A novel methodology for perception-based portfolio management

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Abstract

Selecting and investing in stock market with right proportions is one of the major challenges. Majority of the investors end up losing their invested equity capital due to uncertainty in the market. The present study provides a novel framework for novice investors to construct portfolio based on multicriteria decision making techniques under fuzzy environment. The scores obtained from these techniques were used to introduce two non-dimensional parameters for categorization of risky and non-risky assets. Three perceptions portfolios were constructed based on the proposed non-dimensional parameters along with fractional lion clustering algorithm. In order to demonstrate the proposed framework, an illustrative application is included in equity portfolio selection. The returns and risks of these perception based portfolios are compared to major Index funds for validating the efficiency and are found to overpower the Index funds with significant margins by maintaining the risk comparable to Index funds. Further, Markowitz based efficient frontier is plotted for better understanding of optimal returns and risk for perception based investment.

Keywords Portfolio allocation · Multi-criteria decision making · Fractional clustering algorithm · Stock market index · Perception-based optimization

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1 Introduction

The preliminary objective for equity investments is to construct a portfolio with financial assets for optimum returns by restraining risk within the desired limits. Depending upon the risk appetite of the investors, an optimized portfolio has to be constructed for achieving the financial goals. Studies of portfolio optimization have gained momentum over the recent past after Markowitz's portfolio model by Markowitz (1952). Subsequent advances in portfolio optimization techniques helped novice investors and decision-makers to quantify a wide range of parameters for building a portfolio. The current research focuses on building a portfolio by addressing many shortcomings from earlier studies.

Markowitz (1952) studies on portfolio allocation had revolutionized the field of finance. This portfolio allocation is constructed based on optimizing expected returns and risk using multiple securities. Further, Markowitz's works had helped people to diversify their investments using parameters such as mean, variance, and co-variances for an efficient management of portfolio. Even after six decades, Markowitz's celebrated modern portfolio theory is widely utilized to make decisions for managing a portfolio. But the model received several criticisms for ostracizing some realistic constraints such as cardinality constraints. Further, this model is only restricted to criteria such as mean and variance.

Even though techniques such as Capital-Asset Pricing Model (CAPM) proposed by (Black & Litterman, 1992) addressed some drawbacks in Markowitz's portfolio and are traditionally used for portfolio management, these portfolio are only constructed by utilizing only two criteria return and risk. Hence the need to felicitate multiple criteria led to solicitation of Multiple Criteria Decision-Making techniques (MCDM) for managing portfolio. A considerable number of MCDM's were applied in the area of portfolio management. The initial phase of any MCDM's framework identifies a list of criteria from approved securities for investing through stock exchanges. Subsequently, these criteria are considered to measure multiple components such as analyzing performance of the equity portfolio.

Due to the emerging studies in application of MCDM's in portfolio selection, there is a considerable rise in number of studies based on portfolio allocation especially in the field of finance. Different theories and approaches like Analytical Hierarchy Process (AHP), Technique for Order of Preference by similarity to ideal solution (TOPSIS), ELECTRE Tri outranking, LINMAP, PROMTHEE, PROMETHEE II, DEA etc. are used in managing the portfolios. Further Fuzzy MCDM techniques like Fuzzy AHP and Fuzzy TOPSIS are regressively used to select stocks since equity markets entails uncertainty. The precision of human's decision varies with individuals and are often given in crisp values. Hence to represent the vagueness of judgment, incorporation of fuzzy in MCDM techniques is necessary (Kellner & Utz, 2019).

To invest in appropriate proportions using the above mentioned MCDM's or Fuzzy MCDM's, choosing appropriate criteria for portfolio allocation should be the initial priority. The widely used financial criteria in stock markets include Return on assets, Earnings per share, Price to sales ratio, Price to cash flow ratio, Dividend yield, Price to earn ratio, Book value per share, Return on equity, Price to book ratio. Further, the company's informativeness can be used to determine a firm's stock price (Bennett et al., 2019). The different criteria's which can be used to study the relative dominance of each stock are Sharpe ratio, ordered modular averages, Book value per share, value at risk (VaR), mean–variance, compound annual growth rate (CAGR), and Price to earn ratio (Hota et al., 2018; Li et al., 2019; Silva et al., 2016).

The present study aims to empower investors to construct an efficient portfolio based on various financials. The research attempts to propose an unambiguous methodology to increase returns by controlling the aspect of risk. The novel aspect of the research is to introduce two non-dimensional indices which are utilized to allocate risky and non-risky assets with respect to MCDM cumulative scores. MCDM techniques such as Fuzzy Dematel, Fuzzy AHP and Fuzzy TOPSIS were utilized to construct three perception based portfolios. Construction of perception based portfolio which is another ingenious attribute in the study is overlooked in most of the research based studies. Further, suitable empirical Indian stock index BSE SENSEX example is considered to validate the efficiency of the proposed methodology by evaluating portfolio returns and risk. The risk can be restricted within the desired limits with the proposed methodology. The Markowitz based efficient frontier is also presented to assess returns and risk which can be a safe bet to investors who take low risk.

The remainder of the paper is structured as follows, Sect. 2 presents literature survey of important research works on portfolio management and MCDM in the field of finance and other areas. Further the shortcomings/gaps in methodological aspects of applying MCDM for portfolio allocation are discussed. Section 3 emphasizes on proposed framework along with the introduced non-dimensional indices, while the case study along with main finding and results are presented in Sect. 4. The obtained results were compared to benchmark indices and the comparative statistics were manifested in Sect. 5. Finally, Sect. 6 concludes the study for perception based portfolio management followed by appendix and references.

2 Literature review

This section discusses various significant research works on portfolio management since the Markowitz theory (Markowitz, 1952). After the path breaking mean–variance formulation by Markowitz, many studies suggest various ways to construct a portfolio. (Black & Litterman, 1992) developed the theory for optimizing a portfolio based on the combination of Capital-Asset Pricing Model (CAPM) with returns of expected equilibrium which overcomes downsides to Markowitz's theory (Black & Litterman, 1992). But the works of (Black & Litterman, 1992) only addressed the core aspects of methodology and failed to describe the models implication. Hence, Mankert (2010) explored various applications of the methodology in his works. Walters (2010) further developed a methodology by extending Black–Litterman works. A new model based on Markowitz's mean–variance method was suggested by Cesarone et al., (2013) by including cardinality constraints but haven't considered multiple criteria under consideration. Additionally Dai & Zhu, 2020 and Dai & Zhou, 2020 formed a methodology for prediction of stock market. Further, Table 1 presents list of significant research work along with the drawbacks in each of the model which led to solicitation of MCDM for managing portfolio.

