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Research Article

An Adaptive Heuristic Approach to Optimize Equity Market Neutral Portfolio

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Abstract. An *Equity Market Neutral Portfolio* (EMNP) safeguards a safe portfolio concerning exposure to pertinent market benchmarks. Although it is possible to efficiently solve the problem of EMNP optimization through linear programming techniques, combining the risk budget constraint of risky assets with other constraints of EMNP where there is no market exposure, leveraging, or portfolio beta makes it challenging to resolve this problem via conventional approaches directly. This study aims to propose a novel technique to solve the problem of constrained optimization of EMNP via differential evolution strategies involving multiple crossovers (Exponential as well as binomial together with the Hall of Fame). The suggested automated technique enables portfolio managers to select the portfolio with the highest potential return. Monitoring the optimal combination of evolutionary techniques also confirms the results' consistency. Therefore, impending outcomes were chosen depending on the optimal balance of portfolio returns and risk. This analysis includes Nifty50's monthly stock prices.

Keywords. Adaptive, Neutral, Heuristic, Hall of fame, Crossovers, Optimization

Mathematics Subject Classification (2020). 68TXX, 68UXX, 90B50

1. Introduction

An *Equity Market Neutral Portfolio* (EMNP) combines long- and short-term equity stocks to reduce systematic risks. Short positions provide returns after anticipating a price drop; long positions do the opposite. An EMNP invests using a neutral strategy concerning the stock market to provide risk-free exposure to the appropriate market benchmark. The return of an EMNP may be determined in a couple of different ways: either as the spread between the long and short returns or as the weighted return of the component stocks, where the weights represent the proportions of investments in the constituent securities. The equity market-neutral investing strategy has had a significant and notable historical performance. It was one of the few methods used by market forces in the last three months of the 2008 financial crisis (Law [12]). An EMNP's primary objective is to provide returns less susceptible to market fluctuations. To simulate market risk, the *Capital Asset Pricing Model* (CAPM) employs the concept of financial elasticity, which describes the relationship between stock returns and market returns. When discussing general equity, a portfolio's beta is the computed average of the betas of the portfolio assets, weighted by the proportion of those assets. To ensure risk-free exposure and a return superior to the rate on risk-free lending, an EMNP aims for a portfolio beta of zero. An EMNP can also guarantee the portfolio's net market exposure by requiring the sum of weights to be zero. To increase returns through market protection and investment exposure, an EMNP, as a long-short portfolio, may also include financial leveraging. The optimal design of an EMNP (with or without financial leverage) for any universe of stocks may be swiftly solved using a classical technique, such as linear programming (Chang *et al*. [3], Fernández and Gömez [6], Kendall and Su [10], Maringer [13], Streichert *et al*. [21], Thomaidis [23], Pai and Michel [16]), despite the computationally costly nature of the issue.

The risks the portfolio's assets/asset classes pose are limited under the risk budgeting investment strategy (Pearson [19]). When investment managers impose a limit on high-risk or selective assets in the portfolio during the construction of an EMNP, the constraint transforms the problem into a non-linear programming problem, making straightforward solutions using traditional methods complicated and necessitating the search for a metaheuristic solution to the problem. Pai and Michel [17] recommended a metaheuristic strategy to solve the problem of optimizing short-long term portfolios (risk budgeted). However, this problem model needs to include the constraints of market neutrality, a key attribute regarding EMNP. Alentorn [1] also tried to address the optimization of portfolios based on market-neutral hedge funds. However, the solution adopted in their study merely used the constraint of no market exposure and did not consider the role played by the portfolio beta. At the same time, their model also did not include the risk budget constraint.

Most trading strategies create signals based on pre-decided indicators such as the relative strength index, the breakout of the opening range, as well as the moving averages (Chong *et al*. [4], Gunasekarage and Power [8], Syu *et al*. [22], and Tsai *et al*. [24]). However, many of these indicators only offer short- and long-term (buy and sell) signals, regardless of the quantity of the commodities and risk management. Therefore, portfolio management is utilized for better investment control. Research has also been conducted on selected commodities, resourcing, allocation, and sizing positions (Cooper *et al*. [5], and Reilly and Brown [20]). To successfully use strategies for managing portfolios, such as the Kelley criterion and *Modern Portfolio Theory* (MPT) (Markowitz [14], and Kendall and Su [10]), it is essential to make forecasts of stock prices (in the future) as inputs. MPT strongly depends on the accuracy of future variance/mean accuracy; on the other hand, the Kelly criterion is based on the probability distribution of future returns. However, even minor adjustments in the deployment of strategies can significantly affect the portfolio weights. One of the shortcomings of MPT remains its proclivity to maximize the effects of errors when making input assumptions (Michaud [15]). Problems in predicting the (future) variance and mean of commodity prices imply that this approach is not feasible for managing portfolios in real-time stock market situations. Regarding the variants of the portfolio strategies, the hedging strategy, called neutral in the equity market, improves risk management by maintaining a balance between comparatively robust stocks and the sales of their weaker counterparts (Patton [18]).

