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Portofolio Optimization of Mean-Variance Model Using Tabu Search Algorithm with Cardinality Constraints

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Abstract

Stock investment is increasingly attractive to Indonesians, especially through the IDX30 index, which is known to have high liquidity and solid company fundamentals. In forming an optimal stock portfolio, investors are faced with the challenge of maximizing return and minimizing risk simultaneously. An optimal portfolio is defined as a combination of assets that provides the highest expected return at a certain level of risk, or the lowest risk for the expected level of return. This study aims to form an optimal portfolio on the IDX30 index by considering cardinality constraints, which limit the maximum number of stocks in the portfolio. From 30 IDX30 stocks, 20 stocks were selected based on consistency of existence during the period February 1, 2023 to January 31, 2025. Next, 8 stocks that have positive expected return values are selected, and from these 8, 4 efficient stocks are selected using cardinality constraints. Selection is done with the Tabu Search algorithm, a memory-based metaheuristic optimization method used to find the best solution by avoiding previously explored solutions. The portfolio is formed using the Mean-Variance model, resulting in an allocation of BMRI (30.02%), PTBA (35.18%), INDF (2.48%), and BRPT (32.32%), with an expected return of 0.00207 and a variance of 0.001587.

Keywords: stock; return; risk; IDX30; Mean-Variance; Tabu Search algorithm, optimal.

1. Introduction

Investing in financial assets has become an increasingly popular choice among Indonesians. The capital market, as the main venue for trading financial assets, plays a crucial role in the national economy. Safitri et al. (2020) defines the capital market as activities related to public offerings and trading of securities of public companies, as well as institutions and professions related to securities. Among the various financial instruments traded, stocks are one of the most popular, reflecting an individual's ownership of a company and granting holders the right to receive profit distributions (Tandelilin, 2010).

As of January 13, 2025, the Indonesia Stock Exchange (IDX) listed 951 stocks traded on the Indonesian capital market, with 46 stock indices reflecting the performance of various sectors. One of the most well-known indices is the IDX30, which measures the price performance of 30 stocks with high liquidity, large market capitalization, and good company fundamentals. Stock investment offers the potential for rapid profit growth, but it also comes with commensurate risks. The higher the potential profit, the higher the risk level, including market fluctuations and company performance that can result in losses.

To reduce the risk of stock investment in the long term, diversification is an effective method. Diversification is a technique to reduce risk by allocating investments across various financial instruments, industries, and other categories. Harry Markowitz (1952) proposed the modern portfolio theory, where investment risk can be minimized through the formation of an efficient portfolio, resulting in lower risk than the individual investment instruments that make up the portfolio. One approach proven effective for forming an optimal portfolio in terms of maximizing returns and minimizing risk through diversification is the Mean-Variance model, developed by Harry Markowitz.

However, in practice, investors often face cardinality constraints, which are limitations on the number of assets that can be selected for a portfolio due to various reasons such as transaction costs, regulations, or investment preferences.

These constraints include maximum or minimum limits on the number of assets that must be selected, aiming to reduce transaction costs and simplify asset management. Although the Mean-Variance model has been the foundation for various studies in portfolio optimization (Supandi et al., 2017), this traditional approach has limitations in addressing cardinality constraints, especially when the number of available assets is very large. To address this issue, a more flexible and efficient method is needed to explore complex solution spaces.

Various approaches have been developed to address this constraint, including metaheuristic algorithms. Chang et al. (2000) proposed a mean-variance model with cardinality constraints, using three heuristic algorithms: Genetic Algorithm (GA), Tabu Search (TS), and Simulated Annealing (SA). Maria et al. (2011) also applied stock portfolio optimization considering transaction costs and cardinality constraints using GA, TS, and SA. Kabani (2022) applied stock portfolio optimization using a Mean-Variance model optimized through a metaheuristic approach.

One effective metaheuristic algorithm for addressing this problem is Tabu Search. This algorithm has the ability to explore the solution space extensively and avoid local solution traps during the optimization process by utilizing a tabu list to prevent repetition of the same solution. In the context of investment portfolio formation, this algorithm can help investors determine the optimal weight of each asset, thereby generating a portfolio that can provide the best return with effectively managed risk.

