	0.029789	0.064565
0.2	0.427	0.045	0.003	0.013	0.078	0.257	0.178	0.027408	0.001038	0.026992	0.038452
0.4	0.095	0.005	0.046	0.474	0.004	0.184	0.193	0.029725	0.001058	0.028878	0.036641
0.6	0.464	0.020	0.153	0.205	0.076	0.071	0.010	0.030374	0.000706	0.029527	0.023899
0.8	0.435	0.039	0.089	0.058	0.015	0.164	0.200	0.029533	0.000824	0.028215	0.029213
1	0.163	0.118	0.098	0.096	0.058	0.456	0.011	0.027241	0.001518	0.024204	0.062733

The best optimal portfolio is the portfolio with the highest ratio value, because a higher ratio indicates better potential returns relative to the risk taken.

5. Conclussion

There are 7 stocks included in the formation of the optimal portfolio. The optimal investment portfolio using the Simulated Annealing method is generated when the risk tolerance is 0 ($\tau = 0$). The weight allocation of each stock generated by the Simulated Annealing method for the period from January 3, 2022, to January 2, 2024, are as follows: ADRO 7.4177%; ICBP 1.7817%; INKP 7.3369; ITMG 15.0006%; MIKA 2.5894%; TPIA 63.5506%; and UNTR 2.323%. The return and VaR risk level generated from the optimal portfolio are each equal to 0.001923 and 0.029788.

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