García *et al*. [7] used a multi-objective model for portfolio selection using the Non-dominated Sorting Genetic Algorithm II (NSGA-II) algorithm. Valle *et al*. [25] demonstrated that the objective problem is minimizing the correlation between the portfolio chosen and the return on the benchmark index. They proposed a resolution via mixed-integer non-linear programming. A *Portfolio Management System* (PMS) built with the help of two neural networks (CNN & RNN) was created by Wu *et al*. [26]. A unique incentive function based on Sharpe ratios is suggested to assess further the designed systems' efficacy. Kumar *et al*. [11] proposed a new method to solve the problem of restricted risk budgeted optimization by combining the *hall of fame* (HF) and *differential evolution* (DE) techniques with various crossovers (binomial, exponential, and arithmetic).

2. Proposed Method

However, it is difficult to classify and quantify strong stocks by selling relatively weak ones. Hence, in this paper, we have proposed a novel technique Adaptive Heuristic Optimization of Equity Market Portfolios, to solve the problem of constrained optimization of EMNP via Differential Evolution involving multiple crossovers (Exponential as well as Binomial together with the Hall of Fame (DEHOF)). This automated solution helps portfolio managers adopt the best possible portfolio that yields the most significant returns by utilizing the strategy of a penalty function and employing procedures relating to weight standardization to ensure speedier convergence. The study's results can guide risk management further to select the most viable asset for optimum returns. The monthly Nifty50 Index Stock Prices[1] from February 2020 to January 2022 were used in this study. MATLAB 2019a was used for this study.

As a technique for building portfolios, market-neutral investing allows traders to choose short and long positions without changing the class of assets to neutralize risks. These asset

[1] Nifty50 Index Stocks Prices: www.investing.com/indices/s-p-cnx-nifty-components.

classes can be a particular nation/industry/sector. The ones whose values are likely to go up are held as long stocks, whereas those whose values are likely to reduce are held as short securities. If the stocks behave as expected, the spread will yield positive returns. However, based on market movements, it is possible to approximate the losses/gains/ of long positions by the losses/gains achieved during the process of going short. Market-neutral portfolios aim to construct without linking performance and the market's direction.

A market-neutral strategy retains (individual) risks and returns of assets that are offset due to the assets' short- and long-term nature, and the returns are derived from the spreads involving them. However, the portfolio's performance may need to be improved by volatility in the market. For this reason, it becomes necessary to ensure that the strategy is implemented meaningfully and effectively. A portfolio agnostic to the equity market combines short and long positions in a homogeneous and more extensive market. Such portfolios are associated with higher risk ratios to reward by declining volatility or enhancing returns. It is also possible to leverage market-neutral portfolios to improve returns by protecting the market from exposure. In particular, the risks associated with leveraged portfolios in equity market agnostic scenarios may be much lower than those associated with long-only and unleveraged counterparts.

To ensure that the exposure to net equity remains zero, the weights of the portfolios agnostic to the equity market must be zero. Additionally, stock market-neutral portfolios aim for a zero-portfolio beta to assure risk-free exposure and generate projected returns that are higher than the risk-free lending rate. Therefore, in a portfolio (equity market neutral) P, in the case $W=(w_1,w_2,w_3,\dots,w_N)$ are the asset weights, w_i^+, w_i^- denote the respective weights of the long/short positions within the portfolio while the returns of the assets are represented by μ_i.

The portfolio return is given by:

$$\sum_{i=1}^{N} w_i\cdot\mu_i\,. \tag{2.1}$$

The portfolio risk, σ_p is given by:

$$\sigma_p=\sqrt{W\cdot V\cdot W'}\,, \tag{2.2}$$

where V is the variance-covariance matrix of the returns of the assets.