Subsequently the current manuscript presents the applications of MCDM, fuzzy MCDM and the integrated MCDM methodologies obtained by permuting MCDM's and fuzzy MCDM's for portfolio allocation.

These approaches utilize methods such as AHP, MACBERTH, ELECTRE, PROMETHEE, UTA, UTADIS, and MHDIS (Zopounidis & Doumpos, 2002). Various other methodologies such as Geometric Brownian Motion (Yang et al., 2018) and fractional Brownian motion (Liu et al., 2018) are developed for improved portfolio management and to assess the existing portfolio (Greco & Greco, 2015; Pritam et al., 2019a, 2020). Table 2 presents various applications of MCDM for portfolio management by considering different criteria

Table 1 List of significant research work along with the drawbacks in each of the model

Author	Optimization method	Contributions	Drawbacks
Markowitz (1952)	Markowitz efficient frontier	Markowitz's works had helped people to diversify their investments using parameters such as mean, variance, and co-variances for efficient management of portfolios	Ostracized some realistic constraints such as cardinality constraints. Further, this model is only restricted to criteria such as mean and variance
Black & Litterman, (1992)	Hybrid CAPM	Capital-Asset Pricing Model (CAPM) with returns of expected	Only addressed the core aspects of methodology and failed to describe the model's implication
Walters (2010)	Extended Black-Litterman	Extended Black-Litterman by adding a Tau factor	Model's implication were not explained
Cesarone et al. (2013)	Markowitz's mean–variance method	Included cardinality constraints	Perception of the investor is not considered

Table 2 MCDM Methods along with criteria's

Author	Optimization method	Criteria	Stock exchange
Xidonas et al. (2009)	ELECTRE Tri outranking	ROA, ROE, Net profit margin etc	Athens
Yalcin et al. (2012)	Fuzzy AHP, TOPSIS & VIKOR	ROA, ROE, EPS, P/E,	Turkey
Ferrara et al. (2017)	LINMAP	P/E, EPS, ROE	General
Vogiatzis et al. (2018)	PROMTHEE	P/E, P/B, P/S, DY, EPS	Athens
Basilio et al. (2018)	PROMETHEE II	P/E, DY, EPS, ROE	São Paulo
Pritam et al. (2019b)	Fuzzy TOPSIS	ROE, BVPS, P/E, P/B	Bombay
Pritam et al. (2020)	Fuzzy AHP	ROE, BVPS, P/E, P/B	Bombay
NGUYEN et al. (2020)	GRA, TOPSIS, AHP, MOORA	P/E, P/B, ROA, BVPS, DEBT Ratio	Vietnam
Pla-Santamaria et al. (2021)	Moderate pessimism	P/E, P/B, P/S, ROA, BVPS, ROE, EPS, P/CF	Spanish stock market
Peng et al. (2021)	Z-number ELECTRE	ROE, Profit rate	General
Wu et al. (2021)	Interval type-2 fuzzy analysis	Investment ratios	Shenzhen

like ROA, ROE, Net profit margin, EPS, P/E, P/B, P/S, P/CF, DY, BVPS, DEBT Ratio, and profit ratio. These portfolios are allocated through various major stock exchanges across the world.

Although different MCDM techniques had been combined, finally, a representative score for each of the alternatives is evaluated, which is evident from literature. This single score for each of the alternatives makes investors as captive investors. The perception of the investor is neglected in most of the studies and methodologies. Even though the investor's opinions for the portfolio were taken in the study of T Silva et al. (2017), only the quantitative views obtained by the method of Verbal Decision Analysis but are restricted to few criteria. Most of the studies had overlooked the shortcomings of variations in the portfolio derived from various established multi-criteria or fuzzy multi-criteria methods. The categorization based on perception is not taken into consideration in any of the methodologies. Further, the complexity of a method is directly proportional to the number of criteria considered in a multi-criteria problem. Hence there is a great need to formulate a methodology that surmounts the discussed limitations.

3 Methodology

The study proposes a sophisticated method which not only routs the deficiencies of previous studies but can be highly adaptable in any of the above decision-based portfolios. The steps involved in the proposed methodology are presented in Fig. 1.

In the initial phase of analysis, the nature of each criterion considered is determined, which helps to distinguish the criteria into two classes such as cost and effect. Since the cost criteria have a crucial role in dictating the benefit, only the criteria falling under this category are chosen for further analysis. Fuzzy Dematel technique is used to perform this classification.

To stabilize the differences in proportions of portfolios obtained we consider two of the widely used fuzzy MCDMs in their respective fields. Further, the current study introduce

Fig. 1 Schematic illustration of the proposed framework

two non-dimensional measures *P*-index and multi criterial volatility (MCV) to given equal weight to the considered fuzzy MCDM's based on the variation obtained by the criteria of cost group. The design of a portfolio is profuse combinations of integrating fuzzy multi-criteria techniques in various uncertain environments. Hence the concept of fuzzy logic is integrated with all the MCDM methods used in the study. This will be hugely beneficial to capture the decision-makers views with different perceptions.

Due to the high probability of inclusion of data ratios including financial ratios for embedded complexity axioms in DEA, it has to be noted that the techniques like DEA or fuzzy DEA are to be excluded for smooth transacting of the proposed framework.

Depending upon perception, the study classifies a portfolio based on the perception of an investor. Clustering algorithms are employed to classify perceptions of decision-makers. A detailed insight into the evaluation of MCV is given in Sect. 3.2. The decisions are to be categorized depending on various personal views by using advanced clustering algorithms. Hence, fractional lion algorithm (FLA) is employed for easy finding of cluster centroid and inclusion of memory property which will be discussed in Sect. 3.3.

3.1 P-Index

P-index is one of the non-dimensional indices that refers to a consistent cumulative score derived by considering more than one MCDM technique in an uncertain environment. The proposed priority index is defined by taking the mean of cumulative score obtained from two extensively used fuzzy multi-criteria techniques in the respective fields. The mathematical representation of *P*-index of i^{th} alternative in a considered field is shown in Eq. 1.

$$PI_i = \frac{fmcdm_{1,i} + fmcdm_{2,i}}{2} \quad (1)$$

where $fmcdm_{1,i}$ and $fmcdm_{2,i}$ are the cumulative scores of the i^{th} alternative obtained after the analysis of two widely used MCDM's.

