International Journal on Science and Technology (IJSAT)

E-ISSN: 2229-7677 ● Website: www.ijsat.org ● Email: editor@ijsat.org

Swarm Intelligence in Finance: A Comparative Analysis of ACO and PSO for Mean–Variance Portfolio Optimization

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Abstract

Portfolio optimization poses a significant challenge for modern portfolio managers as they strive to balance expected returns against inherent risks. In the quest to create optimal portfolios, selecting the appropriate tools and techniques is paramount. One of the most widely adopted frameworks is the Markowitz mean–variance model, renowned for its effectiveness in addressing the portfolio selection problem. However, while the standard Markowitz formulation is NP-hard, the complexity escalates considerably when additional variables or constraints, such as cardinality restrictions, are introduced, transforming the problem into a nonlinear mixed integer programming challenge that is far more demanding to solve. Identifying the most effective algorithms for multi-objective portfolio optimization is a crucial task. Therefore, researchers need to identify the most appropriate algorithms. This research examines two prevalent swarm intelligence (SI) algorithms: Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO), for portfolio optimization. The study evaluates the performance of these optimization algorithms in addressing real-world constraints associated with portfolio construction. The performance and robustness of the portfolios are evaluated through anchored and unanchored cross-validation methods, using six years of daily trading data from 20 randomly selected stocks listed on the National Stock Exchange (NSE) of India. Descriptive statistics of this study show that the average Sharpe ratio of five test folds using the anchored cross-validation method is 0.53 for ACO and 0.61 for PSO. The unanchored cross-validation method produced an average Sharpe ratio of 0.90 for ACO and 0.87 for PSO in the five test folds. The detailed analysis of the experimental data set reveals that PSO outperforms ACO. Further, the return obtained from portfolios constructed by ACO and PSO outperforms the Nifty 100 Index returns.

Keywords: Ant Colony Optimization, Mean-Variance Model, Particle Swarm Optimization, Portfolio Asset Allocation, Swarm Intelligence

1. Introduction

Portfolio optimization presents a significant challenge to the portfolio manager. Expected returns and risks are the most important criteria in portfolio optimization problems. Choosing the right tools and techniques to create an optimal portfolio is a crucial task for portfolio managers and investors. Portfolio managers extensively utilize the Markowitz mean–variance portfolio model, as it is considered one of the most effective models for addressing the portfolio selection problem. Although portfolio optimization using the standard Markowitz model is NP-hard, the problem becomes much more difficult to solve if the number of variables increases or more constraints, such as cardinality constraints, are introduced. Such constraints formed nonlinear mixed integer programming problems, which are considerably more difficult to solve than the original mean-variance model introduced by Markowitz (Markowitz,1952). As a result, heuristic methods for addressing the portfolio selection problem have been developed, including evolutionary algorithms, Tabu search (TS), Simulated Annealing (SA), neural networks, Artificial Bee Colony (ABC), particle swarm optimization (PSO), and ant colony optimization (ACO). Identifying the most appropriate algorithms for multi-objective portfolio optimization is a challenging and demanding task. Therefore, research is needed to identify the most appropriate algorithms for portfolio optimization, which could address the real-life constraints introduced in the mean-variance model. Researchers widely recognize ACO and PSO as effective optimization techniques in portfolio optimization (Ertenlice et al., 2018; Erwin and Engelbrecht, 2023). This research paper aims to suggest the most appropriate optimization algorithm by comparing the performance of portfolios generated by two different algorithms. This research examines two prevalent swarm intelligence (SI) algorithms, Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO), for portfolio optimization. The study evaluates the performance of these optimization algorithms in addressing real-world constraints associated with portfolio construction. The performance and robustness of the portfolios are assessed through anchored and unanchored cross-validation methods, utilizing six years of daily trading data from January 1, 2018 to December 31, 2023, for the 20 randomly selected stocks listed on the National Stock Exchange (NSE) of India. The dataset is partitioned into training and testing folds, with each testing fold covering 246 trading days.

This research evaluates and contrasts the performance of ACO and PSO algorithms. The portfolio optimization algorithm is considered efficient if it provides a favourable trade-off between return and risk. Furthermore, the portfolio outcomes are compared with the return of the NIFTY 100 Index for each training and testing rolling window.

The organization of this paper is as follows: Section 2 covers PSO and ACO algorithms. Section 3 outlines the optimization model and constraints. Section 4 describes methodology. Section 5 details the experimental studies, presents the data set, solutions by ACO and PSO algorithms, and result analysis. Section 6 concludes the paper, followed by references.

2. Literature Review on Swarm Intelligence Algorithms

Computational models inspired by natural swarm systems are referred to as swarm intelligence models. The literature has presented various swarm intelligence models, and they have been successfully applied to numerous real-world applications. These models are based on different natural swarm systems. Examples of swarm intelligence models include the Artificial Bee Colony (ABC), Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO), Bacterial Foraging, Cat Swarm Optimization (CSO), and Glowworm Swarm Optimization (GSO). Two notable swarm intelligence models used for optimizing portfolios are Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO) (Ertenlice et al., 2018; Gad, 2022). This study aims to determine the most suitable algorithm between ACO and PSO by comparing experimental results.