The net equity exposure constraint is given by:

$$\sum_{i=1}^{N} w_i=\sum w_j^+ +\sum_k w_k^- =0, \quad j\neq k\,, \tag{2.3}$$

wnd the portfolio beta constraint is given by:

$$\left|\sum_{i=1}^{N}\beta_i w_i\right|\le c\,. \tag{2.4}$$

Here, c is a constant close to zero.

In equity markets, the decision to select short and long positions is related to the volatility of the stocks, which remains a critical factor in investment in a market-neutral scenario. Several strategies can be adopted, and no agreement has been reached on the most optimal one. However, one popularly used approach is using accounting variables to assess the volatility of stocks. These include dividend yields/ payout ratio, firm assets, the market's current value, debt ratio, volatility of net income, etc. A viable strategy could be adopting market-based variables with no accounting variables. Therefore, going short on low-risk stocks and vice versa is an approach that could be looked at by those participating in equity market trading. It is also recommended to adopt an approach that involves going short on highly volatile stocks and going long on low-risk stocks, determining volatility based on the historical returns of the stocks in the process.

2.1 Optimizing an Equity Market Neutral Portfolio

Firstly, we begin by defining the neutral model of the equity market portfolio model, whose aim is to maximize the anticipated return after factoring in some constraints; the exposure to the net market must be zero, the portfolio beta should be close to zero imposing limits and budget constraints on the weights of short/long positions. The mathematical formulation is given by:

$$\max\left(\sum_{i=1}^{N} w_i \mu_i\right) \qquad \text{(Maximize expected portfolio return)} \tag{2.5}$$

subject to

$$0 < w_i^+ \leq 1 \qquad \text{(bound constraints on long positions)} \tag{2.6}$$

$$-1 \leq w_i^- < 0 \qquad \text{(bound constraints on short positions)} \tag{2.7}$$

$$\sum_{i=1}^{N} w_i = 0 \qquad \text{(net market exposure constraint)} \tag{2.8}$$

$$\sum_{i\in L} w_i^+ = 1 \qquad \text{(budget constraint on long positions)} \tag{2.9}$$

$$\sum_{i\in S} w_i^- = -1 \qquad \text{(budget constraint on short positions)} \tag{2.10}$$

$$\left|\sum_{i=1}^{N} \beta_i \cdot w_i\right| \leq c \qquad \text{(portfolio beta constraint)} \tag{2.11}$$

Long and short positions were established based on a simple rating of the stocks' historical return volatilities, in keeping with the research of Blitz and Vliet [2]. As a result, the lowest percentile of the stock, which has high volatility, was kept short, while the top percentile, which has low volatility, was kept long. The most volatile equities, which unmistakably fall under short positions, were considered high-risk investments.

The risk-budgeted equity market-neutral portfolio is a kind of market-neutral investment strategy that aims to maximize return while minimizing risk with the additional constraint of imposing risk budgets on the risky assets in the investor's chosen portfolio in addition to the primary constraints of zero net market exposure and a portfolio approaching portfolio beta of zero, as well as limits and budget constraints imposing the long and short positions of the portfolio, are imposed. Including risk budgets on these high-risk assets assists in mitigating the risk while assisting in generating higher returns. Equations (2.5) to (2.11) are part of the risk-balanced portfolio model's mathematical model. Equation (2.7), the limit constraint for short positions, only applies to highly volatile assets that do not put the budget at risk. Along with the requirements imposed by the naive stock market-neutral portfolio, risk-budgeted assets are also subject to the following unique constraints. Following are some restrictions on risk budgeting that apply to highly volatile assets are as follows:

$$(w_i^H)^2 \cdot \sigma_i^2 \le x\% \text{ of } \sigma_B^2 \qquad \text{(risk-budget constraint)} \tag{2.12}$$

where w_i^H refers to the weights of highly volatile assets' weights, σ_i^2denotes the risk of individual assets, σ_B^2 signifies the risk associated with the portfolio, while $x\%$ refers to the investor's risk budget. Since it is also necessary to shorten the highly volatile w_i^H the emphasis is placed on the constraints shown below:

$$-1 \le w_i^H \le 0 \qquad \text{(shorting of high risk assets)}. \tag{2.13}$$

Thus, if w_i^+, w_i^- and denote the weights of L, S, and H (long position, short position and high-risk positions after risk budgeting), respectively, of a portfolio P, where $P = L \cup S \cup H$, then equations (2.5) to (2.13) provide a formalization of the "neutral portfolio" issue in the context of the risk-budgeted stock market. We decided to solve this problem through penalty functions since the mathematical model remains a problem of nonlinear optimization.