Chen (2012) conducted research on optimal portfolio formation with cardinality constraints using the Artificial Bee Colony (ABC) algorithm. The study showed that the stock portfolio optimization problem with cardinality constraints can be solved using the Mean-Variance Model with the ABC algorithm, by selecting the optimal stock combination based on the best fitness results. The study also recommends solving the portfolio optimization problem with cardinality constraints using other metaheuristic algorithms to find the best method for solving the problem. Based on previous research and existing recommendations, this study aims to explore the formation of an optimal portfolio using the Mean-Variance model with the Tabu Search algorithm approach.

2. Literature Review

2.1. Invesment

Investment is the allocation of capital to one or more assets that are owned and typically held for the long term with the expectation of generating future returns. Essentially, investment is undertaken with the aim of achieving a specific profit. One of the primary motivations for individuals to invest is the uncertainty present in the economic environment. Investment can also serve as a strategic measure to protect the value of assets from inflation and other risks.

2.2. The Capital Market

The capital market, as defined by law, is stipulated in Capital Market Law No. 8 of 1995 as activities related to public offerings and securities trading, public companies related to the securities they issue, and institutions and professions related to securities. Fitria et al. (2022) state that the capital market has two functions, namely:

a) An economic function that provides facilities and has two interests, namely excess funds (investors) and those in need of funds (issuers).
b) A financial function whereby the capital market provides opportunities for fund owners to obtain returns in accordance with their chosen investments.

2.3. Stock

A stock is a security that serves as proof of ownership or participation by an individual or institution in a company. In general terms, a stock is proof of capital participation in a company's share ownership (Rahardjo, 2006). Stocks give their owners the right to receive a share of the company's profits in the form of dividends, as well as the opportunity to profit from an increase in the value of the stock.

a) Return of Stock

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

with

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 $t-1$.

b) Expected Return of Stock

In general, the average return on shares (expected return) for each share i can be calculated using equation (2).

$$E(R_i) = \frac{\sum_{t=1}^{m} R_{it}}{m}, \tag{2}$$

with
$E(R_i)$: expected return of stock i,
R_{it} : return of stock i at time t,
m : the number of observation periods.

c) Risk of Stock
Risk reflects the magnitude of the deviation between the actual return and the expected return. The greater the deviation, the greater the level of risk faced by investors. The stock variance equation can be expressed as equation (3).

$$\sigma_i^2 = \frac{\sum_{t=1}^{m} [R_{it} - E(R_i)]^2}{m-1}, \tag{3}$$

with
σ_i^2 : variance of stock i,
R_{it} : return of stock i at time t,
$E(R_i)$: expected return of stock i,
m : the number of observation periods.

d) Covariance
The covariance of stocks i and j can be calculated using equation (4).

$$\sigma_{i,j} = \frac{\sum_{t=1}^{m} \left(R_{it} - E(R_i)\right)\left(R_{jt} - E(R_j)\right)}{m-1}, \tag{4}$$

with
$\sigma_{i,j}$: covariance return of stock i and j,
R_{it} : return of stock i at time t,
$E(R_i)$: expected return of stock i,
R_{jt} : return stock j at time t,
$E(R_j)$: expected return of stock j,
m : the number of observation periods.

e) Corelation Coefficient
The correlation coefficient between stocks needs to be calculated to assess the strength of the relationship between stocks. The relationship is considered strong if the correlation coefficient is close to one, either in a positive or negative direction. The correlation coefficient can be expressed as equation (5).

$$r_{i,j} = \frac{\sigma_{i,j}}{\sigma_i \sigma_j}, \tag{5}$$

with
$r_{i,j}$: correlation coefficient of stock i and j,
$\sigma_{i,j}$: covariance return of stock i and j,
σ_i : standard deviasion of stock i,
σ_j : standard deviasion of stock j.

