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Investment Portfolio Optimization Using Ant Colony Optimization (ACO) Based on Fama-French Three Factor Model on IDX High Dividend 20 Stocks

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Abstract

Stock investment is one of the investment options that provides both profit and risk for investors. In an effort to maximize profits and minimize risks, investors need an optimal portfolio. The optimal portfolio is a portfolio selected from a collection of efficient portfolios. To form an optimal portfolio, this study combines the Fama-French Three Factor Model (FF3FM) for stock selection and Ant Colony Optimization (ACO) for stock weight optimization in the portfolio. FF3FM considers more factors resulting in more comprehensive stock selection than other methods. While ACO has the ability to explore the solution space widely and efficiently, minimizing the risk of getting stuck on a local solution. The performance of the optimal portfolio is measured using the Sharpe Ratio which considers total risk, thus providing an overview of overall investment efficiency. The research object used is quarterly stock data on IDX High Dividend 20 from the Indonesia Stock Exchange (IDX) for the period 2020-2023. Of the 20 stocks, 12 stocks were selected that were consistently included in the index during the 2020-2023 period. By selecting stocks using the FF3FM method, 10 efficient stocks were selected, namely ADRO, ASII, BBCA, BBNI, BBRI, INDF, ITMG, PTBA, TLKM, and UNTR. Portfolio optimization using ACO produces a portfolio return of 0.0473 and a risk of 0.0257 with the weight of each ADRO stock of 6.90%, BBCA of 17.24%, BBNI of 10.34%, BBRI of 27.59%, INDF of 3.45%, ITMG of 27.59%, TLKM of 3.45%, and UNTR of 3.45%. The results showed that the integration of FF3FM and ACO was able to form a portfolio with optimal performance with a Sharpe Ratio value of 1.41868, which means that the portfolio return is greater than the portfolio risk.

Keywords: FF3FM, ACO, investment, stock, return, risk, optimal portfolio, IDX High Dividend 20

1. Introduction

Investment is the activity of investing a certain amount of capital in the hope of earning profits in the future. When investing, investors tend to consider two important things, namely maximizing profits and minimizing risks. The strategy to achieve these two things is to form an optimal portfolio. The optimal portfolio is a portfolio that provides the highest profit with a certain risk. The formation of an optimal portfolio can be done through the implementation of a diversification strategy, which is a strategy that involves allocating investments in various asset classes to reduce risk or negative impacts when investing (Nisardi et al., 2024).

As part of the diversification process, the first step is to select stocks for portfolio candidates. Several methods can be used for stock selection, such as Capital Asset Pricing Model (CAPM), Single Index Model (SIM), and Fama-French Three Factor Model (FF3FM). Tao (2022) conducted a study comparing the CAPM and FF3FM methods. It was found that portfolio performance measured using the Sharpe Ratio on CAPM is lower than FF3FM because CAPM only considers market risk, while FF3FM is superior because it considers the size of the company (size) and the ratio of book value to the company's market value (book to market).

After performing stock selection, a method for portfolio optimization is required. Some methods that can be used for portfolio optimization are Mean-Variance Optimization (MVO), Genetic Algorithm (GA), Ant Colony Optimization (ACO), and other heuristic methods. Dorigo and Stützle (2004) developed an ACO method inspired by the behavior of ant colonies when searching for the shortest path to a food source. Therefore, the ACO method was initially applied to solve the Traveling Salesman Problem (TSP), such as the research conducted by Wang and Han (2021). As research developed, ACO began to be applied in various fields, including in the financial world for stock portfolio optimization. After the optimal portfolio is formed, it is necessary to evaluate the performance of the portfolio. There are commonly used ratios, namely the Sharpe Ratio and Treynor Ratio. The Sharpe Ratio measures excess return over total risk, making it suitable for assessing overall investment efficiency.

In this study, the FF3FM method is used to select stocks that deserve to be included in the portfolio and ACO to determine the weight of each selected stock. The differences between this research and previous studies can be seen in Table 1.