In conventional optimization, the penalty function strategy mentioned by Pai and Michel [17] refers to a potential approach to dealing with constraints. After the nonlinear mathematical model is transformed via the penalty function by integrating the constraint of portfolio beta and risk budgeting into the objective function, the optimization model that is yielded is as follows:

$$\max\left(\sum_{i=1}^{N} W_i \cdot \mu_i - \Phi(\overline{W},\overline{\beta},\overline{\sigma},c,x)\right), \tag{2.14}$$

where $\Phi(\overline{W},\overline{\beta},\overline{\sigma},c,x$ is the constraint violation function given by

$$\Phi(\overline{W},\overline{\beta},\overline{\sigma},c,x) = G_1 \cdot \psi(\overline{W},\overline{\beta},c)^2 + \sum_{i\in H} G_{2,i} \cdot \gamma_i(\overline{W},\overline{\sigma},x)^2, \tag{2.15}$$

$$\psi(\overline{W},\overline{\beta},c) = \left|\sum_{i=1}^{N} \beta_i \cdot w_i\right| - c, \tag{2.16}$$

G_1 is the Heavy side operator given by

$$G_1 = \begin{cases} 0, & \text{for } \psi(\overline{W},\overline{\beta},c) \le 0, \\ 1, & \text{otherwise}, \end{cases} \tag{2.17}$$

$$\gamma_i(\overline{W},\overline{\sigma},x) = (w_i^H)^2 \cdot \sigma_i^2 - \frac{x}{100}, \quad \sigma_B^2 \le 0, \tag{2.18}$$

$$G_{2,i} = \begin{cases} 0, & \text{for } \gamma_i(\overline{W},\overline{\sigma},x) = 0, \\ 1, & \text{otherwise}, \end{cases} \tag{2.19}$$

Subject to constraints,

$$0 < W_i^+ \le 1, \qquad \text{(bound constraints on long position } L) \tag{2.20}$$

$$-1 \le W_i^- < 0, \qquad \text{(bound constraints on short position } S) \tag{2.21}$$

$$-1 \le W_i^H < 0, \qquad \text{(bound constraints on high volatility assests } H\text{)} \tag{2.22}$$

$$\sum_{i=1}^{N} W_i = 0, \qquad \text{(net market exposure constraint)} \tag{2.23}$$

$$\sum_{i \in L}^{N} W_i^+ = 1, \qquad \text{(budget constraint on long positions)} \tag{2.24}$$

$$\sum_{i \in S}^{N} W_i^- = -1. \qquad \text{(budget constraint on short positions)} \tag{2.25}$$

The changed model of the market-neutral portfolio issue (risk-budgeted) uses metaheuristics, which relate to a refined version of differential evolution with the Hall of Fame. Elitism is performed through a mechanism called the Hall of Fame, and the penalized objective functions (2.14)-(2.19) play the role of the fitness function in this process. Weight-repair techniques deal with constraints (2.20) through (2.25). Selection for the next generation in DEHOF is achieved via mutations and tournaments using the Rand/1, Rand5/Dir4, and Rand4/BestDir5 techniques.

Regarding the problem model defined using equations (2.14) to (2.15), the portfolio beta and the nonlinear risk budgeting constraint dealt with through penalty functions serve to emerge as a fitness function component of DE/rand/1, DE/rand5/Dir4, and DE/rand4/BestDir5 exploits this component when seeking optimal solutions. However, concerning linear constraints about the short and long positions, it is essential to develop a repair strategy for the population to become a viable solution. The portfolio can comprise a couple of pockets consisting of long positions meeting the requirements of the constraints shown in equations (2.20) to (2.25) as well as short positions (which include highly volatile risk budgeted assets) satisfying the constraints. After that, the defined constraint of net market exposure is satisfied automatically because these constraints complement each other. The Deterministic Selection operator selects the most fit individuals from the population by comparing each parent and offspring individually to the objective function value.

2.2 Constraint Handling

The fitness function includes the penalty-handled non-linear risk budgeting constraint and portfolio beta constraint, which can only be employed by DE/rand/1, DE/Rand5/Dir4, and DE/rand4 BestDir5 to discover optimal solutions for the problem model specified by (2.14) to (2.25). However, (2.20)-(2.25) show that there are linear limits to the portfolio's long and short positions, so a repair method must be created to turn the population set into a set of possible solutions.