2.4. Stock of Portofolio

A stock portfolio is a collection of financial assets, including stocks, owned by an investor with the aim of diversifying risk and maximizing returns. Portfolio theory emphasizes the importance of diversification to reduce risk without reducing the expected rate of return (Markowitz, 1952).

a) Return and Expected Return of Portofolio

$$R_{pt} = \sum_{i=1}^{n} (w_i R_{it}), \tag{6}$$

with
R_{pt} : return of the portofolio at time t,
w_i : weight of stock i,

R_i : return of stock i,
n : the number og available stock.
Thus, the equation for calculating the expected return of a portfolio is obtained as equation (7).

$$\mu_p = E(R_p) = \sum_{i=1}^{n} w_i E(R_i), \tag{7}$$

The expected return value can be expressed in vector notation as in equation (8).

$$\mu_p = E(R_p) = \boldsymbol{\mu}^T \mathbf{w} = \mathbf{w}^T \boldsymbol{\mu}, \tag{8}$$

with
$\boldsymbol{\mu}^T$: transpose vector of expected stock returns,
$\mathbf{w}$: portfolio weight vector,
$\mathbf{w}^T$: transpose vector of portfolio weights,
$\boldsymbol{\mu}$: vector of expected stock returns,

b) Risk of Portofolio
Portfolio risk consists of many assets, so it can be expressed as in equation (9).

$$\sigma_p^2 = Var(R_p) = \sum_{i=1}^{n} \sum_{j=1}^{n} w_i w_j \sigma_{ij}, \tag{9}$$

with
σ_p^2 : variance of portofolio,
w_i : weight of stock i,
w_j : weight of stock j,
σ_{ij} : covariance return of stock i and j.

The portfolio risk value in equation (10) can be expressed in vector notation as in equation (10).

$$\sigma_p^2 = Var(R_p) = \mathbf{w}^{\mathrm{T}} \boldsymbol{\Sigma} \mathbf{w}, \tag{10}$$

with
$\boldsymbol{\Sigma}$: covariance matrix of returns between stocks.

2.5. Mean-Variance with Cardinality Constrains Portofolio Model

The weighting or proportion of each asset in a portfolio is usually determined using a mathematical approach. This approach was first introduced by Markowitz and is known as the Mean-Variance theory in modern portfolio theory in 1952. The objective function used to determine the optimal portfolio is written as follows:

$$\text{Maximize } Z = \{2\tau \boldsymbol{\mu}^T \mathbf{w} - \mathbf{w}^T \boldsymbol{\Sigma} \mathbf{w}\}, \tag{11}$$

$$s.t. \quad \mathbf{e}^T \mathbf{w} = 1,$$

$$\sum_{i=1}^{n} z_i = K$$

$$\varepsilon z_i \leq w_i \leq \delta z_i, \quad i = 1,2,\dots,n$$

$$0 \leq w_i \leq 1, \quad i = 1,2,\dots,n$$

$$z_i \epsilon \{0,1\}, \quad i = 1,\dots,n,$$

with
n : the number og available stock,
$\mathbf{e}^T$: transpose vector with entry 1,
$\boldsymbol{\mu}^T$: transpose vector of expected stock returns,
$\mathbf{w}$: portfolio weight vector,
$\mathbf{w}^T$: transpose vector of portfolio weights,
$\boldsymbol{\Sigma}$: covariance matrix of returns between stocks.
w_i : weight of stock i,
K : the number of assets selected for the portfolio,
ε : minimum proportion invested in assets,

δ : maximum proportion invested in assets,
z_i : the binary variable for stock i.