Table 1: Research gap

Author	Research Topic	Using ACO to determine optimal portfolio weights	Using FF3FM to select the best stocks	Using Sharpe Ratio to measure portfolio performance
Steven et al. (2018)	Clustered stocks weighting with ACO in portfolio optimization.	✓	-	-
Anuno et al. (2023)	CAPM and FF3FM for stock portfolio calculation.	-	✓	-
Subekti et al. (2018)	ACO for clustering in portfolio optimization.	✓	-	✓
This research	FF3FM for selecting the best stocks and ACO for portfolio optimization.	✓	✓	✓

Table 1 presents a mapping of previous research relevant to the topic of portfolio optimization using the ACO approach and the FF3FM. The study by Steven et al. (2018) applies ACO to determine the optimal weights in stock clustering-based portfolio optimization, but has not utilized FF3FM or performance measurement with Sharpe Ratio. Meanwhile, the study by Anuno et al. (2023) focused on using CAPM and FF3FM in calculating stock portfolios, but did not involve ACO or portfolio performance evaluation. Subekti et al. (2018) used ACO for the clustering process in portfolio optimization, but did not integrate the FF3FM model or performance evaluation methods. This research comes to fill the gap by combining all three approaches at once: using ACO to determine the optimal weights, FF3FM for the best stock selection, and Sharpe Ratio to measure overall portfolio performance. Thus, this research makes a new contribution to the integration of quantitative approaches for more comprehensive investment decision-making.

2. Literature Review

2.1. Investment and Stock

Investment is the activity of investing a certain amount of capital in the hope of making a profit in the future. An investor has certain preferences and goals for the type of investment they choose. Investing in stocks is one of the many types of investment instruments available. Stockholders in a company have the right to dividends and a role in decision-making.

Stocks are ownership in a company that entitles the holder to dividends and a role in company decisions. Buying stocks can be lucrative when the value of the company rises, but also risks losing value when the company declines. An investor who invests by buying shares has a right to the company's income and wealth after deducting the payment of all the company's liabilities (Nisardi et al., 2024).

2.2. Return and Expected Return of Stock

Return is profit or loss income expressed as a percentage of the initial investment capital (Willmar et al., 2024). Stock returns are calculated using the equation:

$$R_{i,t} = \frac{P_{i,t} - P_{i,(t-1)}}{P_{i,(t-1)}}, t = 1,2, \dots, n, \tag{1}$$

with

$R_{i,t}$: stock return of the i-th stock at time t,

$P_{i,t}$: closing price of stock i at time t,

$P_{i,(t-1)}$: closing price of stock i at time $t-1$

Expected return is the rate of return that investors expect in the future and can be calculated based on the actual return of the stock (Willmar et al., 2024). Expected stock returns are calculated using the equation:

$$E(R_i) = \frac{\sum_{t=1}^{n} R_{i,t}}{n}, t = 1,2,\dots,n, \tag{2}$$

with
$E(R_i)$: expected return of stock i,
$R_{i,t}$: stock return of the i-th stock at time t,
n : amount of observation time.

2.3. Variance (Risk) and Covariance of Stock

Stock risk is a measure of spread to determine the possibility of deviation between actual return and expected return on a stock (Hasbiah et al., 2022). The risk of a stock is calculated using the variance equation as follows:

$$\sigma_i^2 = \frac{1}{n-1} \sum_{t=1}^{n} \left[R_{i,t} - E(R_i)\right]^2, \tag{3}$$

with
σ_i^2 : risk of stock i.

Covariance is a measure that shows the direction of movement of two variables (Hasbiah et al., 2022). Stock covariance is calculated using the following equation:

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

with
$\sigma_{i,j}$: covariance of returns between the i-th and j-th stocks,
$R_{i,t}$: stock return of the i-th stock at time t,
$R_{j,t}$: stock return of the j-th stock at time t,
$E(R_i)$: expected return of stock i,
$E(R_j)$: expected return of stock j.

2.4. Portfolio

Portfolio is a collection of investments formed to achieve the general investment objectives, the portfolio has a meaning as an investment contained in financial instruments traded in the capital market or money market, with the aim of providing information about the acquisition of returns and possible risks to be received. Portfolio optimization is the process of selecting the most efficient combination of assets (such as stocks, bonds, or mutual funds) in achieving certain investment objectives. This goal can be to maximize return with a certain risk, minimize risk with a certain return, or a combination of both (Liestyowati et al., 2023).