3.2 Multi-criteria Volatility (MCV)

It is a measure of percentage deviation in cumulative score with respect to the change in multi-criteria approach and can be expressed using Eq. 2.

$$MCV_i = 200 \left| \frac{fmcdm_{1,i} - fmcdm_{2,i}}{fmcdm_{1,i} + fmcdm_{2,i} - |fmcdm_{1,i} - fmcdm_{2,i}|} \right| \quad (2)$$

The evaluated MCV can be used to classify the chosen alternatives into two different classes which are proposed to be sectors with low and high risk. Fractional Lion clustering algorithm is used in this study to classify the considered sectors into a predefined number of classes. After clustering, the evaluated statistics are further used to determine the share that can be invested by an investor. This share varies with the perception of the investor.

Equation 2, represents the percentage increase from the minimum cumulative score to that of maximum among the considered MCDM's for a sector. This helps investors whose risk tolerance is either low or high which are defined in the following subsection.

3.3 Clustering analysis

Following the evaluation of Multi-criteria volatility, the selected sectors are classified into two clusters. Flexibility is provided for investors in view of their perception. In this study, three different perceptions including the perception obtained from P-index are constructed and optimized portfolio accordingly.

One of the algorithms to cluster the data is the K-means algorithm and subsequently, various techniques for classifications were developed. The extension of the K-means algorithm was depicted by integrating intracluster compactness with intercluster compactness. Further, numerous works and applications on fuzzy C-means (FCM) and its extensions like Minimum Sample Estimate Random FCM and Geometric Progressive FCM were followed. Genetic algorithm and Particle Swarm Clustering (PSC) based clustering techniques are utilized for optimizing portfolios (Cheong et al., 2017; Guan et al., 2019; Mukhopadhyay & Chaudhuri, 2019).

Most of the clustering techniques in the literature adopted functions with only single kernel which consequently rises memory complexity and simulation time. To address this complication, a multiple kernel fitness function was introduced as Fractional Lion Algorithm (FLA), which is an advanced clustering technique (Gope et al., 2019). This technique is introduced with the intent of improving the accuracy for optimizing centroids of different clusters which is not emphasized in the Lion optimization algorithm. In addition to adopting multiple kernels, this algorithm is much effective as compared to most of the clustering techniques which is mainly due to choosing the effective cluster head and to optimize the number of iterations (Sirdeshpande & Udupi, 2017). FLA is widely applied in the fields which includes Big data analytics, Image processing, Tree classifier, Artificial intelligence and Machine learning, etc. for data clustering and has a variety of advantages over other clustering techniques like ease of locating optimal centroids, assigning weights, and smooth upgradation of centroids for division of clusters etc. (Chander et al., 2016, 2018; Mateen et al., 2019; Yadav, 2018).

The two multi-criteria techniques considered suggest the investors obtain the range of investments by considering their cumulative scores for the allotment in a particular sector. Based on the risk tolerance of multi-criteria we construct three portfolios using FLA.

3.4 Fractional lion algorithm for rapid centroid estimation

A detailed discussion of the FLA is presented in this section. Prior to the estimation of the solution point, it is mandatory to initialize the solution point. To cluster data points, the selections of solution points are chosen randomly and are exposed to be solution constraints followed by cross-over and mutation. In the next stage, cross-over is achieved within the range of clustering limits, by exchanging the vector points, which is followed by mutation where the solution points are performed. Further, the solution vectors can be obtained from rapid mutation evaluated by the fitness functions to locate solution points in the process of clustering analysis. From this stage onwards, FLA follows a similar procedure as of the Lion algorithm.

The inclusion of fractional theory in the Lion algorithm made FLA more efficient compared to classical optimization techniques such as PSC and Lion algorithm. From mutation, followed by cross-over, generates new vectors (solution) along with solution points. If the uncertain solution point overshoots value fitness range, then the solution point takes a random

position. Solution points are synonymously used for centroid points. The fitness function is utilized to find optimal centroid in clustering analysis until the tolerance is attained.

Following the attainment of optimal centroid point, a grouping of points is done. The algorithm used for clustering based on perception helps to find highly accurate centroid for the give data points of equity market sectors. Nomad lion in FLA indicates an uncertain solution point chosen until the tolerance is attained. The centroid estimation, along with performance matrices, is evaluated in the last block of evaluation.

As the name suggests, the data considered for FLA is intuited and explained in terms of lions. The important idea used in FLA is survival of the fittest (SF), i.e., only the strongest of the male lions survive in the pride. Based upon the pride behaviour of the lion, three important evolutionary algorithms are developed as given below.

1. The best two among all lions inhabit all pride resources in the mating.
2. A young superior member is chosen and is given the training to become stronger for the successor
3. Stagnation of evolution will lead the way to new lion acquisition and long stagnation lead to mutation of the superior individual.

In the present chapter, optimization corresponds to the evolution process, which can be intuited as the superior member of all animals obtained after FLA. The present section discusses FLA in 9 steps to find optimal centroid rapidly given below.

Step 1: Let the input data which is interpreted as the lion's pride generation be represented as S_M, S_F, S_N where M, F and N represent male, female and nomad lions respectively. The elements S_M and S_F are given by Eq. 3.

$$\begin{aligned} S_M &= [i_1^M, i_2^M, \dots, i_L^M] \\ S_F &= [i_1^F, i_2^F, \dots, i_L^F] \end{aligned} \quad (3)$$

where, L denote the length of solution vector.

The most commonly used fitness, mean square error is opted to calculate S_M and S_F after initialization. The values of fitness are all stored and fitness value is taken to be a male lion, which is also the fitness reference.

Step 2: The lion's (territorial) and lioness fertility is calculated in this step to avoid the local convergence of the optimal point. Further, different factors taken are given below:

Let R^{ref} be reference function of fitness of S_M .

L_r be the rate of laggardness.

S_r be the rate of sterility.

u_c be update count of a female lion.

g_c be generation count of a female lion.

It should be noted that L_r and S_r are independent of the gender of lions. The default value for L_r and S_r are set to zero in the algorithm and the value is gradually increased for evaluating fertility. The male and female lions in the algorithm are calculated using L_r and S_r respectively with female lion's g_c is taken to be approximately 10 using hit and trial method.

Step 3: Updation of a female lion.

Updated female lion S^{F+} can be evaluated by Eq. 4.

$$S_l^{F+} = \begin{cases} i_k^{F+}; & \text{for } l = k \\ i_k^F; & \text{otherwise} \end{cases}$$

$$S_k^{F+} = \min[i_k^{\max}, \max(i_k^{\min}, \Psi_k)] \quad (4)$$

$$\Psi_k = [i_k^F + (0.1r_2 - 0.05)i_k^M - r_1 i_k^F]$$

l and k are solution vectors L which are randomly generated integers in the interval $[0, L]$. Ψ_k is the function of updated female lion count with r_1 and r_2 are randomly generated integers.

Step 4: Cross-over along with mutation.