A binary variable z_i used to indicate whether an asset is selected or not. $z_i = 1$ if the selected stocks in the portfolio and $z_i = 0$ if the stock is not selected. The portfolio weight vector (**w**), the expected return vector of the stock (**μ**), the covariance matrix (**Σ**), and the vector with entries of 1 (**e**) are shown in the following equations, respectively.

$$\mathbf{w} = \begin{bmatrix} \mathrm{w}_1 \\ \mathrm{w}_2 \\ \vdots \\ \vdots \\ \mathrm{w}_n \end{bmatrix}, \boldsymbol{\mu} = \begin{bmatrix} \mu_1 \\ \mu_2 \\ \vdots \\ \vdots \\ \mu_n \end{bmatrix}, \boldsymbol{\Sigma} = \begin{bmatrix} \sigma_1^2 & \sigma_{12} & \sigma_{1n} \\ \sigma_{21} & \sigma_2^2 & \sigma_{2n} \\ \vdots & \ddots & \vdots \\ \sigma_{n1} & \vdots & \sigma_n^2 \end{bmatrix}, \mathbf{e} = \begin{bmatrix} 1 \\ 1 \\ \vdots \\ \vdots \\ 1 \end{bmatrix}. \tag{12}$$

2.6. Tabu Search Algorithm

Tabu Search is a metaheuristic algorithm based on local search that uses a deterministic control mechanism (Maria et al., 2011). The main concept in Tabu Search is that it uses flexible memory, which can be either long-term or short-term memory. According to Wati & Fauzan, (2020) the Tabu Search algorithm process consists of:

a) Representative solutions
   Representative solutions are the starting point for the search process. From these solutions, the algorithm will begin to explore possible neighboring solutions.
b) Initial Solution
   The initial solution is the first step in the Tabu Search algorithm process. The initial solution can be formed using a random method or a heuristic method that will be refined in the next iteration.
c) Neighborhood solution
   Neighborhood solution is an alternative solution obtained by moving nodes (move) or swap move, which is exchanging assets in the portfolio with assets that are not in the portfolio.
d) Evaluate Solution
   At this stage, the solution is evaluated using equation (11).
e) Tabu List
   The tabu list is used to avoid repeating steps that have already been taken, and the taboo test is performed using the existing tabu list. The tabu list contains transfer attributes that have been found previously.
f) Aspiration criteria
   Aspiration criteria are a method for canceling taboo status. The basic rules used in aspiration criteria in the Tabu Search algorithm are the best quality of neighboring solutions and that the generated solutions are not the same as existing solutions.
g) Termination criteria
   The termination criteria are the conditions under which the Tabu Search algorithm calculation process stops. There are three types of termination criteria commonly used in Tabu Search, as follows:
   a. All previously determined iterations have been fulfilled.
   $$g \le G,$$
   g : current number of iterations,
   G : maximum number of iterations.
   b. After several iterations without any improvement in the objective function value.
   $$\Delta Z = 0 \text{ during T consecutive iterations}$$
   T : number of iterations tolerance without correction.
   c. No feasible moves remain
   $$C = \emptyset,$$
   C : a set of candidate assets that can be selected for solution migration.

After reaching the termination criteria, the algorithm will stop and produce the optimal portfolio candidate generated from the largest objective function value.

3. Materials and Methods

3.1. Materials

In this research, the objects used are daily stock closing closing prices of companies listed in the IDX30 index. The period used is from February 1st, 2023, to January 31st, 2025. The data obtained is secondary data obtained from www.investing.com, accessed on February 10th, 2025. In the research, the tools used are Microsoft Excel and Phyton.

3.2. Methods

Here are steps in forming an optimal Mean-Variance with cardinality constrains portfolio using Tabu Search Algorithm:

Step 1. Calculate the return of each stock using equation (1) and expected return of each stock using equation (2).
Step 2. Calculating the risk of stocks with positive expected returns using equation (3).
Step 3. Calculating stock covariance using equation (4) and forming them into the covariance matrix.
Step 4. Calculating the correlation coefficient using equation (5).
Step 5. Determining parameters.
Initialize the parameters used in the calculation process, namely $0.95 \leq \tau \leq 1$ with a gradual change in value of 0.05. Minimum proportion $\epsilon = 0.01$ and maximum $\delta = 0.4$, tabu_tenure $= 10$, $K = 4$, maximum stopping criterion (G) at 100 iterations, no improvement threshold before the algorithm is stopped or stop_thershold when 15 iterations, diversify_after = 10.
Step 6. Determining the initial solution.
At this stage, the initial investment weights for the selected stocks are determined with constraints based on equation (11). Subsequently, binary variables are set based on whether the stock investment weights exceed the minimum threshold ϵ. The weights are evaluated using the equal-weight solution and random-weight solution, selected based on the highest objective function evaluation using equation (11). The initial solution at this stage is added to the tabu list.
Step 7. Forming the neighborhood solution using the swap move, which involves exchanging assets within the portfolio with assets not in the portfolio
Step 8. Evaluate the solution using the objective function from equation (11).
Step 9. Perform a tabu test to check whether the new solution is in the tabu list. If $s_n \in T$, then s_n will enter the aspiration criteria.
Step 10. Check the aspiration criteri
Step 11. Update the tabu list by adding the last step performed
Step 12. Check the termination criteri
Step 13. Calculate the expected return and variance of the optimal portfolio candidate using equations (8) and (10)
Step 14. Determine the optimal portfolio using equation (11) with the largest result
Step 15. Draw conclusions from the results of stock portfolio optimization using the Tabu Search algorithm.

4. Results and Discussion

4.1 Return, Expected Return, and Covariance of Stock Return

Based on equation (1), the returns for each stock using Microsoft Excel are given in Table 1.

Table 1: Return of Stock

Date	ARTO	ADRO	BMRI	⋯	BRPT	MEDC
02/02/2023	0.12853	-0.02712	0.00268	⋯	0.01214	-0.02555
02/03/2023	0.01111	-0.03833	0.02056	⋯	-0.00600	-0.05618
02/06/2023	-0.00275	0.00725	-0.00504	⋯	-0.00603	-0.03175
02/07/2023	-0.04408	0.03957	0.03038	⋯	0.03034	0.04508
⋮	⋮	⋮	⋮	⋯	⋮	⋮
01/30/2025	-0.04255	0.00000	-0.00408	⋯	0.02210	-0.04977
01/31/2025	0.00000	0.01304	-0.01230	⋯	-0.00541	0.02857

Table 2: Expected return of stock

Stock Code	Expected Return	Stock Code	Expected Return
ARTO	-0.000004	MDKA	-0.001957
ADRO	-0.000068	PGAS	0.000216
BMRI	0.000607	SMGR	-0.001826
BUKA	-0.001446	AMRT	0.000095
PTBA	0.004416	TLKM	-0.000662
CPIN	-0.000327	UNVR	-0.001973
GOTO	0.000111	UNTR	0.000186
ITMG	-0.000504	INCO	-0.001688
INDF	0.000375	BRPT	0.001001
KLBF	-0.000939	MEDC	-0.000032

The return value for each stock will be used to calculate the expected return of the stock using equation (2). The results of the expected return calculation using Microsoft Excel are shown in Table 2 above. Stocks with positive expected returns are stocks that can be selected to form an optimal portfolio. Using equation (3), the risk of stocks with positive expected returns is then calculated using Microsoft Excel, as shown in Table 3.

Table 3: Risk of Stock (Variance)

Stock Index	Stock Code	Variance
0	BMRI	0.000297
1	PTBA	0.011373
2	GOTO	0.001736
3	INDF	0.000171
4	PGAS	0.000353
5	AMRT	0.000335
6	UNTR	0.000348
7	BRPT	0.001584

Next, calculate the covariance of two stocks using equation (4) with Microsoft Excel in Table 4.

Table 4: Variance-Covariance Return of Stock

	BMRI	PTBA	GOTO	INDF	PGAS	AMRT	UNTR	BRPT
BMRI	0.000297	-0.000002	0.000072	0.000032	0.000037	0.000060	0.000024	0.000121
PTBA	-0.000002	0.011349	-0.000157	-0.000008	0.000007	-0.000067	0.000004	-0.000094
GOTO	0.000006	-0.000025	0.001736	-0.000011	0.000043	0.000027	-0.000030	-0.000037
INDF	-0.000030	0.000033	0.000018	0.000171	-0.000022	-0.000002	0.000001	-0.000010
PGAS	0.000008	-0.000173	-0.000048	0.000009	0.000353	0.000015	0.000011	0.000009
AMRT	-0.000007	-0.000076	-0.000040	-0.000010	-0.000009	0.000335	-0.000004	0.000028
UNTR	0.000002	-0.000037	0.000004	0.000006	-0.000012	0.000011	0.000348	-0.000059
BRPT	-0.000013	-0.000080	0.000086	-0.000033	-0.000019	-0.000010	0.000027	0.001584