2.5. Expected Return of Portfolio

Expected return portfolio is a weighted average of the expected return of individual stocks, with the weighing factor being the proportion or weight of funds invested in each stock (Hasbiah et al., 2022). Expected return portfolio is calculated using the following equation:

$$E\left(R_p\right) = \sum_{i=1}^{n} w_i \, E(R_i), \tag{5}$$

with
$E(R_p)$: expected return of portfolio,
$E(R_i)$: expected return of stock i,
w_i : weight of stock i.

2.6. Risk of Portfolio

Portfolio risk is a measure calculated from how likely the return obtained deviates from the expected portfolio return (Hasbiah et al., 2022). The portfolio risk for two stocks and n stocks is calculated by the following equation:

$$\sigma_p^2 = \sum_{i=1}^{n} \sum_{j=1}^{n} w_i w_j \sigma_{ij}\ , \tag{6}$$

$$\sigma_p = \sqrt{\sigma_p^2}, \tag{7}$$

with
σ_p^2 : variance (risk) of portfolio,
σ_p : standard deviation of portfolio,
w_i : weight of stock i,
w_j : weight of stock j,
$\sigma_{i,j}$: covariance of returns between the i-th and j-th stocks,

2.7. Multiple Linear Regression

Linear regression is a model in which the dependent variable is expressed as a linear function of one or more independent variables. This model aims to explain the relationship between variables and can be used to predict the value of the dependent variable based on the value of the independent variable. Multiple linear regression is an extension of simple linear regression that involves more than one independent variable. Gujarati (2013) states the general form of multiple linear regression for sample as follows:

$$Y_i = b_0 + b_1 X_{1i} + b_2 X_{2i} + \cdots + b_k X_{ki} + e_i, \tag{8}$$

with
Y_i : dependent variable for i-th observation, $i = 1,2, \dots, n$,
$X_{1i}, \dots, X_{ki}$: independent variable,
$b_1, \dots, b_k$: regression coefficient,
n : number of samples,
k : number of independent variables,
e_i : error.

If there are n number of observations to estimate the model, then for each observation has:

$$\begin{gathered} Y_1 = b_0 + b_1 X_{11} + b_2 X_{21} + \cdots + b_k X_{k1} + e_1, \\ Y_2 = b_0 + b_1 X_{12} + b_2 X_{22} + \cdots + b_k X_{k2} + e_2, \\ \vdots \\ Y_n = b_0 + b_1 X_{1n} + b_2 X_{2n} + \cdots + b_k X_{kn} + e_n. \end{gathered} \tag{9}$$

Equation (9) can be presented in matrix form as follows:

$$\begin{bmatrix} Y_1 \\ Y_2 \\ Y_3 \\ \vdots \\ Y_n \end{bmatrix} = \begin{bmatrix} 1 & X_{11} & X_{21} & \cdots & X_{k1} \\ 1 & X_{12} & X_{22} & \cdots & X_{k2} \\ 1 & X_{13} & X_{23} & \cdots & X_{k3} \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ 1 & X_{1n} & X_{2n} & \cdots & X_{kn} \end{bmatrix} \begin{bmatrix} b_0 \\ b_1 \\ b_2 \\ \vdots \\ b_k \end{bmatrix} + \begin{bmatrix} e_1 \\ e_2 \\ e_3 \\ \vdots \\ e_n \end{bmatrix} \tag{10}$$

The estimated values of $b_0, b_1, b_2, \dots, b_n$ can be obtained using Ordinary Least Square (OLS) with the following equation:

$$\vec{b} = \frac{\boldsymbol{X}'\vec{Y}}{\boldsymbol{X}'\boldsymbol{X}} = (\boldsymbol{X}'\boldsymbol{X})^{-1}\boldsymbol{X}'\vec{Y}. \tag{11}$$

2.8. Sharpe Ratio

Sharpe Ratio is an indicator used to measure the return or return to risk (Hu, 2022). The formula for the Sharpe Ratio uses the expected return divided by the portfolio risk as follows:

$$S_p = \frac{E(R_p) - R_f}{\sigma_p^2}, \tag{12}$$

with
$E(R_p)$: expected return of portfolio,
R_f : risk-free rate,
σ_p^2 : risk of portfolio.

