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Stock Portfolio Optimization of IDX30 Using Agglomerative Hierarchical Clustering and Ant Colony Optimization Algorithm

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Abstract

The stock market offers high return opportunities but also carries significant risks, making portfolio optimization essential to help investors manage risk and maximize returns. This study aims to cluster IDX30 stocks to form a more diversified portfolio, determine the optimal stock weights, and evaluate portfolio performance. The Agglomerative Hierarchical Clustering (AHC) method with Ward linkage was used to group stocks based on financial ratios, and silhouette score was employed to assess cluster quality. Subsequently, the Ant Colony Optimization (ACO) algorithm was applied to optimize stock weights in the portfolio based on the clustering results. The findings show that the best-performing portfolios were obtained from cluster 6 and cluster 5, with a maximum fitness value of 0.064555 and a portfolio return of 0.000814. Portfolio performance evaluation using the sharpe ratio yielded a value of 0.044767 for both clusters, indicating that the resulting portfolios are efficient. This study is expected to contribute to the development of more accurate and data-driven investment strategies for investors.

Keywords: IDX30; agglomerative hierarchical clustering; ant colony optimization; stock portfolio; sharpe ratio; silhouette score.

1. Introduction

Investment is a crucial endeavor in achieving long-term financial stability. In addition to providing potential asset growth, investment is also used to protect the value of money from inflation and achieve specific financial goals (Wray, 2001). In recent years, ease of access through digital technology has encouraged an increase in the number of investors, including in stock market instruments (Kustodian Sentral Efek Indonesia, 2025).

One of the most popular stock indices in Indonesia is the IDX30, which comprises 30 stocks with large market capitalizations and high liquidity levels. However, despite offering attractive profit opportunities, investing in stocks carries a high level of risk. Therefore, a sound portfolio management strategy is necessary to help investors maximize profits while minimizing risks (Ulfa et al., 2022).

Previous studies have combined clustering and optimization methods in the context of portfolio management. Subekti et al. (2018) used ACO in stock clustering. Rezani et al. (2020) combined iterative k-means clustering and ACO in portfolio selection. Nourahmadi & Sadeqi (2023) compared the effectiveness of AHC with random selection in diversification. Meanwhile, Kavitha & Lalitha (2024) demonstrated that ACO outperforms PSO and FFA.

This study proposes the AHC and ACO approaches for optimizing the IDX30 stock portfolio. AHC is used to cluster stocks based on financial ratios, while ACO is used to determine the optimal weights, returns, and risks.

2. Literature Review

The theoretical studies discussed in this research are Agglomerative Hierarchical Clustering (AHC), silhouette score, Ant Colony Optimization (ACO), and Sharpe ratio. The theoretical studies discussed in this research are Agglomerative Hierarchical Clustering (AHC), silhouette score, Ant Colony Optimization (ACO), and Sharpe ratio.

2.1. Agglomerative Hierarhical Clustering

Agglomerative Hierarchical Clustering (AHC) is a clustering method in which each data point is initially considered as a single cluster and gradually merged to form a large cluster. One of the linkage methods used is the Ward method, which minimizes the total variance in each cluster merger.

The distance between clusters is calculated using the following equation (1):

$$\boldsymbol{D_w(C_a, C_b) = \frac{|C_a|, |C_b|}{|C_a| + |C_b|} d(\mu_a, \mu_b)}, \qquad (1)$$

with the notation $|C_a|, |C_b|$ are the numbers of stocks in clusters a, b, and μ_a, μ_b are means of clusters a, b.

2.2. Sillhouette Score

The silhouette score is used to evaluate how well an object fits into its cluster compared to other clusters (Rousseeuw, 1987). For each object i, the silhouette score is calculated using equation (2) as follows:

$$s(i) = \frac{b(i) - a(i)}{\max\left(a(i), b(i)\right)}, \qquad (2)$$

where $a(i)$ is the average distance between object i and all other objects in the same cluster, and $b(i)$ is the minimum average distance between object i and all objects in different clusters (nearest). The value of $s(i)$ ranges from -1 to 1. The closer it is to 1, the better the quality of the cluster.