Based on the covariance values obtained, the correlation between stocks can be calculated using equation (5). The calculation was performed using Microsoft Excel. The results of the calculation are shown in Table 5.

Table 5: Table of correlation value of stock returns

	BMRI	PTBA	GOTO	INDF	PGAS	AMRT	UNTR	BRPT
BMRI	1	-0.000986	0.100319	0.142194	0.115274	0.191793	0.073991	0.175941
PTBA	-0.000986	1	-0.035470	-0.005868	0.003577	-0.034569	0.001794	-0.022095
GOTO	0.008184	-0.005546	1	-0.020458	0.055291	0.035736	-0.038945	-0.022271
INDF	-0.135289	0.023997	0.033430	1	-0.088177	-0.009642	0.005668	-0.019256
PGAS	0.025606	-0.086266	-0.061971	0.036833	1	0.044645	0.031530	0.012665
AMRT	-0.021521	-0.038759	-0.052598	-0.042354	-0.025849	1	-0.010278	0.038622
UNTR	0.005797	-0.018845	0.004693	0.026465	-0.034718	0.033135	1	-0.079170
BRPT	-0.019658	-0.018868	0.051833	-0.063858	-0.025441	-0.014224	0.036312	1

Based on Table 5, it can be seen that the correlation value between stocks is in the range of $-0.135289 < r_{i,j} < 0.191793$, which means that these stocks have a very weak to insignificant relationship. Thus, the price movement of one stock has only a very small or even no direct effect on the movement of other stock.

Next, the expected values are formed into vector form as follows,

$$\mathbf{\mu} = \begin{bmatrix} 0.000607 \\ 0.004416 \\ 0.000111 \\ 0.000375 \\ 0.000216 \\ 0.000095 \\ 0.000186 \\ 0.001001 \end{bmatrix}.$$

and covariances are formed into vector form as follows,

$$\sum = \begin{bmatrix} 0.000297 & -0.000002 & 0.000072 & 0.000032 & 0.000037 & 0.000060 & 0.000024 & 0.000121 \\ -0.000002 & 0.011349 & -0.000147 & -0.000008 & 0.000007 & -0.000067 & 0.000004 & -0.000094 \\ 0.000006 & -0.000025 & 0.001736 & -0.000011 & 0.000043 & 0.000027 & -0.000030 & -0.000037 \\ -0.000030 & 0.000033 & 0.000018 & 0.000171 & -0.000022 & -0.000002 & 0.000001 & -0.000010 \\ 0.000008 & -0.000173 & -0.000048 & 0.000009 & 0.000353 & 0.000015 & 0.000011 & 0.000009 \\ -0.000007 & -0.000076 & -0.000040 & -0.000010 & -0.000009 & 0.000335 & -0.000004 & 0.000028 \\ 0.000002 & -0.000037 & 0.000004 & 0.000006 & -0.000012 & 0.000011 & 0.000348 & -0.000059 \\ -0.00013 & -0.00080 & 0.000086 & -0.000033 & -0.000019 & -0.000010 & 0.000027 & 0.001584 \end{bmatrix}$$

4.2 Optimization of Mean-Variance Investment Portfolio Models with Tabu Search Algorithms.

In the optimization process using the Tabu Search algorithm, the parameter τ is used as the iteration limit or control mechanism for solution exploration. Each variation in the value of τ produces different combinations of stock weights, reflecting variations in asset allocation strategies. From the optimization results, the highest objective function value for each value of τ is selected as the optimal portfolio candidate. Next, for each portfolio candidate, the expected return, portfolio variance, and the ratio between expected return and variance are calculated. A summary of the optimal solutions obtained from each τ value is presented in Table 6.