Sharpe Ratio shows portfolio performance, a portfolio is said to be optimal if the Sharpe Ratio is positive. If the Sharpe Ratio is negative, the portfolio is said to be less than optimal.

3. Materials and Methods

3.1. Materials

The data used is quarterly stock closing price data (data every three months) from companies included in the IDX High Dividend 20 index for the 2020-2023 period and company financial reports from the Indonesia Stock Exchange website. Selected 12 stocks that consistently enter the IDX High Dividend 20 in the period 2020-2023.

Table 2: IDX High Dividend 20 stock companies

No.	Code	Stock Company
1.	ADRO	Adaro Energy Indonesia Tbk.
2.	ASII	Astra International Tbk.
3.	BBCA	Bank Central Asia Tbk.
4.	BBNI	Bank Negara Indonesia (Persero) Tbk.
5.	BBRI	Bank Rakyat Indonesia (Persero) Tbk.
6.	BMRI	Bank Mandiri (Persero) Tbk.
7.	HMSP	H.M. Sampoerna Tbk.
8.	INDF	Indofood Sukses Makmur Tbk.
9.	ITMG	Indo Tambangraya Megah Tbk.
10.	PTBA	Bukit Asam Tbk.
11.	TLKM	Telkom Indonesia (Persero) Tbk.
12.	UNTR	United Tractors Tbk.

3.2. Methods

FF3FM method is used to select stocks that deserve to be included in the portfolio and ACO to determine the weight of each selected stock.

3.2.1. Fama-French Three Factor Model (FF3FM)

Asset pricing models are a set of approaches used to predict the returns of selected risky assets. One of the models that can be used to calculate expected returns is the model developed by Eugene Fama and Kenneth French known as the Fama-French Three Factor Model (FF3FM). The basis of the model initiated by Fama and French is influenced by three factors, namely the market risk premium, company size, and book to market equity (Fama and French, 1996).

The factors that affect stock returns according to Fama and French are as follows:

a) Market Risk Premium (MRP)
The market risk premium is the excess return of a market portfolio over the risk-free rate (Willmar et al., 2024). The calculation of MRP is expressed by
$$MRP_t = R_{m,t} - R_{f,t}, t = 1,2, \dots, n, \tag{13}$$
with
$R_{m,t}$: market return at time t,
$R_{f,t}$: risk-free rate at time t.

b) Size or Market Capitalization
Size is the size of a company which is calculated based on the number of shares outstanding and the closing price. The calculation of size is expressed by
$$Size_{i,t} = P_{i,t} \times B_{i,t}, t = 1,2, \dots, n, \tag{14}$$
with
$P_{i,t}$: closing price of the i-th stock at time t,
$B_{i,t}$: number of outstanding shares i at time t.

The size value will be very large and thus transformed to logarithmic form. Size is used to calculate the Small Minus Big (SMB) value. The calculation of size is expressed by

$$SMB_t = \frac{(S/L_t + S/M_t + S/H_t) - (B/L_t + B/M_t + B/H_t)}{3}. \tag{15}$$

c) Book to Market Equity (B/M)
Book to Market Equity (B/M) is the ratio of book value to the market price of a stock. The calculation of B/M is expressed by

$$B/M_{i,t} = \frac{Total\ Equity_{i,t}}{Size_{i,t}}, t = 1,2, \dots, n, \tag{16}$$

with
$Total\ Equity_{i,t}$: total equity of the i-th stock at time t,
$Size_{i,t}$: size of stock i at time t.
B/M is used to calculate the HML value. The calculation of B/M is expressed by

$$HML_t = \frac{(S/H_t + B/H_t) - (S/L_t + B/L_t)}{2}. \tag{17}$$

The stocks in each quarter are categorized into two, namely small (S) and big (B), as well as categorized into three, namely high (H), medium (M), and low (L). Furthermore, the calculation of the portfolio value for the division of categories is expressed by

$$Portfolio_{i,t} = \frac{Size_{i,t}}{B/M_{i,t}}, t = 1,2, \dots, n. \tag{18}$$

There are several categories based on SMB and HML portfolios, namely S/L, S/M, S/H, B/L, B/M, B/H. Fama (1992) defines the expected return value using the FF3FM as follows:

$$E(R_i)_{FF3FM} = R_f + \beta_i E(MRP) + s_i E(SMB) + h_i E(HML). \tag{19}$$

FF3FM regression model is expressed by

$$R_{i,t} - R_{f,t} = \alpha_i + b_i MRP_t + s_i SMB_t + h_i HML_t + \varepsilon_i, \tag{20}$$

with
$R_{i,t} - R_{f,t}$: excess return,
α_i : intercept,
b_i, s_i, h_i : regression coefficient on the independent variable,
ε_i : error.