Long positions that adhere to the rules of (2.20) and (2.24) go into one side of the portfolio. In contrast, short positions go into the other pocket that meets the constraints set by (2.21), (2.22), and (2.25) meet the specified restrictions, including short positions in risky assets that require risk budgeting (2.25). The limits defined for long and short positions are complementary to each other. Once these limits are met, the net market exposure limit specified by (2.23) is also automatically met. So, the weight repair technique satisfies the constraints imposed on long positions, including positive weights, and will suffice. A similar strategy should be applied for short spots, but finally, supplementing the discovered weights to generate negative weights should provide the desired outcomes.

2.3 Adaptive Heuristic Optimization for Equity Market Neutral Portfolio (AHOEMNP)

A series of steps elucidate below how the process is implemented, and the process flow is presented in Figure 1.

Step 1. To begin with, the problem parameters are set wherein the portfolio's long (L) and short (S) positions are identified, and their respective bounds are set. If i is less than a generation, high-risk assets (H) to be risk budgeted are identified. The beta, mean, and variance-covariance matrix of the return of the assets are obtained.

Step 2. Next, the DEHOF parameters are set, which include generation and population size. The scaling factor β and the probability of recombination (pr) are carried out. The generation index is set to $i = 0$. Hall of Fame (HF) is initialized to null.

Step 3. The initial population of individuals representing the weights is then generated randomly. A repair strategy is applied to each individual in the population, transforming the entire population into a feasible set of solutions that satisfies the constraints. The parent population is set to P, and its fitness is recorded.

Step 4. Trial vectors are derived by implementing the DE/rand/1, DE/Rand5/Dir4 and DE/rand4/BestDir5 strategies and performing multiple crossovers for creating the offspring population. Then, the repair strategy is implemented on all members of the offspring population, thus changing the population into a feasible solution, and the constraints are satisfied. Population O is called as well. The values of the fitness function of the population P are computed using the constraint violation function, and the penalized objective function is represented by equation (2.14).

Step 5. Population P is called. BEST is allowed to be completed with HF. Induct the best of the two into the Hall of Fame. The individual is renamed HF. NEXTGEN is renamed population P. The population of the offspring is set to O, and its fitness is calculated. Employing a Tournament Selection operator, the better version of the parent and offspring individuals are selected for the next generation. The next population is called NEXTGEN. The best-fit individual is selected from NEXTGEN, and the BEST is called.

Step 6. However, if i is not smaller than a generation, the weight 'W' will be extracted from the individual HF in the Hall of Fame. W denotes the optimal weight. This is then followed by the computation of the optimal risk, budgeted equity market, neutral portfolio return, and risk.

Step 7. The one that gives the highest return for the portfolio is chosen from all of the possible permutations.