2.3. Portfolio Optimization

Portfolio optimization is the process of determining the most effective allocation of funds to maximize returns and minimize risk. One commonly used approach is Markowitz's Mean-Variance method, which balances risk and return in forming an optimal portfolio (Zhang & Guo, 2018).

The mean variance model is as follows (Rezani et al., 2020):

$$R_p = \sum_{i=1}^{s} w_i R_i \qquad (3)$$

$$\sigma_p = \sqrt{\sum_{i=1}^{N} \sum_{j=1}^{M} w_i w_j \sigma_{ij}} \qquad (4)$$

with

$$\sum_{i=1}^{s} w_i = 1 \, dan \begin{cases} w_i > 0 \forall_i \in p \\ w_i = 0 \forall_i \notin p \end{cases} \qquad (5)$$

where R_p is the portfolio return, R_i is the expected return of stock i, w_i is the weight of stock i, and σ_{ij} is the covariance between stocks i and j.

2.4. Ant Colony Optimization

Ant Colony Optimization (ACO) is a metaheuristic algorithm based on the behavior of ants in searching for optimal routes. In this algorithm, each ant chooses a path (in this context, a stock weight) based on a probability influenced by pheromone trails (Dorigo & Blum, 2005).

The probability of an ant choosing a weight is calculated using the following equation (6):

$$P_{ic} = \frac{\tau_{ic}}{\Sigma \tau_{ic}} \qquad (6)$$

where τ_{ic} is the pheromone concentration on the path to weight c for stock i.

After all ants have completed their solutions, the pheromone is updated using the following equation (7):

$$\tau_{ic}(t+1) = \tau_{ic}(t)(1-\rho) + \delta_{ic}, \quad (7)$$

where ρ is the evaporation constant, where $0 < \rho \leq 1$ and δ_i is the amount of pheromone added to stock i with weight c.

2.5. Sharpe Ratio

The Sharpe ratio measures portfolio performance by comparing excess returns to risk. The Sharpe ratio is calculated using equation (8) as follows:

$$Sharpe\ ratio = \frac{E(R_p) - R_f}{\sigma_p} \quad (8)$$

where $E(R_p)$ is the expected return of the portfolio, R_f is the return on risk-free assets, and σ_p is the risk of the portfolio.

3. Methods

This study employs a quantitative approach, utilizing stock price data from the IDX30 index as the object of analysis. The stock diversification process is carried out using the Agglomerative Hierarchical Clustering (AHC) method to group stocks based on specific financial ratios. After the clusters are formed, the Ant Colony Optimization (ACO) algorithm is applied to determine the optimal stock portfolio.

The data used in this study consist of daily closing prices of IDX30 stocks for the year 2024, along with five types of financial ratios extracted from the company's financial reports. Eight stocks from different sectors were selected to maintain portfolio diversity: ADRO, SMGR, ACES, GOTO, AKRA, INDF, KLBF, and TLKM.

Five types of financial ratios, normalized using the Min-Max Scaling method based on ratio type and closing price, were used to calculate stock returns. Min-max scaling calculations utilized equations (9) and (10).

Calculations of NPM, CR, and RoE financial ratios used equation (9):

$$\boldsymbol{Score = 100\left(\frac{x_{i,k} - \min(x_{i,k})}{\max(x_{i,k}) - \min(x_{i,k})}\right).} \quad (9)$$

The calculation of the PER and DER financial ratios uses equation (10):

$$\boldsymbol{Score = 100\left(\frac{x_{i,k} - \max(x_{i,k})}{\min(x_{i,k}) - \max(x_{i,k})}\right).} \quad (10)$$

Normalization data and returns are processed using Microsoft Excel and Python.

