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Original Paper

A MULTI-OBJECTIVE ASSET ALLOCATION APPROACH USING ANT COLONY OPTIMIZATION FOR PORTFOLIO MANAGEMENT

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ABSTRACT

Effective Portfolio allocation is a fundamental to financial management. To achieve maximum return while controlling risk, investors need to select the most suitable tools and techniques. Traditional portfolio optimization methods often rely on single-objective approaches, neglecting the importance of incorporating multiple objectives such as return, risk, and diversification. In this research paper, a multi-objective approach to Assets allocation using the Ant Colony Algorithm for optimization of mean variance model is proposed. This algorithm draws inspiration from the foraging behaviour of ants to effectively explore the solution space and provides assets allocations for optimal portfolios. The objective is to find an optimal balance between maximizing returns at targeted risks across different asset allocation options. The proposed approach offers a powerful tool for investors to make an automated informed decisions based on asset price movement in an uncertain financial market to readjust portfolio periodically to minimize risk and maximize return. ACO Forecasted portfolio return are compared with attained return, equal weightage portfolio return and NIFTY 50 Index return at every quarter.

KEYWORDS

Ant colony optimization, Portfolio asset allocation, Mean-variance model.

1. INTRODUCTION

Portfolio optimization is a crucial aspect of finance and investment management. It involves the selection of assets for portfolio or investments and best possible allocation of each asset that aims to achieve the best possible balance between expected returns and risk. The goal of portfolio optimization is to maximize returns while minimizing the associated risks, considering the investor's preferences, constraints, and investment objectives.

Traditionally, portfolio optimization approaches relied on single-objective optimization techniques, where the primary goal is to achieve higher return or minimize the portfolio risk. Mean-Variance Optimization theory introduced by Harry Markowitz,[17] provided a valuable method for portfolio diversification and efficient frontier construction to arrive at the best possible portfolio for maximum return and minimum risk. However, they often overlooked the complex nature of the decision-making process involved in portfolio allocation, as they focused on a single criterion and did not consider constrains to take care of liquidity and investors' preferences for different risk-return trade-offs.

In recent years, the field of portfolio optimization has evolved to incorporate a multi-objective perspective. Multi-objective portfolio optimization aims to simultaneously optimize multiple conflicting objectives, such as maximizing returns, minimizing risk, and achieving diversification. This approach recognizes that investors have diverse preferences and varying levels of risk tolerance. Multi-objective portfolio optimization presents a range of optimal solution, allowing investors to choose the best option according to their unique risk-return priorities and preferences.

This research paper focuses on applying a multi objective approach to portfolio Assets allocation using the Ant Colony Algorithm. The Ant Colony Algorithm draws inspiration from the behaviour of ants and their ability to find optimal paths between their nests and food sources. By applying this algorithm to portfolio optimization, we aim to explore the solution space efficiently and generate a set of Pareto optimal portfolios that represent trade-offs between returns and risks.

The main aim of this research is to deliver stockholders with a reliable, robust and flexible methodology for portfolio allocation that considers multiple objectives and preferences. By applying the Ant Colony Algorithm to multi-objective function, we aim to overcome the limitations of traditional portfolio optimization methods and provide a reliable and more comprehensive framework for decision-making to automate the process of portfolio balancing and rebalancing.

Through an empirical evaluation using National Stock Exchange of India (NSE) asset data, we proposed to access the reliability of multi objective approach with traditional portfolio allocation methods by comparing the result with attend return, equal weightage portfolio return and NIFTY50 index return at every quarter.

The outcome of this research highlights the effectiveness and practicality considering multiple objectives in the process of portfolio allocation.

This paper is structured as follows: section 2 outlines the objective of this research paper. Section 3 presents an overview of portfolio optimization and the multi objective approach. Section 4 discuss the ant colony optimization algorithm. Section 5 provides methodology and algorithm. Section 6 covers the experimental work and result. Finally, Section 7 conclude with finding and discuss the scope for future.