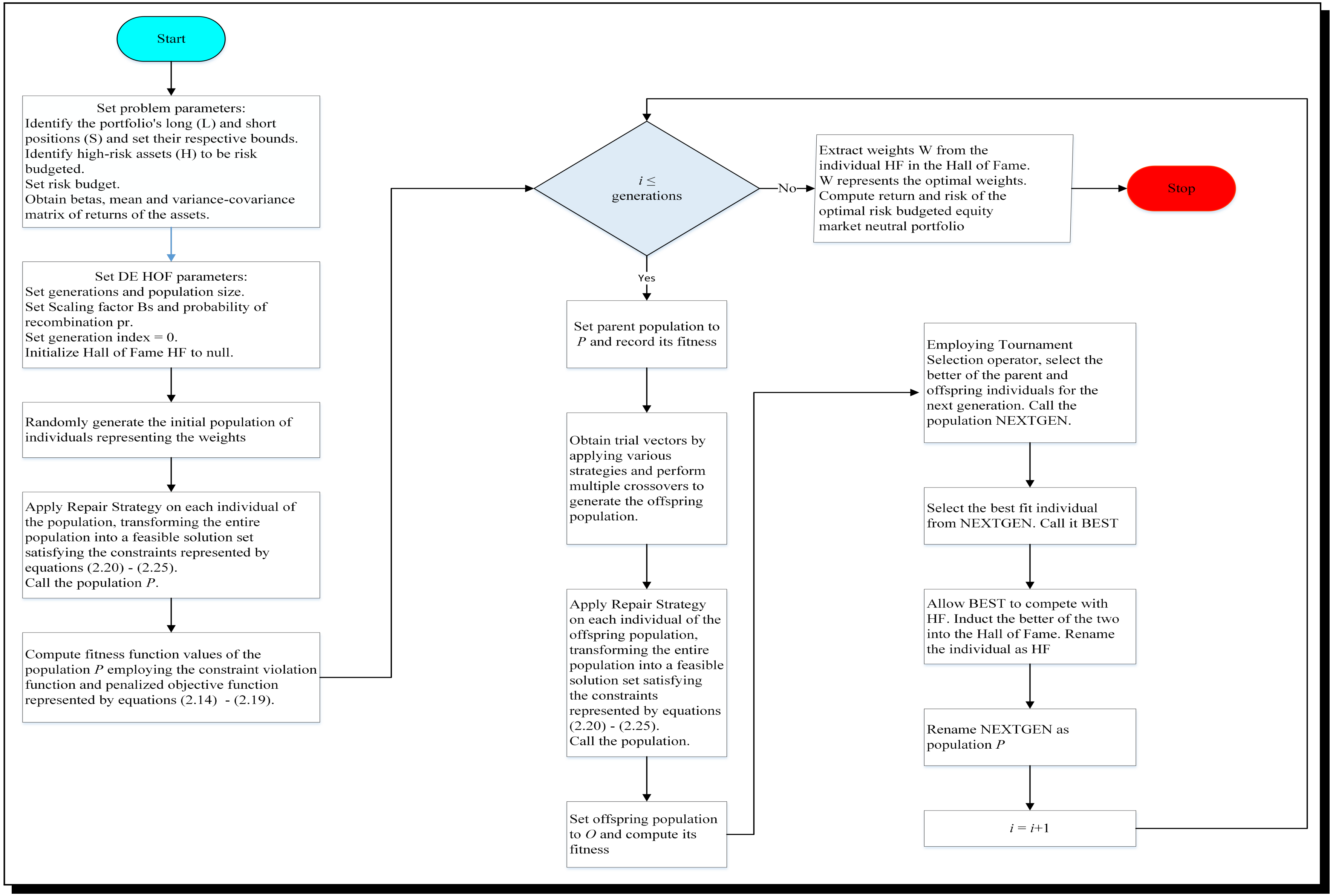

Figure 1. Process flow of adaptive heuristic optimization for equity market neutral portfolio

3. Experiment and Performance Analysis

3.1 Data Collection

An equity market neutral portfolio over the Nifty50 Index[1] from February 2020 to January 2022 involves a composition of short and long positions within the top and bottom 50%iles of stocks ranked by historical volatility. Table 1 and Table 2 Attributes of an optimal portfolio (equity market neutral) related to the Nifty50 dataset consisting of long & short positions. Table 3 represents the Neutral market constraints.

Table 1. Assets and their premiums comprising the Nifty50 portfolio – long positions

S. No.	Description	Beta	Volatility %	Mean Daily Returns %
1	GAIL (India) Ltd.	1.02	0.38	0.15
2	Nestle India Ltd.	9.57	4.86	−0.75
3	Bharti Airtel Ltd.	20.12	6.20	−1.35
4	Power Grid Corporation of India Ltd.	48.69	6.34	−1.97
5	Hindustan Unilever Ltd.	4.06	6.50	−0.28
6	Britannia Industries Ltd.	45.02	6.64	−2.03
7	ITC Ltd.	53.52	6.90	−0.43
8	HDFC Life Insurance Co.	76.73	7.41	−0.74
9	Infosys Ltd.	57.72	7.53	−3.86
10	Asian Paints Ltd.	46.98	7.57	−2.65
11	Sun Pharmaceutical Industries Ltd.	47.05	7.59	−3.35
12	Cipla Ltd.	9.75	7.84	−3.36
13	Divi's Laboratories Ltd.	42.81	8.30	−3.00
14	Tata Consultancy Services Ltd.	73.05	8.34	−3.31
15	Wipro Ltd.	35.14	8.71	−4.36
16	Dr. Reddy's Laboratories Ltd.	18.18	8.73	−1.60
17	UltraTech Cement Ltd.	83.14	8.91	−2.39
18	Shree Cement Ltd.	86.96	9.08	−0.40
19	Indian Oil Corporation Ltd.	91.35	9.44	−0.62
20	Reliance Industries Ltd.	81.51	9.48	−2.76
21	Eicher Motors Ltd.	83.73	9.69	−2.17
22	NTPC Ltd.	83.88	9.96	−0.98
23	Kotak Mahindra Bank Ltd.	59.01	10.08	−0.66
24	SBI Life Insurance Co.	108.46	10.11	−1.32
25	Coal India Ltd.	74.83	10.25	0.23