Cross-over is defined as the dual probabilities at a single point along with the probability of random cross C_r .

$$S^C(R) = B_R^\circ S_M + \overline{B_R}^\circ S_F; R = 1, 2, 3, 4 \quad (5)$$

here S^C is the cub generated after cross-over evaluated by Eq. 5, R denotes the length of cross-over and $^\circ$ is Hadamard's product.

3.4.1 Mutation

Mutation helps to form S^{new} from S^C through mutation probability T_r . Further, both S^{new} and S^C are exposed to the cub pool for gender clustering.

Step 5: Growth function of a cub.

Thus the function is a mutation function observed after the gender clustering. The male cubs (S_{M_C}) and female cubs (S_{F_C}) are extracted from gender clustering have a greater value of fitness, then the cubs are reviewed to be the new male and female cubs. A_c is the cub age after mutation and N_r is rate obtained from growth which is less than or equal to the rate of mutation T_r .

Step 6: Generation based on fractional calculus.

For enhanced estimation of the centroid, a male lion is produced with the help of the theory of fractional operators to obtain a new male lion by calculating fitness function. The generation based on fractional calculus can be evaluated by the following equations.

The value of fitness function is computed using Eq. 6.

$$f(S_{l+1}^M) = f(S_l^M) \quad (6)$$

For negligible change in optimal solution, we obtain Eq. 7.

$$S_{l+1}^M = S_l^M \quad (7)$$

Let the order of the considered GL fractional derivative be α which is in closed unit interval, then for $\alpha = 1$, $D^\alpha(S_{l+1}^M) = 0$.

The discrete version with order 2 can be given by Eq. 8.

$$\begin{aligned} D^\alpha(S_{l+1}^M) &= S_{l+1}^M - \alpha S_l^M - 0.5\alpha S_{l-1}^M \\ S_{l+1}^M - \alpha S_l^M - 0.5\alpha S_{l-1}^M &= 0 \end{aligned}$$

Then,

$$S^{\text{lion}} = \alpha S_l^M + 0.5\alpha S_{l-1}^M \quad (8)$$

Step 7: Provincial defense.

The area where the lion is a preliminary operator is assumed for a wider search space. If the nomad lion wins a fight with the existing territorial lion, then the pride will be updated to nomad lion. Let S_1^N and S_2^N be two nomad lions. Due to the consideration that L_r is restricted to only male lion, the initialization is dependent on male individuals for provincial defense. A survival fight between the nomad lion with superior fitness function is done. If the nomad lion fails to sustain, then the other nomad lion will be replaced until the below condition succeeds.

S_2^N is updated after the loss of fight with S_1^N , then $E_2^N \geq e$ which is evaluated by the following equation Eq. 9.

$$E_2^N = \exp\left(\frac{d_2}{\max(d_2, d_1)}\right) \frac{\max(f(S_1^N), f(S_2^N))}{f(S_2^N)} \quad (9)$$

where d_1 and d_2 are Euclidean distances between S_1^N , S^M and S_2^N , I^M respectively.

Step 8: Territorial occupancy.

When the age of cub reaches the maximum threshold value, which is based on the growth function of the cub, then the cub occupies the territory. This is the procedure followed after they reach maturity age and have high strength than the existing male or female lions. Once done, the S_r is set to be zero. Then the whole process completes a generation cycle and then the value is set to one.

Step 9: Final iteration.

This algorithm is iterated till $N_f^{\max} < N_f$ is reached. Here N_f is number of function evaluations. The pseudo-code for the algorithm is given in the Appendix.

4 Application of the proposed methodology

As discussed in the methodology, the initial step is choosing the crucial criteria influencing the construction of the portfolio. For the demonstration of the proposed methodology, financial portfolio management is considered and the findings of each step as shown in Fig. 2 are presented. However, it has to be noted that the proposed methodology can be extended for portfolio management in other fields.

4.1 Identification and classification of criteria

Step 1: The crucial criteria which influence the financial portfolio construction are identified by considering the past research works. The identified criteria include Return on assets (ROA), Earnings per share (EPS), Price to sales ratio (P/S), Price to cash flow ratio (P/CF), Dividend yield (DY), Price to earn ratio (P/E), Book value per share (BVPS), Return on equity (ROE), Price to book ratio (P/B). The aforementioned criteria are classified into cost and effect groups. Fuzzy DEMATEL is used in this study to perform this activity. Three senior academicians, two portfolio managers, and a financial analyst were chosen as expert panel and responses were garnered in linguistic form (Table 3).

Step 2: The intermediate 5-scale approach (0 indicating negligible or no influence and 4 indicating prominent influence) has been used to transform individual subject proficient and connoisseur's linguistic opinions into the numerical scale and then into an equivalent

Fig. 2 Effect-cause Ishikawa diagram of criteria in BSE SENSEX

Table 3 Aggregate Linguistic scale used of subject proficient and connoisseurs

	ROA	EPS	P/S	P/CF	DY	P/E	BVPS	ROE	P/B
ROA	No	H	L	L	VL	L	L	H	VL
EPS	H	No	L	VL	L	H	L	H	VL
P/S	L	VL	No	L	L	H	L	L	VL
P/CF	VL	VL	H	No	VL	L	VL	L	L
DY	VL	VL	H	VL	No	VL	L	L	L
P/E	VH	L	VH	VH	H	No	H	VH	VH
BVPS	H	VH	VH	H	H	L	No	H	VH
ROE	VH	H	L	VH	H	VH	VH	No	H
P/B	H	H	VH	H	VL	VH	VH	VH	No

trapezoidal fuzzy number (TrFN) by the transformation function $Trfn : X \rightarrow [0, 1]^4$ where $X = \{0, 1, 2, 3, 4\}$ which can be depicted from Table 4. The TrFN's are represented by fuzzy criteria evaluation matrices for each individual subject proficient and connoisseurs. The 5-scale approach used for transformation of opinion along with transformation function can be derived from Table 4. The fuzzy scores corresponding to Return on Assets and Return on equity are shown in Table 5. The equivalent data sets are prepared for the rest of the criteria which is not presented in this manuscript. Here $x \in X$.

Step 3: Fuzzy criteria relation matrix (R) is generated by the bisection of area defuzzification method (Boby et al., 2017) of the TrFN elements of the corresponding fuzzy criteria evaluation matrix. Further, the fuzzy average criteria matrix (A) is obtained by taking the average of all fuzzy criteria relation matrices with an order $m \times m$ is shown in Table 6.