2. OBJECTIVE

The main objectives of this research paper are:

1. To develop an automated decision-making process for portfolio optimization using mean-variance model of portfolio and Ant Colony Optimization algorithm.

2. To validate the forecasted return of the proposed algorithm by comparing the result with: (1) portfolio attained returned, (2) equal weightage portfolio returns and (3) NIFTY50 return of the same period.

3. PORTFOLIO OPTIMIZATION

Traditional portfolio allocation methods have been thoroughly researched and widely used in the financial sector. One of the revolutionary works in portfolio optimization is Harry Markowitz's mean-variance model, introduced in the 1950s [17]. The mean-variance model aims to identify an optimal portfolio by evaluating the trade-off between the expected return and the portfolio variance. Markowitz's model established the basis for modern portfolio theory and introduced the idea of the efficient frontier. This represents the set of portfolios that suggestion the highest return for a specified level of risk.

Several extensions and variations of the mean-variance model have been proposed over the years to address its limitations. Some prominent approaches include the Capital Asset Pricing Model (CAPM), which uses the risk-free rate and the market risk premium to determine optimal portfolios [12],[16], and the Arbitrage Pricing Theory (APT), which explains asset returns by considering various factor. 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 Liquidity, diversification and investor preferences. In this research paper, a multi-objective approach is proposed to overcome these limitations.

3.1 LISS-III Data Set

Multi-objective optimization focuses on simultaneously optimizing two or three conflicting objectives in real time. Multi-objective portfolio optimization [1],[2],[15] finds to identify portfolios that balance conflicting objectives effectively, including maximizing returns, minimizing risk, and ensuring diversification. This approach allows investors to select portfolios that align with their risk-return preferences.

A mathematical formulation of a multi-objective optimization problem [1-2][15] is:

$x_{1,}x_{2,} \dots\dots, x_n$ The variables of the problem

$f1, f2, \dots\dots,$ The functions to optimize.

Assuming maximization, multi objective optimization problem are define as,

$$\text{maximize} \;\; f_1(x_{1,}x_{2,} \dots\dots, x_n), \dots, f_m(x_{1,}x_{2,} \dots, x_n) \quad (1)$$

$$Subject\ to\ \ g_1(x_{1,}x_{2,} \dots\dots, x_n) \leq \;\; b_1 \quad (2)$$

$$g_r(x_{1,}x_{2,} \dots\dots, x_n) \leq \;\; b_r \quad (3)$$

Where,

g1, g2,….,,gr The constrain to take care of portfolio diversification.

b1, b2,…..,r The allocated value based on fundamentals of assets.

Solution to this multiple objective problem leads to assets allocation weightage in the portfolio for maximum return.

3.1.1 Mean-Variance Portfolio Model

Modern portfolio mathematical framework is utilized to determine the optimal mixture of mean and variance. Introduced by Markowitz in 1952[17], who is regarded as the father of modern portfolio theory, this model focuses on identifying the efficient frontier. This frontier represents the best portfolio that achieves expected return at minimal risk.

The model proposed a formula to calculate the risk and return to set the portfolio [1][2].

Risk is calculated using:

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

Where n represents the number of assets, $w_i$and w_j denote the weighting of assets i and j respectively, and σ_{ij} is the covariance between assets i and j.

Return is calculated using :

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

Where R_i represents the return of asset and w_i denotes the weight of assets i.

The constraint known as the budget constraint is defined as :

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

Additionally, the weight of each asset must be nonnegative, i.e,

$$w_i \geq 0 \qquad (7)$$

Further, to address the portfolio diversification based on fundamental analysis of assets and other factors, the equation is modified as :

$$w_i \geq c1 \qquad (8)$$

$$w_i \geq c2 \qquad (9)$$

Where, c1 and c2 are diversification constant based on asset fundamental.