2.1 Existing Surveys on PSO-Based Portfolio Allocation

Previous studies have demonstrated the effectiveness of the particle swarm optimization (PSO) algorithm for portfolio allocation. For example, Ertenlice and Kalaycı (2018) reviewed over 76 publications from 2006 to 2017 that applied swarm intelligence algorithms to the portfolio optimization problem. This paper summarizes that particle swarm optimization (PSO) is the most adopted method for portfolio optimization. Around 63% publications is for particle swarm optimization (PSO), while 16% for artificial bee colony (ABC), 6% for bacterial foraging optimization (BFO), 4% for ant colony optimization (ACO),4% for firefly algorithm(FA), and only 1% for cat swarm optimization(CSO).

(Erwin, et al., 2023), performed an extensive review of more than 140 papers that address the portfolio optimization problem using swarm and evolutionary intelligence algorithms. These papers are divided into two categories: single-objective and multi-objective approaches. The first category is based on the type of portfolio optimization problem, either unconstrained or constrained. The study concludes that genetic algorithms (GAs) and particle swarm optimization (PSO) are the most widely used meta-heuristic methods for portfolio optimization.

(Jarchelou et al., 2024), evaluates the performance of various optimization algorithms—Quadratic Programming (QP), Genetic Algorithm(GA), Pareto-search, Pattern-search, and PSO. The results show that QP, Pareto-search, and PSO algorithms closely match expected values, while GA and Pattern-search exhibit lower efficiency. Using the Kruskal-Wallis test, the study compares algorithm performance, finding no significant difference between QP and other algorithms in terms of portfolio returns. The findings contribute to understanding algorithm efficiency in financial optimization tasks.

2.2 Existing Surveys on ACO-Based Portfolio Allocation

Previous studies have shown that the Ant Colony Algorithm (ACO) is effective for portfolio allocation (Erwin, et al., 2023). Reviewed over 140 papers on algorithms for portfolio optimization, categorizing them by type and objective approaches. (Sefiane, et al., 2013) Applied ACO to multi-objective portfolio optimization, finding it competitive with genetic algorithms (GA). (Ahmed et al., 2019) Compared neural network and ACO for stock forecasting, concluding ACO had the highest accuracy, sensitivity, and specificity. (Steven, et al., 2018) Used ACO for stock portfolio optimization via clustering and stock allocation based on financial metrics, which demonstrates reduced portfolio losses. (Uthayakumar, et al., 2020) proposed an ACO-based financial crisis prediction model outperforming PSO, GA, and GWO algorithms.

While promising, further research is needed to explore its full potential against other techniques. This study applies ACO to a multi-objective portfolio allocation problem involving twenty stocks and evaluates its effectiveness in generating optimal portfolios.

In summary, the literature review highlights the shift from single-objective to multi-objective optimization in portfolio allocation. ACO and PSO present effective methods, providing diverse optimal portfolios. The following sections will cover the methodology, experimental design, results, and discussions on using ACO and PSO for multi-objective portfolio allocation.

3. Problem Formulation

3.1 Portfolio Optimization

Portfolio optimization involves selecting assets to balance expected returns and risk, to maximize returns while minimizing risks. It takes into account the investor's preferences, constraints, and objectives. It provides a spectrum of optimal solutions that enable informed decision-making based on individual risk-return priorities. Portfolio optimization leverages a range of quantitative tools and models to enable investors to achieve diversification, reduce transaction costs, and make informed investment decisions.

Modern Portfolio Theory (MPT) is a widely used method for portfolio optimization. Developed by Harry Markowitz in the 1950s (Markowitz,1952; Chen, et al.,2022). MPT is based on the idea that investors can achieve the optimal balance of risk and return by diversifying their investments across a range of assets. Mean-Variance optimization is a method of portfolio optimization that is based on MPT. Mean-variance optimization seeks to construct portfolios that maximize the expected return for a given level of risk. Markowitz's model laid the foundation for modern portfolio theory and introduced the concept of the efficient frontier, which represents the set of portfolios that offer the highest return for a given level of risk.

Over the years, various extensions and variations of the mean-variance model have been developed to address its limitations. Some notable approaches include the Capital Asset Pricing Model (CAPM), which incorporates the risk-free rate and the market risk premium to determine optimal portfolios, and the Arbitrage Pricing Theory (APT), which considers multiple factors to explain asset returns. These models provide valuable insights into portfolio diversification and risk management, but often assume a single objective optimization framework, neglecting other important aspects such as transaction costs and investor preferences.

3.2 Mathematical Model for Portfolio Optimization

A multi-objective optimization problem entails the concurrent optimization of multiple conflicting objectives. Acknowledging the necessity of evaluating various objectives and preferences, this paper presents a mathematical model that integrates real-life constraints for portfolio allocation that aims to maximize profit while minimizing risk.

Besides the main objectives, this study introduces constraints on asset allocations to limit the number of assets in the portfolio, restrict each asset's contribution, and cap the investment value. This portfolio optimization model identifies a set of assets and their allocation values that provide an efficient balance between return and risk, resulting in a diversified portfolio for investors. This approach enables investors to select assets in a portfolio that align with their risk-return preferences as well as other asset-dependent factors.