A stock is said to be efficient or worthy of being an optimal portfolio candidate, if the expected return is greater than the expected return of FF3FM (Santhi, 2014).

$$E(R_i) > E(R_i)_{FF3FM}, \tag{21}$$

with
$E(R_i)$: expected return,
$E(R_i)_{FF3FM}$: expected return of FF3FM.

3.2.2. Ant Colony Optimization (ACO)

Ant Colony Optimization (ACO) is a meta-heuristic solution approach to optimization. ACO is inspired by observations of the natural foraging behavior of native ants. At the core of foraging behavior is indirect communication between ants. This indirect communication is facilitated by chemicals produced by ants, called pheromones (Dorigo and Stützle, 2004).

Referring to Steven et al. (2018), in the initial stage of the ACO algorithm, it is necessary to set several parameters, namely, many ants (num_ants), many iterations ($num\_iterations$), setting value (Q), the evaporation rate of the pheromone (γ), and the maximum weight of the stock (m). The next step is the allocation of weights written as $x = [0,1,2, \dots, m]$ to stocks written as $i = [1,2,3, \dots, n]$. ACO algorithm is based on ant pheromone trails, where ant pheromone trails are symbolized by τ. To build the ACO solution, a pheromone matrix is formed consisting of n as columns, where n is number of stocks, and m as rows, where m is number of weights. The following is the pheromone matrix of the ACO algorithm:

Table 3: The pheromone trail matrix for ants

Weight	Stock			
	1	2	...	n
0	τ_{01}	τ_{02}		τ_{0n}
1	τ_{11}	τ_{12}		τ_{1n}
2	τ_{21}	τ_{22}		τ_{2n}
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$
m	τ_{m1}	τ_{m2}		τ_{mn}

The probability of a weight being chosen by the ants for each stock is expressed by

$$p_{xi} = \frac{\tau_{xi}}{\sum_{x=0}^{m} \tau_{xi}}, \tag{22}$$

with
p_{xi} : the probability of the x-th weight being selected for the i-th stock,
τ_{xi} : pheromone at the x-th weight of the i-th stock.

The probability values are cumulatively calculated to get the probability interval. The ants then choose a stock weight for each stock based on a random value [0,1]. After the ants have chosen weights for each share or building solution, the quality of each solution is assessed based on the fitness value calculated by

$$Fitness = \frac{R_p}{\sigma_p}. \tag{23}$$

After all ants have completed their paths, the pheromone trails on those paths are updated which is calculated by

$$\tau_{xi}(t+1) = \tau_{xi}(t)(1-\gamma) + \delta_{xi}, \tag{24}$$

and

$$\delta_{xi} = Q\,\frac{\frac{R_p}{\sigma_p}}{\frac{R_p^*}{\sigma_p^*}}, \tag{25}$$

with
τ_{xi} : pheromone at the x-th weight of the i-th stock,
t : iteration,
γ : evaporation rate of pheromone,
δ_{xi} : amount of pheromone added at the x-th weight of the i-th stock,
Q : setting value,
$\frac{R_p^*}{\sigma_p^*}$: the largest fitness value of all ants at the t-th iteration.

The algorithm is performed iteratively up to a predetermined maximum number of iterations. After reaching the specified iteration, the optimal portfolio is obtained based on the largest fitness value.

3.2.3. Research Steps

The steps in this research are

a) Collecting IDX High Dividend 20 quarterly stock closing price data, the Jakarta Composite Index (JCI), and total equity from the company's financial statements.
b) Calculate FF3FM factors using Microsoft Excel.
c) Regression coefficient estimation.
d) Calculate the expected return value of FF3FM stocks and selecting stocks.
e) Portfolio optimization using ACO with Python.
f) Calculate the return and risk of the optimal portfolio.
g) Calculate the Sharpe Ratio value.