Table 6: Optimal Portfolio candidate

τ	Selected asset	z	w	$Z(s')$	μ_p	σ_p^2	$\frac{\mu_p}{\sigma_p^2}$
0.95	[0, 1, 3, 7]	[1 1 0 1 0 0 0 1]	[0.2755 0.3469 0.0192 0.3584]	0.002345	0.002066	0.00158	1.327667
0.955	[0, 1, 3, 7]	[1 1 0 1 0 0 0 1]	[0.3822 0.3521 0.0138 0.2519]	0.002360	0.002045	0.001545	1.341969
0.96	[0, 1, 3, 7]	[1 1 0 1 0 0 0 1]	[0.3227 0.3572 0.0633 0.2569]	0.002374	0.002057	0.001576	1.466981
0.965	[0, 1, 3, 7]	[1 1 0 1 0 0 0 1]	[0.3205 0.3780 0.0296 0.2719]	0.002386	0.002148	0.00176	1.497092
0.97	[0, 1, 3, 7]	[1 1 0 1 0 0 0 1]	[0.3002 0.3518 0.0248 0.3232]	0.002428	0.00207	0.001587	1.547202
0.975	[0, 1, 3, 7]	[1 1 0 1 0 0 0 1]	[0.3296 0.3340 0.0117 0.3247]	0.002452	0.002005	0.001457	1.375528
0.98	[0, 1, 3, 7]	[1 1 0 1 0 0 0 1]	[0.3962 0.3009 0.0104 0.2925]	0.002452	0.001866	0.001206	1.304328
0.985	[0, 1, 3, 7]	[1 1 0 1 0 0 0 1]	[0.3581 0.3105 0.0296 0.3019]	0.002478	0.001903	0.001271	1.220484
0.99	[0, 1, 3, 7]	[1 1 0 1 0 0 0 1]	[0.3115 0.3099 0.0232 0.3554]	0.002497	0.001923	0.001311	1.305279
0.955	[0, 1, 3, 7]	[1 1 0 1 0 0 0 1]	[0.3822 0.3521 0.0138 0.2519]	0.002360	0.002045	0.001545	1.323082
0.995	[0, 1, 3, 7]	[1 1 0 1 0 0 0 1]	[0.2462 0.3347 0.0352 0.3839]	0.002523	0.002027	0.00151	1.307439
1	[0, 1, 3, 7]	[1 1 0 1 0 0 0 1]	[0.2896 0.3522 0.1019 0.2563]	0.002533	0.002032	0.00153	1.327667

Based on the results shown in Table 4.12, the optimal portfolio was selected based on the largest expected return to variance ratio, which was obtained at parameter τ = 0.97. Out of the total eight assets analyzed, four assets were selected for the optimal portfolio, namely BMRI, PTBA, INDF, and BRPT, each representing indices 0, 1, 3, and 7. The weight allocations for each stock are as follows: BMRI at 0.3002, PTBA at 0.3518, INDF at 0.0248, and BRPT at 0.3232. This composition yields an expected portfolio return of 0.00207 with a variance of 0.001587, indicating high portfolio efficiency within the context of the Mean-Variance model optimized using the Tabu Search algorithm.

5. Conclussion

Through the application of the Tabu Search algorithm in the Mean-Variance model, this study successfully identified efficient stocks in the IDX30 index as candidates for forming an optimal portfolio while considering cardinality constraints. Out of the total 8 assets analyzed, four stocks were identified as forming the optimal portfolio: BMRI, PTBA, INDF, and BRPT. The optimal weight allocations for each stock are as follows: BMRI at 30.02%, PTBA at 35.18%, INDF at 2.48%, and BRPT at 32.32%. This portfolio has an expected return of 0.00207 and a variance of 0.001587, reflecting a balance between return and measurable risk. These results indicate that the Tabu

Search algorithm is effective in generating optimal solutions in the context of stock portfolio formation in the Indonesian capital market.

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