Table 2. Assets and their premiums comprising the Nifty50 portfolio – short positions

S. No.	Description	Beta	Volatility %	Mean Daily Returns %
26	Titan Company Ltd.	106.33	10.27	−3.04
27	Housing Development Finance Corporation Ltd.	119.37	10.33	−0.70
28	HCL Technologies Ltd.	82.57	10.37	−3.45
29	Tech Mahindra Ltd.	87.20	10.40	−3.40
30	Hero MotoCorp Ltd.	92.99	10.42	−1.30
31	HDFC Bank Ltd.	120.25	10.42	−1.10
32	Bharat Petroleum Corp. Ltd.	117.16	10.45	0.09
33	Adani Port and Special Economic Zone Ltd.	112.12	11.59	−3.28
34	Grasim Industries Ltd.	107.05	11.65	−4.17
35	Larsen and Toubro Ltd.	129.86	11.68	−2.26
36	Bajaj Auto Ltd.	123.28	11.87	−0.76
37	Maruti Suzuki India Ltd.	128.77	11.91	−1.17
38	Oil And Natural Gas Corporation Ltd.	114.60	12.16	−2.49
39	ICICI Bank Ltd.	161.89	14.45	−2.08
40	Tata Steel Ltd.	142.64	15.07	−4.84
41	Mahindra and Mahindra Ltd.	171.71	15.42	−2.82
42	State Bank of India	161.92	15.74	−2.19
43	UPL Ltd.	151.53	16.03	−1.78
44	JSW Steel Ltd.	162.46	16.91	−4.56
45	Hindalco Industries Ltd.	196.92	17.98	−5.17
46	AXIS Bank Ltd.	230.76	19.82	−0.11
47	Tata Motors Ltd.	222.42	22.35	−5.93
48	Bajaj FinServ Ltd.	31.10	23.47	−2.63
49	Bajaj Finance Ltd.	283.50	24.44	−2.21
50	IndusInd Bank Ltd.	546.21	46.49	1.09

Table 3. Neutral market constraints

Net market exposure constraint	Equals 0	Satisfied
Portfolio beta constraint	Equals 0.1	Satisfied
Budget constraints long position L	Equals 1	Satisfied
Budget constraints short positions S	Equals −1	Satisfied
Bounds constraints on long positions L	$0.001 < W_i^+ \leq 1$	Satisfied
Bounds constraints on short positions S	$-1 < W_i^- \leq -0.001$	Satisfied

This section explores the implementation of a metaheuristic equity market-neutral portfolio model wherein budgets related to risk are defined across selective high-risk assets to a category of portfolios defined over Nifty50 (February 2020-January 2022). We considered the Nifty50 portfolio to carry out the experiments explored in the current section, imposing risk budgets on selective, highly volatile stocks in all portfolios.

Nifty50's portfolio, to reiterate, consists of the bottom and top 50 percentiles of the equities specified in accordance with their traditional volatile levels (that is, short and long positions). The bounds for the short, long, and risk-budgeted positions were as follows: W^+, W^- as well as W^H denoted their respective weights: $0.0001 \le W^+ \le 1$, $-1 \le W^- \le -0.0001$ and $-1 \le W^H \le -0.0001$. The objective was to obtain the optimal portfolio using the model defined by using the adaptive heuristic optimization of the equity market neutral portfolio strategy (AHOEMNP) with tournament selection.

The optimal risk-budgeted equity market neutral portfolio for Nifty50 consisted of 25 long positions denoting the top 50% of stocks, as well as 25 short positions signifying the bottom 50% ranked based on the sequence of volatilities in the past. In this context, it is notable that Indusland Bank and Bajaj Finance were the two risk-budgeted assets in Nifty50.

3.2 DE/rand/1 Approach Along Various Crossovers

The AHOEMNP technique was executed to attain an excellent portfolio, including DE/rand/1 approach along various crossovers. It is clear from Table 4 that the DE/rand/1/Exp approach produces the optimum gains for the portfolio. This technique was run repeatedly to check the coherence of its results. Table 5 presents the results of 10 sample runs where the annualized return remained constant through all cycles with the sole objective of maximizing the optimal portfolios.