Table 4 Linguistic opinions to trapezoidal fuzzy conversion scale

Linguistic opinions	X	$Trfn(x)$
Negligible influence (No)	0	(0, 0, 0.1, 0.2)
Very low influence (VL)	1	(0.1, 0.2, 0.3, 0.4)
Low influence (L)	2	(0.3, 0.4, 0.5, 0.6)
High influence (H)	3	(0.5, 0.6, 0.7, 0.8)
Very high influence (VH)	4	(0.7, 0.8, 0.9, 1)

Table 5 Fuzzy scores of corresponding to ROA and ROE over other criteria

ROA							ROE					
ROA	No	0	0	0	0.1	0.2	H	3	0.5	0.6	0.7	0.8
ROE	H	3	0.5	0.6	0.7	0.8	No	0	0	0	0.1	0.2
BVPS	L	2	0.3	0.4	0.5	0.6	VL	1	0.1	0.2	0.3	0.4
EPS	VL	1	0.1	0.2	0.3	0.4	VL	1	0.1	0.2	0.3	0.4
DY	VL	1	0.1	0.2	0.3	0.4	VL	1	0.1	0.2	0.3	0.4
P/E	VH	4	0.7	0.8	0.9	1	L	2	0.3	0.4	0.5	0.6
P/B	H	3	0.5	0.6	0.7	0.8	VH	4	0.7	0.8	0.9	1
P/S	VH	4	0.7	0.8	0.9	1	H	3	0.5	0.6	0.7	0.8
P/CF	H	3	0.5	0.6	0.7	0.8	H	3	0.5	0.6	0.7	0.8

Table 6 Fuzzy criteria relation matrix

	ROA	ROE	BVPS	EPS	DY	P/E	P/B	P/S	P/CF
ROA	0.08	0.65	0.45	0.45	0.25	0.45	0.45	0.65	0.25
ROE	0.65	0.075	0.45	0.25	0.45	0.65	0.45	0.65	0.25
BVPS	0.45	0.25	0.075	0.45	0.45	0.65	0.45	0.45	0.25
EPS	0.25	0.25	0.65	0.075	0.25	0.45	0.25	0.45	0.45
DY	0.25	0.25	0.65	0.25	0.075	0.25	0.45	0.45	0.45
P/E	0.85	0.45	0.85	0.85	0.65	0.075	0.65	0.85	0.85
P/B	0.65	0.85	0.85	0.65	0.65	0.45	0.075	0.65	0.85
P/S	0.85	0.65	0.45	0.85	0.65	0.85	0.85	0.075	0.65
P/CF	0.65	0.65	0.85	0.65	0.25	0.85	0.85	0.85	0.075

Step 4: The normalized criteria relation matrix (N) is derived using the Eq. 10 and Eq. 11. The matrix obtained by these equations enables to identify key financial ratios of BSE SENSEX as shown in Table 7.

$$k = \min \left[\left(\max \sum_{h=1}^m |a_{gh}| \right)^{-1}, \left(\max \sum_{g=1}^m |a_{gh}| \right)^{-1} \right] \quad (10)$$

Table 7 Normalized criteria relation matrix

	ROA	ROE	BVPS	EPS	DY	P/E	P/B	P/S	P/CF
ROA	0.01	0.11	0.07	0.07	0.04	0.07	0.07	0.11	0.04
ROE	0.11	0.01	0.07	0.04	0.07	0.11	0.07	0.11	0.04
BVPS	0.07	0.04	0.01	0.07	0.07	0.11	0.07	0.07	0.04
EPS	0.04	0.04	0.11	0.01	0.04	0.07	0.04	0.07	0.07
DY	0.04	0.04	0.11	0.04	0.01	0.04	0.07	0.07	0.07
P/E	0.14	0.07	0.14	0.14	0.11	0.01	0.11	0.14	0.14
P/B	0.11	0.14	0.14	0.11	0.11	0.07	0.01	0.11	0.14
P/S	0.14	0.11	0.07	0.14	0.11	0.14	0.14	0.01	0.11
P/CF	0.11	0.11	0.14	0.11	0.04	0.14	0.14	0.14	0.01

Table 8 Effective criteria relation matrix

	ROA	ROE	BVPS	EPS	DY	P/E	P/B	P/S	P/CF
ROA	0.23	0.28	0.30	0.28	0.21	0.28	0.27	0.32	0.23
ROE	0.33	0.21	0.32	0.26	0.25	0.32	0.29	0.34	0.24
BVPS	0.27	0.22	0.23	0.27	0.23	0.30	0.26	0.28	0.22
EPS	0.22	0.20	0.30	0.19	0.18	0.25	0.21	0.26	0.23
DY	0.22	0.20	0.30	0.21	0.16	0.22	0.24	0.26	0.23
P/E	0.46	0.36	0.50	0.45	0.36	0.35	0.42	0.48	0.42
P/B	0.41	0.40	0.47	0.40	0.35	0.38	0.31	0.43	0.40
P/S	0.45	0.39	0.43	0.44	0.36	0.45	0.44	0.36	0.39
P/CF	0.43	0.38	0.48	0.42	0.30	0.45	0.44	0.47	0.30

$$N = k \times A \quad (11)$$

Step 5: Effective criteria relation matrix (E) is constructed by Eq. 12 and the obtained matrix is shown in Table 8.

$$E = N(I - N)^{-1} \quad (12)$$

where I represents the identity matrix.

Step 6: The row and column aggregates R & D respectively of effective criteria relation matrix is calculated using Eq. 13 and Eq. 14.

$$R = \left\{ \sum_{h=1}^m e_{gh} \right\}_{m \times 1} \quad (13)$$

$$D = \left\{ \sum_{g=1}^m e_{gh} \right\}_{1 \times m} \quad (14)$$

Table 9 Datasets of $D + R$ and $D - R$ for sector criteria in BSE SENSEX

	D	R	$D + R$	$D - R$	Nature
Return on assets	2.40	3.02	5.42	− 0.61	Effect
Earnings Per Share	2.55	2.63	5.18	− 0.09	Effect
Price on sales	2.28	3.33	5.61	− 1.05	Effect
Price on cashflow	2.04	2.91	4.95	− 0.87	Effect
Dividend yield	2.03	2.40	4.43	− 0.37	Effect
Price on earnings	3.81	3.01	6.82	0.79	Cause
Book Value Per Share	3.54	2.88	6.42	0.66	Cause
Return on equity	3.71	3.22	6.93	0.50	Cause
Price on book	3.68	2.63	6.31	1.04	Cause

where ' e_{gh} ' are elements of Effective criteria relation matrix E and $R \& D$ gages the overall impact of g^{th} criteria over h^{th} criteria and overall impact of h^{th} criteria over g^{th} criteria respectively.

Step 7: The effect-cause graph is plotted by data set ($R - D$; $R + D$).