A mathematical description of a multi-objective optimization problem (Erwin, et al., 2023; Chen, et al.,2022; Dioşan, 2006):

Let $x_1, x_2 \ldots, x_n$ be the variables of the problem.

$f_1, f_2 \ldots f_n$ The functions to optimize.

Assuming maximization, multi-objective optimization problems are defined as

$$\text{Maximize } f_1(x_1, x_2, \ldots\ldots, x_n), \ldots\ldots, f_m(x_1, x_2, \ldots\ldots, x_n) \quad (1)$$

$$\text{Subject to } g_1(x_1, x_2, \ldots\ldots, x_n) <= b_1 \quad (2)$$

$$g_r(x_1, x_2, \ldots\ldots, x_n) <= b_r \quad (3)$$

Where,

$g_1, g_2 \ldots g_r$, the constraint on asset allocations, restriction on investment, etc.

$b_1, b_2, \ldots, b_r$ are the limiting values on constraints.

The solution to this multiple objective problem leads to asset allocation weightage in the portfolio for optimal trade-offs between return and risk.

3.2.1 Mean-Variance Portfolio Model.

The modern portfolio mathematical framework was used to produce the best combination of mean and variance. The concept of this mean-variance portfolio model is that the best portfolio is one that achieves expected return at minimal risk (Erwin, et al., 2023; Chen, et al.,2022).

The formula for risk and return is used to set the portfolio.

Risk is calculated using.

$$\sum_{i=1}^{n} w_i \, w_j \sigma_{ij} \qquad (4)$$

Where n is the number of assets, w_i and w_j are the weights of assets i and j, respectively, and σ_{ij} is the covariance between assets i and j.

Return is calculated using,

$$\sum_{i=1}^{n} R_i \, w_i \qquad (5)$$

The objective function for maximizing portfolio return is formulated as follows:

$$\max \sum_{i=1}^{n} R_i \, w_i \qquad (6)$$

Where w_i represents the weight of asset i in the portfolio,

R_i is the expected return of asset i,

n is the total number of assets in the portfolio.

The objective function mentioned in equation 10 must account for real-life constraints and diversification. The constraints discussed in this paper are detailed below.

The investment value constraint is:

$$\sum_{i=1}^{n} w_i = 1 \qquad (7)$$

The weight of each asset must be nonnegative, i.e.,

$$w_i >= 0 \qquad (8)$$

Furthermore, constraints on the minimum and maximum value of asset weight are introduced for effective diversification to take care of factors such as the fundamentals of assets, qualitative factors, etc.

i.e., $$w_i >= c_1 \qquad (9)$$

$$w_i <= c_2 \qquad (10)$$

Where c_1 and c_2 are allocation restriction constraints based on asset selection factors.

This study leverages Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO) algorithms to develop and evaluate solutions for a multi-objective optimization model embedded with real-world constraints

4. Methodology

To proposed portfolio optimization model was evaluated using a basket of twenty stocks. These stocks are selected arbitrarily from the listed stocks on the NSE, India (National Stock Exchange of India, n.d.). The methodology followed in this research is described below.

1. **Data Acquisition:** Historical daily stock price data were obtained using the yfinance package in Python for the period January 1, 2018 to December 31, 2023.
2. **Data Preprocessing and Feature Extraction:** Closing prices were obtained from the dataset and converted into daily log returns for analysis. The data matrix consists of 1480 trading days for evaluation.
3. **Apply the Anchored and Unanchored Cross-Validation:** The data are structured into training and testing folds, as per the strategy adopted for anchored and unanchored cross-validation techniques. The training and testing fold data are as per Figures 4 and 5.
4. **Return and Covariance Matrix Calculation:** The mean return and covariance matrices of each asset are calculated over the training and testing fold data are computed by the equations specified in section 3.2.1.
5. **Portfolio Optimization Modeling:** The mathematical problem formulation for portfolio optimization, including constraints created as discussed in sections 3.2 and 3.2.1.
6. **Optimization Algorithms:** The optimization problem is solved for maximum return with a cap on risk using Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO), as discussed in sections 2.1 and 2.2. Return, risk, and weight allocations are obtained for analysis and validation.
7. **Portfolio Generation and Analysis:** The methodology produced five distinct portfolios, each corresponding to the training and testing folds for each cross-validation technique. Each portfolio has varied asset allocations, returns, and risk values. These results are tabulated and analyzed to compare the performance of portfolios.
8. **Comparison with Nifty100 Index:** The performance of the NIFTY 100 Index for each portfolio's timeframes is obtained from NSE, India. The constructed portfolio's performance is compared with the NIFTY 100 Index.

The anchored and unanchored cross-validation strategy adopted in this study for portfolio generation and validation is presented in Figures 1 and 2

Figure 1: Anchored Cross-validation for Portfolio Generation and Validation.