Table 4. Risk/ Returns accomplished by AHOEMNP with various crossovers

Crossovers	Annualized Risk %	Annualized Return %
Binomial	1.843	9.927
Exponential	1.855	9.962

Table 5. Risk/Returns accomplished by DE/rand/1 approach with exponential crossover

Runs	Annualized Risks %	Annualized Returns %
1	1.854	9.977
2	1.867	9.944
3	1.872	9.966
4	1.882	9.965
5	1.876	9.939
6	1.861	9.952
7	1.864	9.956
8	1.871	9.921
9	1.852	9.927
10	1.878	9.929

3.3 DE/rand5/Dir4 Approach Along Various Crossovers

The AHOEMNP technique was executed to attain an excellent portfolio, including DE/rand 5/Dir4 approach along various crossovers. It is clear from Table 6 that the DE/Rand 5/Dir4/Bin approach produces the optimum gains for the portfolio. This technique was run repeatedly to check the coherence of its results. Table 7 presents the results of 10 sample runs where the annualized return remained constant through all cycles with the sole objective of maximizing the optimal portfolios.

Table 6. Risk/ Returns accomplished by AHOEMNP with various crossovers

Crossovers	Annualized Risk %	Annualized Return %
Binomial	1.878	10.205
Exponential	1.881	10.196

Table 7. Risk/Returns accomplished by DE/rand5/Dir4 approach with binomial crossover

Runs	Annualized Risk %	Annualized Return%
1	1.883	10.221
2	1.884	10.191
3	1.885	10.209
4	1.890	10.200
5	1.884	10.206
6	1.890	10.222
7	1.885	10.223
8	1.888	10.205
9	1.885	10.214
10	1.889	10.209

3.4 DE/rand4/BestDir5 Approach Along Various Crossovers

The AHOEMNP technique was executed to attain an excellent portfolio, including DE/rand 4/BestDir5 approach along various crossovers. It is clear from Table 8 that the DE/Rand 4/BestDir5/Bin approach produces the optimum gains for the portfolio. This technique was run repeatedly to check the coherence of its results. Table 8 presents the results of 10 sample runs where the annualized return remained constant through all cycles with the sole objective of maximizing the optimal portfolios.

Table 8. Risk/Return accomplished by AHOEMNP with various crossovers

Crossovers	Annualized Risk %	Annualized Return %
Binomial	1.886	10.228
Exponential	1.883	10.211

Table 9. Risk/Return accomplished by DE/rand4/BestDir5 approach with binomial crossover

Runs	Annualized Risk %	Annualized Return%
1	1.882	10.205
2	1.888	10.210
3	1.888	10.206
4	1.885	10.213
5	1.889	10.211
6	1.887	10.213
7	1.887	10.209
8	1.887	10.203
9	1.887	10.224
10	1.887	10.217

4. Results and Discussion

This research looks at a long-term equity market neutral portfolio that uses heuristic risk budgeted portfolio value creation for targeted optimization of the annualized return for assets in the Nifty50 portfolio using the AHOEMNP algorithm with various evolution techniques. Table 10 shows that the combining of binomial crossover and DE/rand4/BestDir5 evolutionary strategy yields the highest annualized return of 10.228% combined with 1.886% risk on Nifty50 assets.

Table 10. Best risk/return accomplished by AHOEMNP with various evolution approaches

Approach	Best Crossover	Annualized Risk %	Annualized Return %
DE/rand1	Exponential	1.855	9.962
DE/rand5/Dir4	Binomial	1.878	10.205
DE/rand4/BestDir5	Binomial	1.886	10.228

5. Conclusion

This study examines the most effective way to build a risk-budgeted equity market-neutral portfolio by employing a heuristic strategy known as AHOEMNP, which also incorporates the Hall of Fame and multiple crossovers. The findings show that (i) while it is likely to precisely iron out the optimization issue in its credulous form using formal methods, the risk budget constraint levied on the high-risk assets in the portfolio, in conjunction with the other EMNP-specific controls and multiple crossovers, makes it a complicated problem. The AHOEMNP approach sorts out that. (ii) The AHOEMNP delineated that the performance was consistent throughout all the runs. (iii) The suggested AHOEMNP with Hall of Fame assists in finding the optimal mutation and crossover mix for the highest portfolio returns in an equity market-neutral portfolio.

Competing Interests

The authors declare that they have no competing interests.

Authors' Contributions

All the authors contributed significantly in writing this article. The authors read and approved the final manuscript.

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