The prominent criteria in the SENSEX can be derived from the dataset of $R + C$, whereas the magnitude of $R - C$ represents the effect of each criterion. The threshold value of $R - C$ with '0' distinguishes the criteria into cause group and effect group. The criteria with magnitude less than the threshold promote the variable fall under effect group and rest falls under the category of cause group. The effect-cause plot can be depicted from the Ishikawa diagram Fig. 2 and is presented in Table 9.

4.2 Identification of multi-criteria techniques for equity-based portfolio

As evident from Sect. 1 AHP and TOPSIS are widely used in the field of financial portfolio management and hence used in this current research. Fuzzy AHP and Fuzzy TOPSIS are derived based on AHP and TOPSIS respectively in an uncertain environment and decision making outcomes. Since its inception, the AHP and TOPSIS methods are widely adopted in portfolio management. It is evident that the attributes (sectors in the present study) are crisp and hence are ineffective for dealing with real-life applications in volatile markets. To improve the precision in projection, both Fuzzy AHP and Fuzzy TOPSIS are used for a greater understanding of the market. The present study adopts both these fuzzy MCDM techniques which are easy to use in the proposed methodology and has various advantages like hierarchical structures and scalability. The crisp scale proposed by Saaty is used for evaluation using AHP and rating scale on an 11 scale explained qualitatively is used in TOPSIS. Further, the major equity index of India stock exchange namely BSE SENSEX is considered in the present study due to its high informativeness and market capitalization.

Studies of Pritam et al., (2019a, 2019b and 2020) considered six sectors including Automobile, Finance, Information technology, Oil, Pharmaceuticals, and Power which are denoted by S_1 to S_6 and the breakup of the cumulative score using Fuzzy AHP and Fuzzy TOPSIS is evaluated. Both studies considered the same data sets i.e. from March 2014 to March 2018 in BSE SENSEX. The criteria weights obtained by the expert committee are consistent in

Table 10 Ranking of six sectors using Fuzzy AHP (Pritam et al., 2020)

	$\lambda = 0$	$\lambda = 0.5$	$\lambda = 1$	Ranking
S_1	0.239305	0.174449	0.478611	3
S_2	0.248428	0.176461	0.496855	2
S_3	0.336948	0.247883	0.673896	1
S_4	0.106747	0.07501	0.213495	5
S_5	0.205555	0.145593	0.411109	4
S_6	0.107185	0.07398	0.214371	6

Table 11 Ranking of six sectors using Fuzzy TOPSIS (Pritam et al., 2019a)

Sectors	$\tilde{R}_k$	Ranking
S_1	0.524705	4
S_2	0.735503	1
S_3	0.662943	2
S_4	0.09158	6
S_5	0.580726	3
S_6	0.129655	5

Table 12 *P*-Index and MCV of the sectors

	Automobiles	Banking	IT	Oil	Pharmaceutical	Power
<i>P</i> -Index	0.237785	0.220558	0.232321	0.048982	0.199568	0.060787
MCV	31.22748	29.09832	9.894184	91.50788	14.55013	55.52535

both of the studies and will be used in the present study. The cumulative scores and ranks of fuzzy AHP can be inferred from Table 10.

The investor's risk level can be derived from λ which is an optimism index and fuzzy TOPSIS relative index scores ($\tilde{R}_k$) in Table 11.

Based on these scores obtained from both the techniques, a portfolio is constructed which convey optimal investment percentage by the level of risk an individual can take to invest in a particular sector. This is achieved with the introduction of *P*-index, MCV, and FLA which are discussed in subsequent sections.

4.3 Evaluation of *P*-index and MCV

As discussed in the proposed methodology, the objective of this study to manage the portfolio by giving due consideration to the perception of an investor. This flexibility facilitates the captive investors to transform into choice investors, where they will have a specific range of percentages to invest, based on the perception. The obtained cumulative scores are used in determining *P*-index and the attributes of *P*-index and MCV are shown in Table 12.

Table 13 Investors in accordance to perspective

	Group	I_L	I_N	I_H
Automobiles	1	25.55788	26.98982	21.78791
Banking	1	23.53838	24.85717	20.39725
IT	1	23.03653	24.3272	23.45081
Oil	2	3.182291	3.360585	6.817766
Pharmaceutical	1	20.17956	21.31016	19.70751
Power	2	4.505365	4.757788	7.838749

MCV determines the volatility of derived cumulative scores using both the multi-criteria techniques. For instance, say if the deviation between the cumulative score obtained using both the methods is significant, in such cases MCV corresponding to that sector would reasonably higher. Higher MCV refers to high volatility. High volatility can be inferred with the fact that the choice taken by the investor may likely to deviate the expectation. The range of MCV values is considered and divided into two groups using FLA clustering, which is performed using the pseudocode developed by Chander et al. (2016). Group-1 refers to less volatility and Group-2 refers to high volatility. Depending on the perception of an investor, Investors are classified into three different groups referred to as Neutral or Medium risk-tolerant (I_N), High risk-tolerant (I_H) and Low risk-tolerant (I_L). If the sector belongs to Group-1, then I_L can opt for higher range which is evident from Table 13. Similarly, in the sectors belonging to Group-2, I_L will opt for the lower end. I_N can always invest by considering the P-index values.

5 Robustness check and empirical results

This section presents a comparative analysis of the proposed perception portfolios. The portfolios were benchmarked with most popular Indian index funds SENSEX and NIFTY. The data of financial derivatives considered in this study were retrieved from Yahoo Finance using Yfinance® API for the period between March 2013 to March 2021. Based on the collected data Markowitz based efficient frontier is plotted for better understanding of optimal returns and risk. Further, various descriptive statistics are presented for perusing the proposed methodology.

The daily returns index can be calculated by Eq. 15.

$$DR_i = \ln\left(\frac{d_i}{d_{i-1}}\right) \quad (15)$$

where DR_i indicated daily returns and d_{i-1} and d_i denotes BSE SENSEX close price for the $i - 1^{\text{th}}$ and i^{th} day respectively. In the current study, the daily returns of the considered data for all the three perception based portfolios were compared to major Indian indices SENSEX and NIFTY from years 2013 to 2021.

Using the proposed methodology, the constructed perception based portfolios had outperformed major Indian indices. Further, it can be observed from Fig. 3 that there is a sharp decline in the initial quarters of the year 2020 due COVID-19 pandemic and later had a ‘V-shaped’ recovery in the Indian stock market and proposed optimized portfolios.