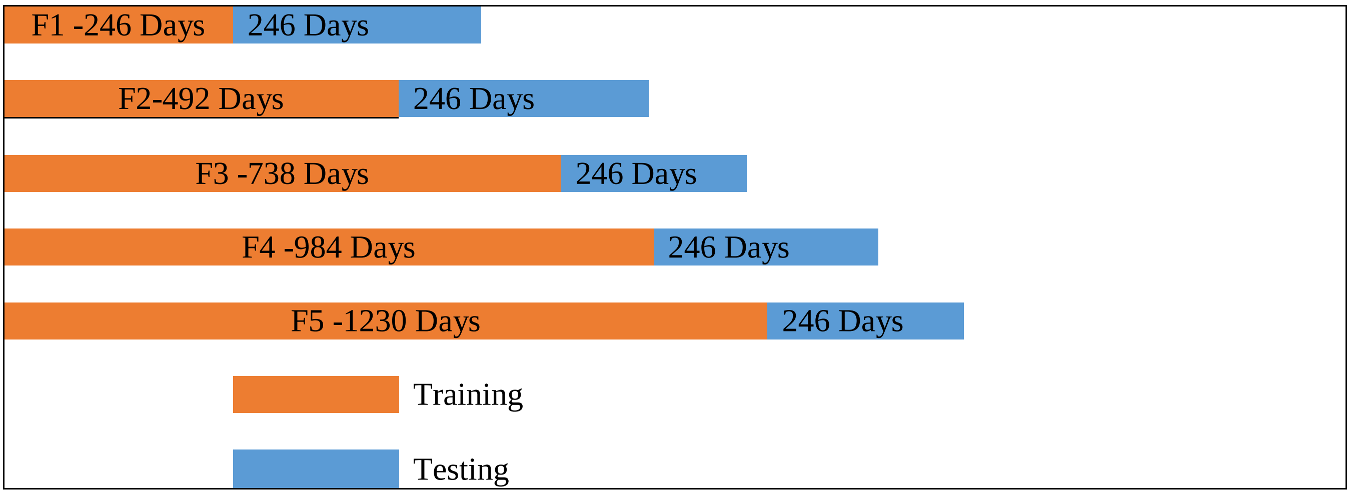
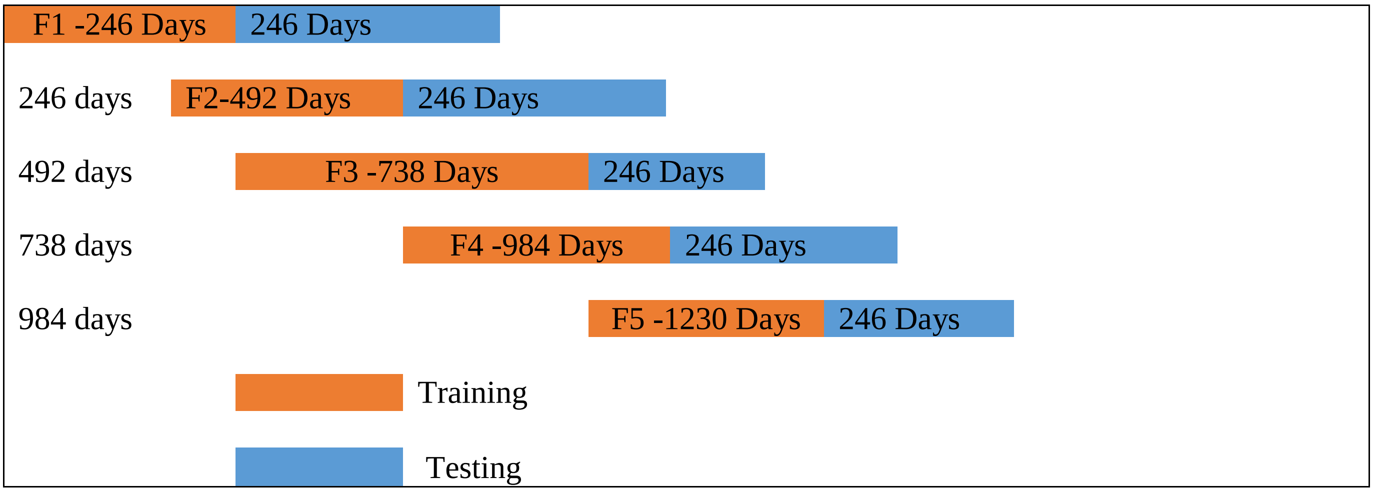


Figure 2: Unanchored Cross-validation for Portfolio Generation and Validation.



5. Experimental Analysis

An experimental study was conducted, following the described methodology, to compare the effectiveness of ACO and PSO techniques for solving the proposed optimization model, which includes real-world constraints as previously discussed.

Table 1 DATASET – Selected Assets for Portfolio

Stock No	**Stock Name**	**Stock No**	**Stock Name**
Stock1	BAJFINANCE	Stock 11	KOTAKBANK
Stock2	BHARTIARTL	Stock12	MARUTI
Stock3	BLUEDART	Stock13	MUTHOOTFIN
Stock4	DABUR	Stock14	PAGEIND
Stock5	DIVISLAB	Stock15	PGHH
Stock6	DMART	Stock16	PIDILITIND
Stock7	HATSUN	Stock17	RELAXO
Stock8	HDFCBANK	Stock18	SBIN
Stock9	HDFCLIFE	Stock19	SOLARINDS
Stock10	ICICIGI	Stock20	TATACOMM

The closing values of the assets from January 1, 2018 to December 31, 2023 are obtained from the yfinance package in Python coding. Daily log returns are computed based on the closing prices of the selected twenty stocks in the portfolio. The summary statistics of the data are presented in Table 2, generated using the describe method in Python.