To solve the equation (1) along with (2) to (9), Various multi-objective optimization algorithms have been applied, here in this research paper, Ant colony optimization technique is selected and algorithm is developed to solve the above equations.

4. ANT COLONY OPTIMIZATION ALGORITHM

Ant Colony Optimization (ACO) was initially introduced by M. Dorigo and his team in the late 1980s to solve discrete optimization problems. The method is inspired by the natural foraging behaviour of ants when searching for food. As ants travel, they leave pheromone, which other ants use to follow their path. The amount of pheromone deposited on the return journey depends on the quality and quantity of the food collencted. Pheromone evaporation is increase by the number of ants using that path. Ant determine the optimal route by following the trails with the highest pheromone deposition [7-8].

The Ant Colony Optimization Algorithm (ACO) is a Meta heuristic algorithm inspired by the way ants seach for food. It has been successfully applied to numerous optimization challenges, such as portfolio optimization [1][7]. The Ant colony optimization (ACO) is based on the concept of positive feedback, where ants lay down pheromones on paths they traverse, attracting other ants to follow the path. This positive feedback mechanism helps ants to find the optimal paths between their nests and food sources.

In the context of portfolio optimization, the ACO can be used to explore the solution space and find optimal portfolios. By treating investment options as paths and pheromone levels as indicators of desirability, the ACO can effectively search for diverse and high-quality solutions. The algorithm iteratively updates the pheromone levels based on the quality of the solutions found, leading to the emergence of a set of Pareto optimal portfolios.

In optimization problem, pheromone model decides to determine the selection of solutions or paths in each iteration. These potential solutions are referred to as transition probabilities, as described in equation 10 [5].

$$P_{ij} = \frac{[\tau_{ij}]^{\alpha}.[\eta_{ij}]^{\beta}}{\sum_{k=1}[\tau_{ij}]^{\alpha}.[\eta_{ij}]^{\beta}} \qquad (10)$$

Where, T_{ij} is amount of pheromone deposition on edde i,j.

α is a parameter control the influence of T_{ij}

η_{ij} is desirability of edge i,j.

where $\eta_{ij} = 1/d_{ij}$, where d_{ij} is the distance between i and j nodes.

β is a parameter control the influence of η_{ij}.

α , β are positive parameters rage between 0 and 1.

Pheromone updating which comprises pheromone evaporation and deposition, is directed by equation 11[5].

$$\tau_{ij} \leftarrow \tau(1-\varrho).\tau_{ij} + \sum \Delta\tau^{K}{}_{ij} \qquad (11)$$

Where, Tij is used for pheromone updating, ΔTkij is amount of pheromone on each edge and ρ is evaporation constant.

Previous studies have verified the effectiveness of the Ant Colony Algorithm for portfolio allocation. For instance, [1] reviews over 140 papers that applied evolutionary and swarm intelligence algorithm to the portfolio optimization problem. These papers are categorized based on portfolio type, such as constraint or unconstrained, as well as single objective and multi objective approaches.

Some studies, such as [7], have explored the ACO method, a meta-heuristic approach to portfolio optimization. This approach formulates the optimization problem as a complete cost function that wants to be minimized. The aim is to minimize risk while simultaneously maximizing return. The study compared the efficiency and execution time of ACO with genetic algorithm (GA). Finally conclude that ACO delivers better outcome in less time compared to GA.

The research paper [10] delves into the realm of stock portfolio optimization, which involves scoring parameters are derived from stock data using key financial metrics such as P/E (price-to-earnings) and EPS(earning per share) ratios. This data is subjected to the K-means clustering algorithm used to cluster the data. A few stocks are selected for the portfolio using clustering. Each stock portfolio's weight was established to ensure that the goal is met. Each stock's weight is ascertained using the Ant Colony Optimization algorithm. The proposed model is choosing the weighted stock in the stock portfolio and numerical result suggest how to reduce the losses of portfolio.