4. Results and Discussion

4.1. Fama-French Three Factor Model (FF3FM) Calculation

In this section, the MRP, SMB, and HML factors are calculated and then regressed using OLS to estimate the regression coefficients. After that, the expected return of FF3FM is calculated to select stocks that deserve to be optimal portfolio candidates.

4.1.1. MRP Calculation

The first step is to calculate stock return $\left(R_{i,t}\right)$, excess stock return $(R_{i,t} - R_{f,t})$, and market return $(R_{m,t})$. $R_{m,t}$ is calculated using equation (2.1) with JCI data. Risk-free rate $(R_{f,t})$ is obtained from the Bank Indonesia website. Then, using equation (3.1), the MRP calculation is presented in Table 4.

Table 4: MRP calculation result

Date	t	MRP
01/03/2020	1	−0.32448
01/06/2020	2	0.03824
⋮	⋮	⋮
01/12/2023	16	−0.01203

A positive MRP means that the market provides higher returns than risk-free investments, reflecting healthy market conditions. Conversely, a negative MRP indicates that the market provides lower returns or losses than risk-free investments, usually occurring when market conditions deteriorate.

4.1.2. Size Calculation

Number of shares outstanding $(B_{i,t})$ and the closing price $(P_{i,t})$ is obtained from IDX website. Size is calculated using equation (2). After obtaining the size or market capitalization of each stock, the stocks in each quarter can be categorized into two, namely small (S) and big (B). Below is the categorization of small (S) and big (B) sizes in March 2020.

Table 5: Small (S) and big (B) categories in March 2020

Date	Small (S)	Big (B)
March 2020	UNTR	BBRI
	INDF	HMSP
	BBNI	TLKM
	ADRO	ASII
	PTBA	BBCA
	ITMG	BMRI

Size for the other periods is calculated using the same steps. There are six stocks that belong to the small (S) category, as well as six stocks that belong to the big (B) category.

4.1.3. Book to Market (B/M) Calculation

Total equity of company $(Total\ Equity_{i,t})$ is obtained from financial report of each company. B/M is calculated using equation (4). After obtaining the B/M of each stock, the stocks in each quarter can be categorized into three, namely high (H), medium (M), and low (L). Below is the categorization of high (H), medium (M), and low (L) B/M in March 2020.

Table 6: High (H), medium (M), and low (L) categories in March 2020

Date	High (H)	Medium (M)	Low (L)
March 2020	BBNI	BBCA	PTBA
	ADRO	ASII	TLKM
	BMRI	UNTR	BBRI
	ITMG	INDF	HMSP

B/M for the other periods is calculated using the same steps. Four stocks are categorized as high (H), four as medium (M), and four as low (L).

4.1.4. Portfolio Categories Based on Size and B/M

After obtaining the size and book to market ratio of all stocks in each period, then each stock can be made into six categories, namely S/L, S/M, S/H, B/L, B/M, and B/H. For March 2020, the stock portfolio categories are presented in Table 7.

Table 7: Six portfolio categories in March 2020

Date	S/L	S/M	S/H	B/L	B/M	B/H
March 2020	PTBA	UNTR	BBNI	BBRI	ASII	BMRI
		INDF	ADRO	HMSP	BBCA	
			ITMG	TLKM		

Then, the value of portfolio for each period is calculated using equation (6). Portfolio values are used to calculate SMB and HML.

4.1.5. SMB and HML Calculation

Size is projected to the SMB value, while B/M is projected to the HML value. SMB and HML is calculated using equation (3) and (5). Excess return is the dependent variable (Y), while the MRP (X_1), SMB (X_2), and HML (X_3) are the independent variables. Table 8 shows the data to be regressed for ADRO stock. The regression coefficient of each independent variable is estimated using OLS.