Table 2. Portfolio Summary Statistics for the Selected Period

Stock	**Count**	**Mean**	**Std**	**Min**
S1	1480	0.0010	0.0245	-0.2644
S2	1480	0.0005	0.0198	-0.1273
S3	1480	0.0003	0.0200	-0.0928

Stock	**Count**	**Mean**	**Std**	**Min**
S11	1480	0.0004	0.0180	-0.1393
S12	1480	0.0001	0.0192	-0.1852
S13	1480	0.0009	0.0232	-0.1808

S4	1480	0.0004	0.0148	-0.1151	S14	1480	0.0003	0.0204	-0.1083
S5	1480	0.0009	0.0190	-0.1246	S15	1480	0.0005	0.0139	-0.0971
S6	1480	0.0008	0.0202	-0.1175	S16	1480	0.0008	0.0161	-0.1665
S7	1480	0.0005	0.0223	-0.2225	S17	1480	0.0007	0.0169	-0.1589
S8	1480	0.0004	0.0160	-0.1348	S18	1480	0.0005	0.0212	-0.1446
S9	1480	0.0004	0.0196	-0.2000	S19	1480	0.0012	0.0195	-0.1252
S10	1480	0.0004	0.0196	-0.1952	S20	1480	0.0010	0.0234	-0.1735

The portfolio optimization model, as detailed in sections 3.2 and 3.2.1, is evaluated, subject to the following constraints.

1. Total weight constraint: The sum of the weights of all the assets in the portfolio must be equal to 1. Indicating full allocation of the investment amount.

$$\sum_{i=1}^{n} w_i = 1$$

2. Minimum weight constraint: The weight of each asset must be at least 1% of the total investment amount.

$w_i >= 0.01$

3. Maximum weight constraint: the weight of any single asset must not exceed 12% of the total portfolio value.

$w_i <= 0.12$

The minimum and maximum constraints for the portfolio are a cap on the allocation of stocks. An equal-weight distribution assigns each stock a 5% allocation. To ensure adequate diversification, the maximum allocation for a single asset is capped at 12%, while the minimum allocation is limited to 1% (approximately 20% of the equal-weight allocation). These limits have been established arbitrarily.

The optimization model is solved using ACO and PSO algorithms in Python programming. The selection of appropriate parameters is crucial as it significantly impacts the performance. In this study, the parameters for ACO and PSO are chosen based on existing literature (Ertenlice & Kalayci, 2018; Abolmaali & Roodposhti,2018; Benbouziane & Sefiane,2013). The parameters used in this work are presented in Table 3.

Table 3. ACO and PSO Parameters

Description of Parameter for ACO	**Value for this Experiment**	**Description of Parameter for PSO**	**Value for this Experiment**
Number Of Ants.	40	Number of swarms	40
Number of iterations.	1000	Number of iterations	1000
Alpha (α): Influence of pheromone tails on the ant's decisions.	2	Cognitive coefficient C_1	1.5
Beta (β): Influence of heuristic information on the ant's decisions.	3	Social coefficient C_2	1.5
Evaporation rate (ϱ): The rate at which pheromone trails evaporate over time.	0.5		

The Sharpe ratio is evaluated using a risk-free return of 6.85%, based on the average annual return of the 10-year Indian Government Bond from January 1, 2018 to December 31, 2023 (Reserve Bank of India - NSDP Display, n.d.).

This study compares the performance of ACO and PSO portfolios across all training and testing rolling windows and evaluates optimized portfolios against the NIFTY 100 Index. Tables 4 and 5 present the statistical comparison of results obtained from the ACO and PSO algorithms across five distinct rolling windows, considering both anchored and unanchored cross-validation for training and testing folds. Additionally, the asset weights derived from each fold are analyzed and detailed in Tables 4 and 5.

Table 4. Comparison Statistics of ACO and PSO with the Anchored Cross Validation Method

Algorithm	**Parameter**	**Sample Size**	**Min**	**Max**	**Average**	**Standard Deviation**	**P-value from the T-test of the Sharpe ratio**
ACO Training	Sharpe Ratio	5	0.41	0.86	0.68	0.16	0.051
	Return	5	0.13	0.20	0.18	0.02	
	Weight	100 (20*5)	0.01	0.12	0.05	0.044	
PSO Training	Sharpe Ratio	5	0.46	0.97	0.75	0.19	
	Return	5	0.14	0.21	0.19	0.02	
	Weight	100 (20*5)	0.01	0.11	0.05	0.049	
ACO Testing	Sharpe Ratio	5	-1.23	1.34	0.53	1.03	0.043
	Return	5	-0.13	0.26	0.14	0.16	
PSO Testing	Sharpe Ratio	5	-1.02	1.38	0.61	0.96	
	Return	5	-0.09	0.27	0.16	0.15	