Similarly, [16] proposed ACO based financial crisis predication (FCP) model with five different type of dataset and compare with three other algorithm like PSO,GA and GWO. They demonstrated that the ACO-based approach provided superior compared to other three algorithm.

While the Ant Colony Algorithm has shown promise in portfolio optimization, there is still a need for further research to explore its full potential and compare its performance with other optimization techniques. This research aims to enhance the existing body of literature by utilizing the Ant Colony Algorithm to tackle the multi-objective portfolio allocation problem for a selected group of stocks. This study evaluate the effectiveness of this algorithm in generating optimal portfolios, thereby offering a novel approach to portfolio manangement.

5. ALGORITHM AND METHODOLOGY

In this research paper, python programming was done based on following algorithm.

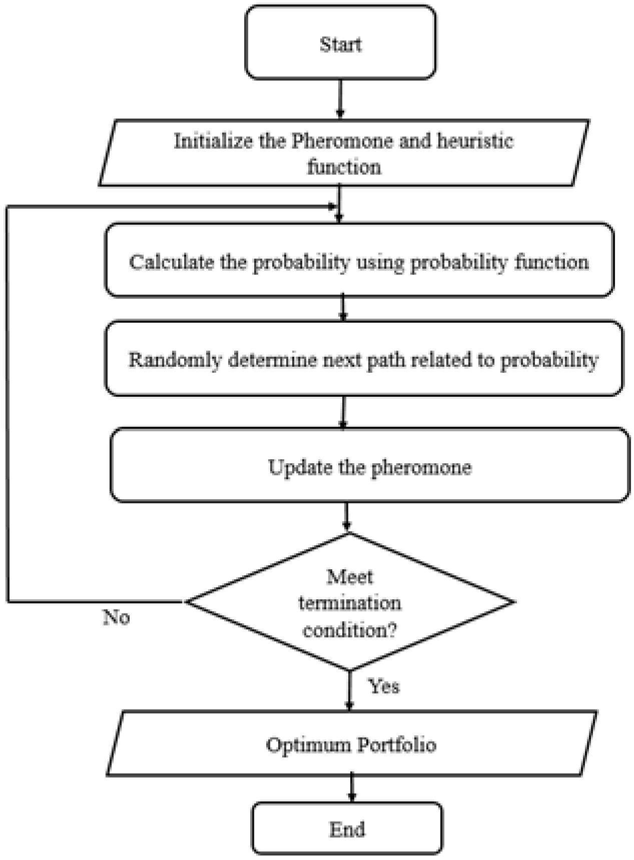

Fig.1. ACO Algorithm.

Followings methodology is adapted to optimise the portfolio return:

1. Select the Assets (Stocks) based on fundamental Analysis
2. From historical data arrive at the mean return for given period.
3. Find the co-variance matrix of the selected assets.
4. Find maximum return (R) and asset weight (Wi) using ACO algorithm by solving equation (1) to (9).
5. Compare forecasted results with equal weightage portfolio and NIFTY 50 index return.

6. EXPERIMENTAL ANALYSIS

In this research paper, a portfolio of 16 assets of diversified sectors is created based on fundamental analysis. The selected assets of portfolio are given in Table 1:

Table 1. Selected Assets for portfolio.

Stock1	Bajaj finance Ltd	Stock 9	Dabur India Ltd
Stock2	Bharti Airtel Ltd	Stock10	Solar Industries India
Stock3	Divis Laboratories Ltd	Stock11	United Phosphorus Ltd –UPL
Stock4	ICICI Bank Ltd	Stock12	Page Industries Ltd
Stock5	Maruti Suzuki India	Stock13	NHPC
Stock6	Proctor & Gamble Health	Stock14	TATA Chemicals
Stock7	State Bank of India	Stock 15	Bajaj auto Ltd
Stock8	HDFC Bank Ltd	Stock 16	Tata Consultancy Services -TCS

The historical daily data of the selected stocks from June 2015 to December 2022 (Total 93 Months) were obtained from the Yahoo Finance Website. The daily data includes: opening price and closing price. From these data, % of annual return attained for each stock for every month and mean return of each quarter is worked out. From these return five quarters' mean return were worked out for each stock. Thus, annual return for total 31 quarters were obtained for each stock. The quarterly mean returns are given in Table 2.