Fig. 3 “V” shaped recovery of perception based portfolios

Fig. 4 Comparison of perception based portfolios returns with SENSEX and Nifty from year 2013 to 2018

Further various comparisons of three perception based portfolios and SENSEX and NIFTY portfolios were plotted based on the cumulative weighted returns are shown in Figs. 3, 4, 5. The cumulative weighted returns can be calculated from Eq. 16.

$$c_w = \sum_i w_i \cdot c_i \quad (16)$$

where c_w stands for cumulative weighted returns and w_i is the weight of the i^{th} stock and is calculated using Fuzzy MCDM and c_i represents the closing price of the i^{th} stock. Here i is the number of stocks considered in a given day. The cumulative scores obtained from

Fig. 5 Comparison of perception based portfolios returns with BSE SENSEX and Nifty for tested data from year 2018 to 2021

Table 14 Returns and CAGR Comparison of perception based portfolios with BSE SENSEX and Nifty from year 2013 to 2018

Asset basket	Percent return	CAGR
BSE SENSEX	80.69087808924003	12.56%
Nifty	84.52540245618343%	13.03%
IL Portfolio	159.69379406088136	21.03%
IH Portfolio	165.64238307687944	21.58%
IN Portfolio	165.64239400546340	21.58%

the constructed portfolios and Indian indices were normalized and the equity prices of these portfolios were plotted in Fig. 4.

The range of years were plotted on the x-axis on the Y-axis, percentage of returns (in hundreds) were plotted. It is also important to mention that the portfolio is dynamic, as a company drops out of BSE SENSEX it is also dropped out of portfolio and vice versa. As it can be seen from the graph that portfolio constructed using the proposed methodology significantly outperforms Nifty and SENSEX.

The weights were calculated based on data collected for years 2013 to 2018 and as seen from the above statistics the constructed portfolios do very well in that time span when compared to BSE SENSEX and NSE Nifty. But when these portfolio weights are applied to create asset buckets for a different time period they still out-perform BSE SENSEX and NSE Nifty but, by a smaller margin.

From the above Fig. 4, it can be concluded that the portfolios constructed based on the proposed methodology significantly outperform the Indian indices. The perception based portfolios are delivering almost double the expected returns. The percentage returns for the five year period i.e. 2013 to 2018 (train data period) along with the Compound annual growth rate (CAGR) are shown in the Table 14.

The data collect during this period can be considered as train data and the methodology is tested for the next three years i.e. from April 2018 to March 2021. The percentage returns along with the CAGR is presented in Table 15.

Table 15 Returns and CAGR Comparison of perception based portfolios with SENSEX and Nifty from year 2018 to 2021

Asset basket	Percent return (%)	CAGR (%)
BSE SENSEX	44.21262602	12.98
Nifty	38.92393096	11.58
IL Portfolio	54.33720726	15.56
IH Portfolio	56.85295748	16.19
IN Portfolio	54.41689708	15.58

Figures 3 and 5 provides the V shaped recovery of all the three portfolios after the pandemic.

Since returns alone doesn't provide the efficiency of the portfolio, other parameters which captures the risk along the expected returns are considered in the study. Sharpe's ratio, Jensen's Alpha and Beta are evaluated for comparison of returns and risk of the portfolios proposed to the portfolios based on Indian indices.

5.1 Sharpe ratio

The Sharpe ratio (Altay et al., 2021) is evaluated to compare the optimized portfolio with Indian Index funds. Sharpe ratio for risky assets can be evaluated by Eq. 17.

$$S_R = \frac{R_p}{\sigma_p} \quad (17)$$

where, R_p denotes mean returns rate of the portfolio and σ_p represents standard deviation. Further, helps investors understand the expected returns with respect to the risk of the portfolio. Since this ratio assumes normality of the data, other measures such as Jensen's alpha and beta are to be considered to study the behavior of portfolio returns and risks.

5.2 Jensen's Alpha

Jensen's Alpha estimates the performance of the portfolio by evaluating the expected returns and adjusting risk with the help of CAPM pricing model. This measure for risky assets can be calculated by the Eq. 18.

$$\alpha_R = R_p - R_I \beta_p \quad (18)$$

where, R_I represents mean returns rate of Indian Index funds and β_p is the beta of the portfolio (Masmoudi & Abdelaziz, 2018) calculated by the formula given by Eq. 19.

$$\beta_p = \frac{\text{Covariance}(R_p, R_I)}{\text{Variance}(R_I)} \quad (19)$$

Beta represents the ratio between covariance with the market and market variance. Beta less than unity indicates less correlation with the market index and higher value in beta of a constructed portfolio is supposed to be riskier. Further, the negative beta indicates that the constructed portfolio investments are negatively correlated with the markets.

These measures along with other statistical measures such as Variance, Standard Deviation, Skewness, Excess Kurtosis are compared and presented in Table 16.

Table 16 Proposed portfolio's return statistics and performance with respect to benchmark Indian indices

Asset buckets	Variance	Skewness	Excess Kurtosis	Beta	Jensen's Alpha
IH Portfolio	2.241×10^{-4}	0.3564	24.8859	- 0.0807	0.0573
IL Portfolio	2.576×10^{-4}	0.3054	28.1174	- 0.0911	0.0566
IN Portfolio					
2.376×10^{-4}	0.5183	26.5826	- 0.0850	0.0570	
NSE Nifty	8.56×10^{-5}	- 0.4079	2.8496	-	-
BSE SENSEX	8.26×10^{-5}	- 0.3999	2.8804	-	-

The beta and Jensen's Alpha of Nifty and BSE SENSEX cannot be evaluated since they are considered as base benchmarks

As it can be seen from the variance and standard deviation column that the volatility of the portfolios is very comparable to index funds. Sharpe's ratio as seen from the Table 16 is over 1 thus indicating a strong portfolio. Skewness and kurtosis were calculated using the stats module of the Scipy® library. From Table 16, it can be observed that all three portfolios have significantly higher excess kurtosis which means that the distribution of event outcomes has lots of instances of outlier results. Additionally, the positive skewness indicates that the portfolios generate small losses and extreme gains.

A positive alpha corresponding to the list of assets with respective Index funds indicates that the performance of the portfolio outperforms the markets. From the historical data, less than ten percent of mutual funds were able to outperform the index funds over eight year period or obtain a positive Jensen's alpha (Fichtner et al., 2017; Marti-Ballester, 2019). Further, if additional charges like transaction costs, stock broker fee or fund manager fee are taken under consideration, this percentage further inflates. The portfolios based on the proposed methodology not only outperforms in terms of the measured indices but also manages risk systematically as evident from the findings.