Table 5. Comparison Statistics of ACO and PSO with the Unanchored Cross Validation Method

Algorithm	**Parameter**	**Sample Size**	**Min**	**Max**	**Average**	**Standard Deviation**	**P-value from the T-test of the Sharpe Ratio**
ACO Training	Sharpe Ratio	5	0.34	2.31	1.34	0.80	0.0007
	Return	5	0.12	0.44	0.29	0.13	
	Weight	100 (20*5)	0.01	0.12	0.05	0.0451	
PSO Training	Sharpe Ratio	5	0.57	2.55	1.53	0.81	
	Return	5	0.16	0.48	0.32	0.14	
	Weight	100 (20*5)	0.01	0.11	0.05	0.0491	

ACO Testing	Sharpe Ratio	5	-0.15	1.99	0.90	0.77	0.6107
	Return	5	0.04	0.36	0.21	0.12	
PSO Testing	Sharpe Ratio	5	-0.36	1.93	0.87	0.82	
	Return	5	0.01	0.36	0.21	0.13	

The above tables 4 and 5 indicate the P value from the T-Test. According to the P values obtained from Tables 4 and 5, ACO and PSO exhibit similar performance in anchored training and unanchored testing, while significant differences emerge in anchored testing and unanchored training.

Figure 6 illustrates the weight distribution for the first fold, under both anchored and unanchored cross-validation techniques.

Figure 3: Weight Allocation for Anchored

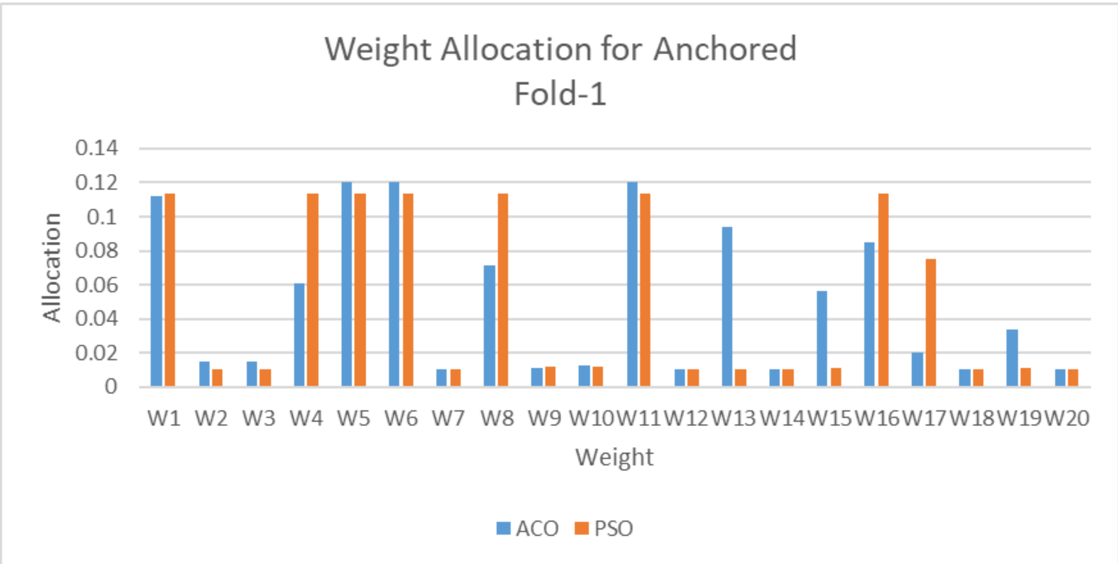
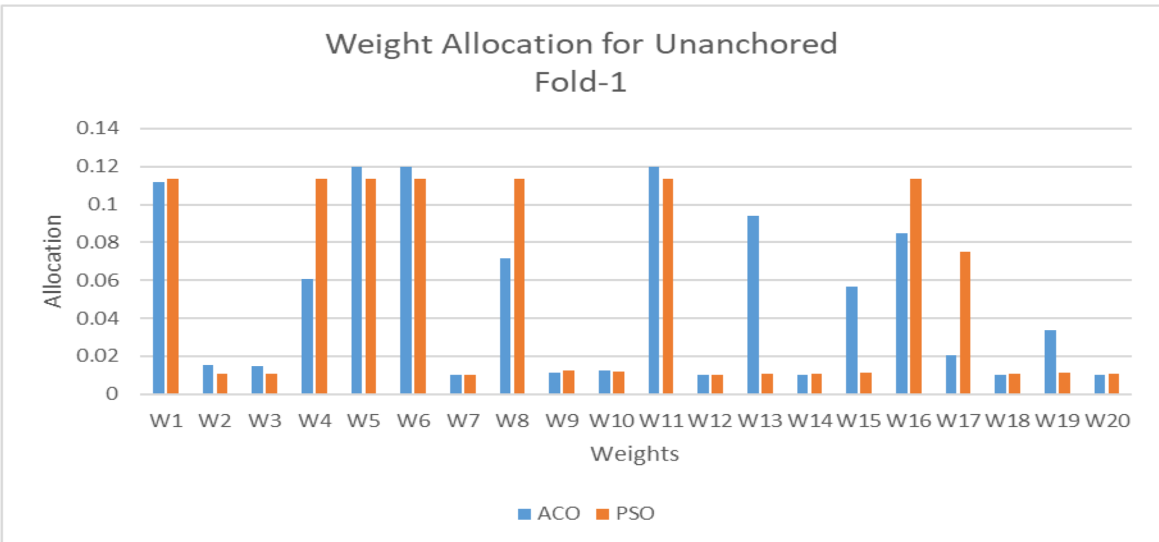