Table 2. Quarterly Mean Return of Assets.

	Stock No									
Quarter	1	2	3	4	5	..	13	14	15	16
1	.853	.165	.318	.322	.643	..	.096	.406	.066	.143
2	-.221	-.796	.793	-.457	.679	..	-.602	-.468	-.363	.055
3	.664	.006	.085	-.178	-.084	..	1.069	.208	.379	-.246
4	.649	.121	-.586	-.387	-.797	..	.493	-.262	-.190	.108
5	.559	.178	.548	.097	.528	..	.245	.576	.477	.091
..	..	..	..	..	..	..	..	..	..	..
31	-.414	.014	-.303	.160	-.270	.	.432	-.569	.101	.355

From the historical return of assets, covariance matrix between assets is worked out from programming. The Covariance matrix can be found in Table 3:

Table 3. Covariance Matrix.

Quater	Stock No									
	1	2	3	4	5	6	..	13	14	15	16
1	.122	.022	.025	.019	0.012	-0.06	..	-.23	.022	-.01	.009
2	.022	.252	.14	-.2	0.106	0.152	..	-.09	.041	-.08	.144
3	.025	.14	.156	-.05	0.084	0.106	..	-.16	.041	.045	.108
4	.019	-.2	-.05	.262	-0.02	-0.12	..	.084	.049	.182	-.05
5	.012	.106	.084	-.02	0.09	0.074	..	.042	.076	.048	.109
6	-.06	.152	.106	-.12	0.074	0.148	..	.054	.023	-.01	.103
7	-.06	-.28	-.14	.398	0.031	-0.13	..	.591	.16	.3	-0
8	-.02	-.04	-.02	.032	-0.02	-0.01	..	.041	-.01	.02	-.02
9	.041	.11	.061	-.11	0.023	0.044	..	-.17	-.01	-.07	.037
10	-.28	.204	-.04	.107	0.4	0.279	..	1.739	.486	.308	.464
11	-.24	.144	-.1	-.03	0.22	0.198	..	1.257	.264	.091	.263
12	.056	-.27	-.16	.192	-0.14	-0.22	..	-0.1	-.07	.019	-.19
13	-.23	-.09	-.16	.084	0.042	0.054	..	.901	.098	.093	.043
14	.022	.041	.041	.049	0.076	0.023	..	.098	.09	.078	.085
15	-.01	-.08	.045	.182	0.048	-0.01	..	.093	.078	.191	.043
16	.009	.144	.108	-.05	0.109	0.103	..	.043	.085	.043	.135

In this research following constrains are considered.

Sum of weight of all assets of portfolio is 1. i.e $\sum_{i=1}^{n} w_i = 1$

Furthermore, the minimum and maximum weight of assets in the portfolio are assumed as :

1. W_{min} >= 2%
2. W_{max} <= 25%
3. Risk <= 5%

The equation (4) and (5) of Mean variance portfolio model described above in 3.1.1 are used under above constrains to find maximum return at expected risk using proposed algorithm. Algorithm for optimum assets allocation is written in python programing. Table 4 and Figure 1 present the forecasted return at the beginning of each quarter alongside the actual returns achieved for the portfolio at the end of each quarter.

The return obtain from the proposed algorithm is also compare with return obtained from equal asset allocation portfolio and return from NIFTY 50 Index for the same period. The comparison of result is given in Table 5. The result of Table 4 is shown in graphical represented in Fig. 2.

Table 4. Quarterly Annualized Portfolio Returned.