4. Results and Discussion

The AHC results with ward linkage are shown in the dendrogram visualization in Figure 1. The clustering results were evaluated based on the three highest silhouette scores.

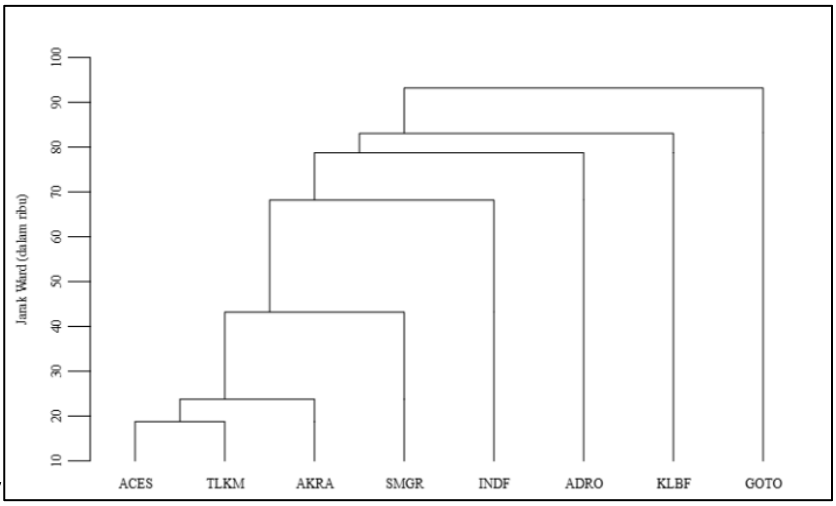

Figure 1: Visualization of the dendrogram results of AHC

Figure 1 illustrates that ACES and TLKM stocks share the most similar financial characteristics, as they were grouped in the early stages. Conversely, GOTO stocks were grouped in the final stage with the highest grouping distance, indicating that these stocks are the most different from the others. This structure reflects the potential for diversification, where stocks from clusters with high grouping distances can reduce portfolio risk.

Cluster 7 produced the highest silhouette value of 0.79544, followed by cluster 6 with a value of 0.74906, and cluster 5 with a value of 0.65616. This indicates that the cluster structure with seven groups offers the best separation between stocks and exhibits high compactness within each cluster.

Table 1. Members of clusters 5, 6, and 7

5 clusters		**6 clusters**		**7 clusters**	
Clusters	**Stocks**	**Clusters**	**Stocks**	**Clusters**	**Stocks**
1	ADRO	1	ADRO	1	ADRO
2	ACES TLKM AKRA SMGR	2	SMGR	2	SMGR
3	GOTO	3	ACES TLKM AKRA	3	ACES TLKM
4	INDF	4	GOTO	4	GOTO
5	KLBF	5	INDF	5	AKRA
		6	KLBF	6	INDF
				7	KLBF

The three stock clusters that were formed were then used as input in the portfolio optimization process using ACO to determine the optimal portfolio based on fitness.

The optimization results obtained showed that clusters 5 and 6 both provided the best results with a fitness value of 0.064555. The portfolio formed from this optimization yields a return of 0.000814 with a risk of 0.012603, resulting in a Sharpe Ratio of 0.064555. A positive Sharpe Ratio indicates that the portfolio is capable of generating returns that exceed the level of risk incurred.

5. Conclusion

This study successfully demonstrated that the combination of AHC and ACO methods is effective in optimizing the IDX30 stock portfolio. AHC provides diversified stock clustering, while ACO produces optimal weights that maximize returns and minimize risk. Clusters 5 and 6 are the best compositions. For future research, it is recommended to explore other clustering methods, such as DBSCAN, k-means++, or hybrid clustering, to compare with AHC in terms of portfolio diversification and stability. Additionally, it is recommended to compare other optimization algorithms, such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Simulated Annealing (SA), to gain a broader understanding of the effectiveness of each algorithm in forming an optimal portfolio.

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