Figure 4: Weight Allocation for Unanchored



International Journal on Science and Technology (IJSAT)

E-ISSN: 2229-7677 ● Website: www.ijsat.org ● Email: editor@ijsat.org

Table 6 summarizes the performance of ACO and PSO by evaluating return and Sharpe ratio across each training and testing fold, under both Anchored and Unanchored cross-validation techniques.

Table 6 ACO and PSO Performance on Return and Sharpe ratio per Training and Testing fold

FOLD	ACO TRAINING		PSO TRAINING		ACO TESTING		PSO TESTING	
	Return	Sharpe Ratio	Return	Sharpe Ratio	Return	Sharpe Ratio	Return	Sharpe Ratio
ANCHORED CROSS-VALIDATION								
1	0.1833	0.7272	0.1998	0.8653	0.2317	1.1098	0.2361	1.1812
2	0.1874	0.8603	0.2021	0.9727	0.2318	0.5395	0.2497	0.6009
3	0.2040	0.7116	0.2191	0.7342	0.2614	1.3409	0.2757	1.3845
4	0.1970	0.7162	0.1944	0.7326	-0.1374	-1.2358	-0.0978	-1.0285
5	0.1367	0.4173	0.1445	0.4648	0.1536	0.9040	0.1629	0.9569
Mean	**0.1816**	**0.6865**	**0.1920**	**0.7539**	**0.1482**	**0.5317**	**0.1653**	**0.6190**
UNANCHORED CROSS-VALIDATION								
1	0.1833	0.7272	0.1998	0.8653	0.2317	1.1098	0.2361	1.1812
2	0.3098	1.8173	0.3383	2.0019	0.2742	0.7689	0.2925	0.7813
3	0.4433	1.5367	0.4840	1.6830	0.3663	1.9940	0.3669	1.9317
4	0.4089	2.3175	0.4279	2.5540	0.0457	-0.1536	0.0143	-0.3632
5	0.1236	0.3484	0.1612	0.5732	0.1387	0.8093	0.1452	0.8572
Mean	**0.2938**	**1.3494**	**0.3222**	**1.5355**	**0.2113**	**0.9057**	**0.2110**	**0.8776**

Figure 5: Cumulative Return Comparison Anchored Training

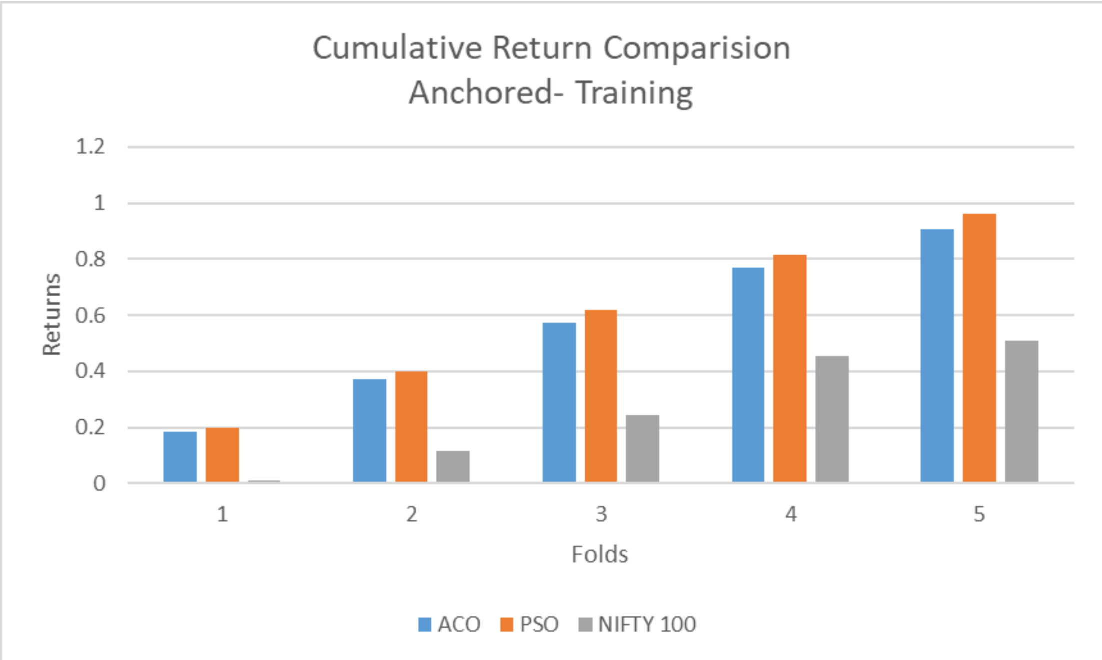
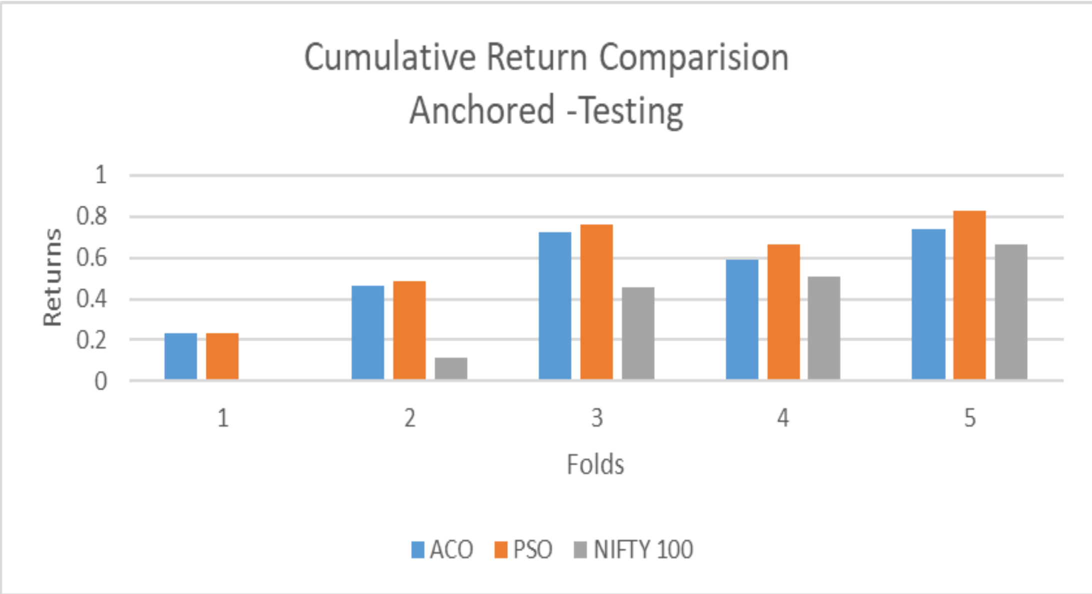