Qtr. Ending on	Forecasted Return %	Actual Attained Return %	Equal Weightage Portfolio Return %	Nifty 50 Index Return%	Qtr. Ending on	Forecasted Return %	Actual Attained Return %	Equal Weightage Portfolio Return %	Nifty 50 Index Return %
Dec22	20.62	5.57	6.75	24.08	Dec18	36.13	20.95	21.73	-1.80
Sep22	25.55	86.12	58.29	35.62	Sep18	34.74	20.68	15.63	7.40
Jun-22	20.62	5.57	6.75	-39.76	Jun18	39.61	103.21	37.5	22.88
Mar22	61.44	28.47	4.25	1.14	Mar18	45.84	-6.67	-27.34	-14.43
Dec21	68.87	12.09	5.26	-3.30	Dec17	42.27	41.85	61.57	25.81
Sep21	78.13	35.66	41.24	45.11	Sep17	44.57	30.81	23.46	12.74
Jun21	31.29	74.75	30.85	25.86	Jun17	34.24	29.03	24.03	15.94
Mar21	32.85	74.75	19.34	22.93	Mar17	30.32	73.97	40.53	49.23
Dec20	24.16	74.75	7.34	92.63	Dec16	23.31	-50.13	-9.26	-21.05
Sep20	9.7	52.71	31	40.32	Sep16	24.82	53.45	26.28	16.99
Jun20	4.08	47.91	68.18	81.07	Jun16	23.67	44.1	38.18	30.84
Mar20	41.08	-127.52	-89.32	-118.60	Mar16	33.87	-6.11	-12.45	-11.11
Dec19	39.47	14.48	27.28	23.86	Dec15	39.81	21.07	10.03	
Sep19	50.82	19.84	-0.39	-10.96	Sep15	74.74	-0.3	-23.9	
Jun19	39.59	11.35	18.8	5.99	Jun15	71.7	48.8	26.58	
Mar19	37.25	59.13	24.45	28.80					

Table 5. Result Comparison.

Result obtain from experimental Study	Forecasted Return	Actual Return	Equal weightage Return	NIFTY 50 Return
Mean Annualized Return	38.23%	29.04%	16.54%	13.86%
Standard Deviation	17.87	43.45	29.79	38.39
Deviation from Actual Return	+31.64%	0%	-43.04%	52.27%