It is evident from in Table 16 that beta is less than 1 which indicates that the volatility of all the three constructed portfolios is less than the Index funds. Further, all the three optimized portfolios delivered significant expected returns in comparison to Index funds and risk comparable to Index funds. The Jensen's Alpha is also calculated and is positive which indicated that the returns of the portfolios are way significant to benchmark or Index funds (Jarrow & Protter, 2013). Hence based on the above research methodology it can be concluded that the proposed methodology is efficient and is expected to yield higher returns to investors by controlling risk systematically. The perception based portfolios yields a positive Jensen's alpha with a negative beta which is highly useful in counteracting systematic returns.

Further, it is to be noted that the performance is also highly dependent asymmetric relationship magnitude of the markets and time horizon. Our results showed that all of the three strategies performed well and reacted in ways very much in line with the original study (Noddeboe & Faergemann, 2015).

In addition to validating the efficiency of the proposed methodology and performing comparative analysis, Markowitz based efficient frontier is plotted in the next section for better understanding of optimal returns and risk for perception based investment.

6 Markowitz efficient frontier

Markowitz efficient frontier is used to analyze the estimated returns with respect to the risk of the constructed portfolio. The estimated returns of the proposed portfolio can be evaluated by Markowitz model using Eq. 20.

$$E(RP) = \varphi^1 \mu \quad (20)$$

where $E(RP)$ is the expected returns of the portfolio obtained by the proposed methodology, φ^1 is the transpose of sectoral weightage matrix and μ represents the expected returns of individual sectors.

Similarly the portfolio variance could be derived by the Eq. 21.

$$\text{Var}(RP) = \varphi^1 . \varphi \quad (21)$$

Further, various parameters such as Variance, standard deviation, excess kurtosis, skewness, Sharpe's ratio and Beta are calculated to measure different aspects of returns and risk of the proposed portfolio by taking Index funds as base performance measure.

The efficient frontier is obtained by solving objective function Eq. 22.

$$\min S_R \leq k \quad (22)$$

Here S_R is Sharpe's Ratio for some positive constant k .

Another objective function given by Eq. 23 optimizes both expected returns and risk of portfolio.

$$\min S_R \leq \sigma_1^2 \quad (23)$$

where σ_1^2 denotes return variance of the portfolio.

The Markowitz frontiers of the I_N portfolios are shown in Figs. 6, 7, 8, 9 of each for 2013 to 2018. The scatter plot shows the portfolios in which every stock is included, the plot contains 1,00,000 different sets of weights that are randomly generated Sharpe's ratio.

In this approach each stock is given some significant weightage, thus none of them are discarded. This is a more practical approach as it reduces dependency on 1 particular stock. The red dot in each graph shows the highest Sharpe's ratio. The plotted line is another

Fig. 6 Markowitz efficient frontier (2013–2015)

Fig. 7 Markowitz efficient frontier (2015–2016)

Fig. 8 Markowitz efficient frontier (2016–2017)

Fig. 9 Markowitz efficient frontier (2017–2018)

Markowitz's frontier where there are no restrictions on how much weightage can be given to 1 particular stock. It was plotted using the minimize function provided by the optimize module of the Scipy library.

7 Conclusion

Even though several advancements to Markowitz's and Black–Litterman's portfolio theories were made, the perception of investors was neglected in most of the studies. Further, the inconsistencies in different MCDM's have confused investors to allocate a portfolio. Hence, a framework based on different fuzzy multi-criteria techniques like Fuzzy Dematel, Fuzzy AHP and Fuzzy TOPSIS is proposed in this study which can be adapted in several areas like network structures, supply chain management, research institutes feasibility, and large-scale rooftop photovoltaic. Fuzzy DEMATEL is assimilated to evaluate cost criteria, and widely used fuzzy MCDM's to rather obtain a stabilized cumulative score in a fuzzy environment. The precedence memory effect of fractional calculus is utilized in the form of fractional lion algorithm which allocates portfolios based on the perception of an investor. The portfolio allocation in six different sectors in BSE SENSEX based on nine crucial parameters namely Price to earn ratio, Return on assets, Earnings Per Share, Price on sales, Price on cash flow, Dividend yield, Price on earnings, Return on equity, and Price on book ratio were considered to obtain perception-based portfolios. Four cost criteria Return on equity, Book value per share, Price-earnings ratio, and Price to book ratio were scrutinized by using Fuzzy DEMATEL. Widely used fuzzy AHP and fuzzy TOPSIS techniques are adopted in the case study and a consistent cumulative score is obtained by the introduction of two non-dimensional numbers namely MCV and P-index. P-index determines the share that an investor can invest in each of these sectors. It has to be noted that this index is a crisp value which doesn't take the perception of investor into account. MCV evaluated for each of the sectors determines the deviation of score that changes with the multi-criteria technique. The deviation is an indirect measure of risk associated with the expectation of the investors. This can be inferred with the fact that if the variation i.e. MCV is small for a sector; it is more likely that investors can invest in the proportion of maximum share value. MCV is clustered into two groups by fractional based technique Fractional Lion Algorithm for allocating portfolios to High risk-tolerant and Low risk-tolerant. The findings of this study consider investors as choice investors with the option of investing based on their perception. This helps in the management of a portfolio based on MCV.

The proposed methodology for constructing perception based portfolio is efficient and is expected to empower investors by delivering significant profit margins by keeping risk under desired limits. Three perception based portfolio are optimized and were significantly outperformed the most prominent index funds in India for the majority of the eight year period 2013 to 2021. The data is trained for the period of 2013 to 2018 and is tested for the period 2018 to 2021. Various statistical measures were calculated and found to surpass Indian markets at various stages.

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Appendix

Fractional Lion Algorithm Pseudo-code

Input: Data points S_M, S_F, S_N

Output: Optimal centroid

Procedure

Start

Read initial points, S_M, S_F

Evaluate fitness function

Calculate Fertility

If $R^{ref} \leq f(S_M)$

$R^{ref} \leftarrow f(S_M)$

End

If $f(S_l^{F+}) \leq f(S_l^F)$

$S_l^{F+} \leftarrow S_l^F$

End

Reset L_r and S_r

Cross-over and mutation S^{new} and S^C

Gender clustering S_{M_c} and S_{F_c}

Set A_c

Generation based on fractional calculus

$S^{lion} = \alpha S_l^M + 0.5\alpha S_{l-1}^M$

Provincial defense

If S_N wins

$S_M \leftarrow S_N$

End

Territorial occupancy

If $f(S_M) \leq f(S_{M_c})$

$S_M = S_{M_c}$

else if $f(S_F) \leq f(S_{F_c})$

$S_F = S_{F_c}$

End

Clear S_r

Until then iterate

$N_f^{max} < N_f$, Optimal centroid obtained

End

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