Table 8: Calculation results of FF3FM factors

Excess Return (Y)	MRP (X_1)	SMB (X_2)	HML (X_3)
−0.40834	−0.32448	−0.55748	−1.19785
−0.03745	0.03824	−0.61144	−1.28355
0.10070	−0.04721	−0.47087	−1.16035
0.22241	0.19023	−0.41684	−1.13219
−0.21332	−0.03392	−0.51904	−1.17522
−0.00947	−0.03501	−0.55426	−1.19996
0.42558	0.01536	−0.30284	−0.96366
0.24341	0.01185	−0.39522	−0.95081
0.16056	0.03945	−0.61839	−1.20400
0.02820	−0.05761	−0.56665	−1.21655
0.34212	−0.02380	−0.24045	−1.16611
−0.08278	−0.08201	−0.28100	−1.14496
−0.30425	−0.06412	−0.66836	−1.29864
−0.28853	−0.07857	−0.91269	−1.37065
0.22053	−0.01577	−0.48235	−1.26255
−0.22491	−0.01203	−0.49831	−1.25060

4.1.6. Selection of candidate portfolio stocks using FF3FM

The data in Table 8 is regressed to obtain the regression coefficient to calculate the expected return of FF3FM. The results of the expected return calculation for other stocks are presented in Table 9.

Table 9: Stock selection using FF3FM

Stocks	β_i	s_i	h_i	$E(R_i)$	$E(R_i)_{FF3FM}$	Candidate?
ADRO	1.196	0.473	0.676	0.05496	−1.06605	Yes
ASII	1.627	−0.437	0.244	0.00409	−0.10665	Yes
BBCA	0.787	0.104	0.053	0.02686	−0.12822	Yes
BBNI	1.824	0.067	0.148	0.04406	−0.25272	Yes
BBRI	1.196	−0.005	0.035	0.03297	−0.06426	Yes
BMRI	1.268	0.271	−0.304	0.04009	0.19681	No
HMSP	0.847	0.045	−0.555	−0.04130	0.62080	No
INDF	0.233	−0.309	0.275	−0.00719	−0.16596	Yes
ITMG	1.696	0.614	0.195	0.08861	−0.58203	Yes
PTBA	1.051	0.185	0.526	0.01414	−0.73841	Yes
TLKM	0.980	−0.165	0.437	0.00847	−0.45323	Yes
UNTR	0.749	0.252	−0.043	0.02108	−0.08818	Yes

Based on Table 9, it is obtained that BMRI and HMSP stocks do not pass the selection so they are excluded from the optimal portfolio candidates. While the other 10 stocks, namely ADRO, ASII, BBCA, BBNI, BBRI, INDF, ITMG, PTBA, TLKM, and UNTR passed the selection and became portfolio candidates which will then be optimized using Ant Colony Optimization (ACO).

4.2. ACO for Optimization Portfolio

a) The initialization parameters used in the calculation are $num\_ants = 100$, $num\_iterations = 100$, $num\_stocks = 10$, $\gamma = 0.01$, $Q = 1$, and $max\_weight = 9$.
b) Calculate the return, expected return, variance, covariance of stocks using equations (1), (2), (3), and (4).
c) Initialize the pheromone matrix with the same initial value of 1.
d) Start iteration with initialization $t = 1$. If $t \leq num\_iterations$, the process goes into looping for each ant. Ant looping starts with $k = 1$. If $k \leq num\_ants$, the process enters the loop for each stock. Stock looping starts with $i = 1$. If $i \leq num\_stocks$, the process goes to the next step which is to calculate the probability of the weight being selected by the ants.
e) Calculate the probability value of the weight selected by ant 1 for each stock using equation (10).
f) After all weights have their probability values calculated, then the probability values are calculated cumulatively. Next, a random number $r = [0,1]$ is taken.
g) The obtained stock weights of ant 1 in iteration 1 are 1, 7, 5, 7, 3, 5, 6, 4, 2, 7. Furthermore, each stock weight is normalized so that the amount is 100%.
h) After obtaining weights for all stocks, then calculate R_p and σ_p using equations (5) and (7).
i) Fitness value is calculated using equation (11). The calculation of fitness value is done for all ants, in this study 100 ants. After the fitness value of all ants in iteration 1 is calculated, the process exits the ant loop.
j) Calculate the pheromone update using equation (12). Where there are two conditions for the addition of pheromones, namely $\delta_{xi} = 0$ for stock weights that are not selected by ants. As for the weight of the selected stock, the pheromone is increased by the amount based on equation (13).
k) After all iterations, the pheromone matrix has been updated by each ant throughout the iterations. After performing all iterations, take the largest fitness value that stores the weight as a feasible solution. The ACO algorithm calculation is aided by Python programming.
l) From the calculation results using Python, it is obtained that in the last iteration, the largest fitness value is 0.2949, with $R_p = 0.0473$, $\sigma_p = 0.1604$, and $\sigma_p^2 = 0.0257$. The weights obtained for each stock in the portfolio are presented in Table 10 as follows:

Table 10: ACO algorithm result

Stock	w_i
ADRO	6.90%
ASII	0.00%
BBCA	17.24%
BBNI	10.34%
BBRI	27.59%
INDF	3.45%
ITMG	27.59%
PTBA	0.00%
TLKM	3.45%
UNTR	3.45%

From the optimization results using ACO, it can be seen that the largest weights fall on BBRI and ITMG stocks, which reflect both as the main stocks of the portfolio because they are considered the most optimal in terms of return and risk. BBCA and BBNI stocks also received considerable weight, signaling the dominance of the financial sector in this portfolio. On the other hand, small weighted stocks such as INDF, TLKM, and UNTR add elements to diversify the portfolio so that an optimal portfolio is formed.

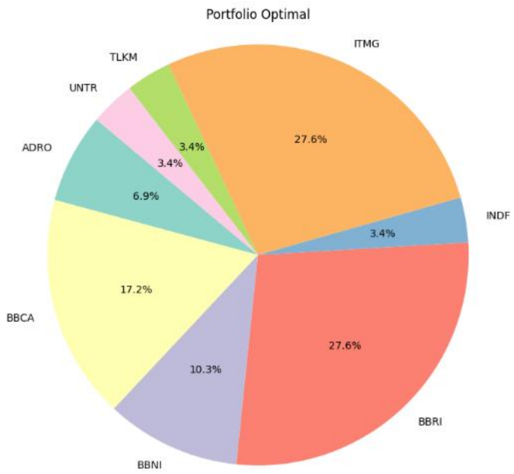

Figure 1: Pie chart of stock weights in the optimal portfolio

4.3. Sharpe Ratio Calculation

After obtaining the expected return value and portfolio risk, the Sharpe Ratio value is calculated as a measure of portfolio performance as follows:

$$S_p = \frac{0.0473 - 0.01084}{0.0257} = 1.41868$$

It is obtained that the Sharpe Ratio is positive, thus, the portfolio formed has shown good performance because it meets the criteria, so the optimal portfolio is worth investing in.

Based on the calculation, the portfolio generates an excess return per unit of portfolio risk of 1.41868. This value indicates that any risk taken by investors can achieve a return of 1.41868 above the risk-free asset return. In other words, the portfolio performs well because it can provide more return than the risk that needs to be borne. This is a key indicator in investment decision making, as investors generally want a portfolio that not only offers high returns, but also provides effective risk management.

5. Conclussion

From the 12 stocks studied, the 10 best stocks were selected from the comparison of average return and expected return using the Fama-French Three Factor Model (FF3FM).The best stocks are ADRO, ASII, BBCA, BBNI, BBRI, INDF, ITMG, PTBA, TLKM, and UNTR. The best stocks are selected as optimal portfolio formation candidates using Ant Colony Optimization (ACO). The weight of the ACO optimal investment portfolio on IDX High Dividend 20 stocks is for ADRO shares by 6.90%, ASII by 0%, BBCA by 17.24%, BBNI by 10.34%, BBRI by 27.59%, INDF by 3.45%, ITMG by 27.59%, PTBA by 0%, TLKM by 3.45%, and UNTR by 3.45%. With these weights, the expected return of the portfolio is 0.0473 and the portfolio risk is 0.0257. Obtained Sharpe Ratio results as a measure of optimal portfolio performance of 1.41868, this value indicates that the portfolio shows good performance, with a return greater than the risk taken.

This study uses the Fama-French Three Factor Model for the selection of stocks that become optimal portfolio candidates, which only involves three factors. Therefore, for future research it is recommended to use the Fama-French Five Factor Model which involves two additional factors for the stock selection process, namely profitability and investment. This research uses Ant Colony Optimization (ACO) for portfolio optimization. For further research, it is recommended to use other metaheuristic models in the formation of investment portfolios such as Particle Swarm Optimization (PSO) and Bee Colony Optimization (BCO) in order to get a comparison of the portfolio results formed with other models.

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