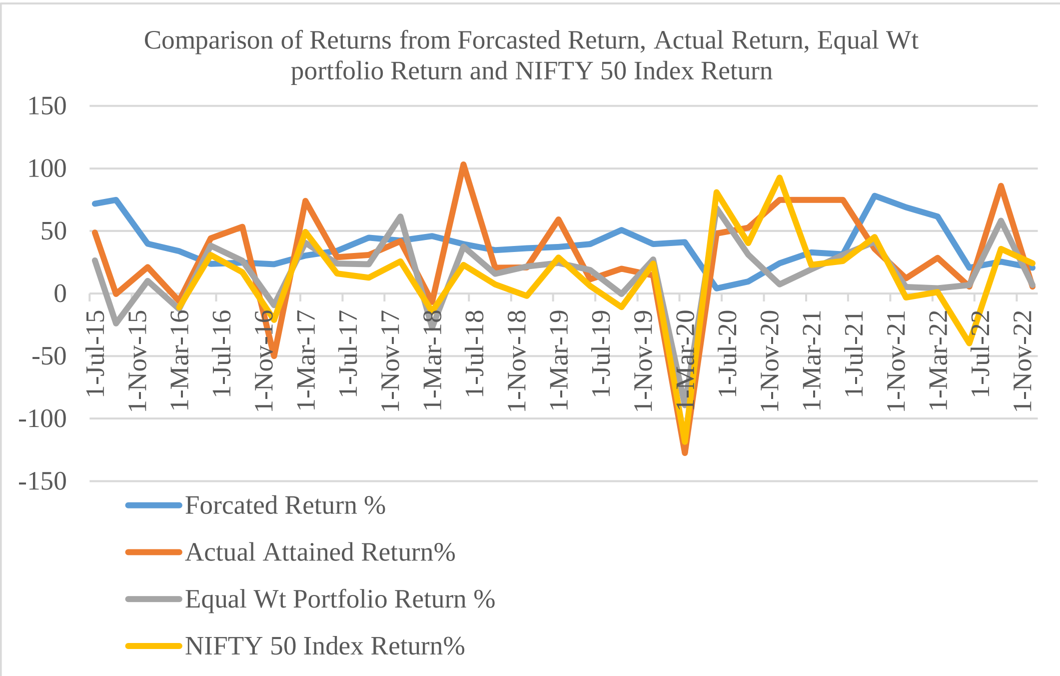

Fig.2. Comparison Chart.

7. CONCLUSION AND FUTURE WORK

In the present study, mathematical formulation of asset allocation to maximise return at expected risk is developed based on Mean variance portfolio model. Solution of the mathematical problem to find Maxima at given risk is worked out using proposed ACO algorithm. The results are compared with the Equal weightage Asset Allocated portfolio and NIFTY50 Index for all the 31 quarters.

From the experimental analysis it is found that:

Mean Annualised forecasted return derived from the proposed framework is 38.23% and the Mean Annualised Realized return is 29.04%. Thus, return realized by proposed Ant Colony Algorithm (ACO) is @ 75% of the actual return. Thus, one can bank on the asset allocation in portfolio using this framework algorithm

Mean Annualised return for Equal Weightage Asset Portfolio is 16.54% and that of NIFTY50 INDEX is 13.86%. Mean Annualised return attained by the proposed framework of asset allocation 29.04%. Thus, the return attained by using the frame work of this research paper is far better as compared to NIFTY50 Index return and Equal Weightage Portfolio.

Deviation from actual return for proposed framework, equal weightage asset portfolio and NIFTY50 index is +31.64%, -43.04 and -52.07% respectively. Thus, it is clear that the proposed framework is far better than other two criteria.

The modern theory of portfolio creation along with Ant Colony Algorithm can identify the optimal return at expected risk and given the best asset allocation for portfolio and also address the desired constraints. The proposed framework for portfolio generation is proved to be reliable based on the experimental analysis of 93 months data for the selected assets. In addition, the execution time to get the optimum solution of mathematical framework is found less than 2 seconds.

Although there are some limitations of present research they are:

(1) The experimental analysis was carried out on one set of 16 Assets for 31 quarters. Experimental analysis involving multiple sets is required to validate the effectiveness of the proposed framework of optimum portfolio creation.

(2) In the present framework only 16 assets are selected and these assets remain in the portfolio, even though some of the asset's return are poor, therefore, further work is required to create a framework to include new assets in the portfolio or exclude some of assets from the portfolio as and when required for better portfolio return using AI tools. This could be done by adopting AI tools for asset selection for portfolio.

(3) The current research employs Ant Colony optimization techniques. To further improve the efficiency and effectiveness of the portfolio allocation process, future research should explore the potential of hybridizing the Ant Colony Algorithm with other optimization algorithms or heuristics. For example, combining the Ant Colony Algorithm with Genetic Algorithms or Particle Swarm Optimization may leverage their respective strengths and lead to improved results.

In conclusion, the multi objective approach to portfolio allocation using the Ant Colony Algorithm and mean variance portfolio model offers a promising avenue for investors seeking optimized portfolios that consider multiple objectives and preferences. The research presented in this paper helps as a foundation for further investigation and development in the field of portfolio optimization, by incorporating AI tools for asset selection, hybridizing optimization techniques, and conducting empirical evaluations on more portfolio, future work can enhance the practicality and performance of the approach, ultimately benefiting investors in achieving their financial goals.

Authors Contributions (Compulsory):

All authors have equally contributed.

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