Figure 6: Cumulative Return Graph for Comparison of Anchored Testing



Figures 5 and 6 illustrate the cumulative returns comparison for anchored training and testing cross-validation, highlighting the performance of ACO, PSO, and the NIFY 100 Index. The graph demonstrates that both ACO and PSO outperform the NIFTY 100 Index, indicating their effectiveness in portfolio optimization within the proposed framework.

6. Conclusion and Future Work

This paper provides a comparative analysis of portfolios formulated using the mean-variance model, where optimization is executed via Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO) algorithms employing both anchored and unanchored cross-validation methodologies. The objective function aimed to maximize returns within specified limits on asset allocation and risk. Annualized mean returns and covariance matrices were calculated from daily closing value data of 20 listed stocks on the NSE, India, across all training and testing folds. For each training fold, the optimized portfolios had different weight allocations for the ACO and PSO algorithms for both anchored and unanchored cross-validation techniques. Returns and the Sharpe ratio are calculated and validated for the next testing fold. The performances of the optimized portfolios constructed by the ACO and PSO methods are compared to determine the most suitable method between ACO and PSO. Portfolio returns validation is also conducted using the performance of the NIFTY 100 Index for each fold. The comparison results for training and testing folds across five rolling windows for the anchored and unanchored cross-validation techniques are tabulated in Table 6.

Figure 5 compares the cumulative returns of portfolios using ACO and PSO methods for training folds with the NIFTY 100 Index. Figure 6 does the same for testing folds. Both figures show that portfolios built with ACO and PSO outperform the NIFTY 100 Index. Further, it is also pointed out that the PSO portfolios perform better than the ACO portfolios.

Tables 4 and 5 compare the Sharpe ratios and returns of portfolios constructed by ACO and PSO algorithms over five folds, using both anchored and unanchored cross-validation techniques. P-value is derived for the Sharpe ratio across all folds. For anchored cross-validation, the P value is 0.051 from training folds (no significant difference) and 0.043 from testing folds (significant difference). For unanchored cross-validation, the P value is 0.0007 from training folds (highly significant difference) and 0.6107 from testing folds (no significant difference).

The overall analysis of the specific data matrix reveals that the performance of portfolios constructed by PSO algorithms outperforms the portfolios constructed by ACO algorithms.

This research assesses a single portfolio comprising 20 randomly selected stocks from the National Stock Exchange (NSE) of India. The experimental study utilized daily closing values of these stocks from January 1, 2018 to December 31, 2023. Testing additional portfolios could provide more comprehensive conclusions. A major limitation of this study is its reliance on conclusions drawn from a single arbitrarily selected portfolio of stocks.

Future research should explore the inclusion of transaction cost, asset allocation cost, taxation cost, and similar costs to improve ACO or PSO algorithms for more effective portfolio management. Additionally, combining the PSO algorithm with the ACO algorithm or genetic algorithms is recommended for enhancing portfolio performance.

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