Chapter 4 A Novel Methodology for Perception Based Portfolio Management

4.1 Introduction

The order of hierarchy and the relative dominance of six sectors obtained from two MCDM's, i.e., fuzzy AHP and fuzzy TOPSIS in Chapter 3 are different and further the perception of user is not considered. Hence, a single score for each of the alternatives is proposed in the current chapter, which makes novice investors as captive investors. Further, categorization based on perception is taken into consideration in the study that aims a sophisticated method which not only routs the limitations of previous studies but can be highly adaptable in any of the above decision-based portfolios.

This study presents a methodology that considers the perception of investors while managing the portfolio. Two non-dimensional numbers introduced as P-index and Multi-criterial volatility (MCV) are the building blocks of the methodology. P-index determines the fraction of capital be invested in a particular sector from the portfolio, whereas MCV quantifies the volatility associated with the respective sectors. Few parameters of each sector representing financial ratios are identified among the numerous existing ratios using the fuzzy DEMATEL approach. It is observed that ROE, BVPS, PE ratio, and PB ratio are the parameters which influence the choice of selecting a sector. Owing to this finding, the historical data of these parameters corresponding to various sectors that are found to be consistently outranking other sectors as per BSE SENSEX is collected. Subsequently, P-index and MCV of each sector are computed. To embed the perception of investors in deciding investing options, Fractional Lion Algorithm (FLA) is integrated with the fields of P-index and MCV and used in developing three different portfolios suitable for three different perceptions, which include Low risk-tolerant, Neutral risk-tolerant, High risk-tolerant and respectively. Further, the proposed measure also determines the proportion of investment in a different sector based on the perception of the investor.

The widely used financial criteria considered in Chapter 3, which include ROA, EPS, PS ratio, EPS, PS ratio, PCF ratio, DY, ROE, BVPS, PE ratio, and PB ratio are taken to determine perception based portfolio management. Further, the company's information is used to identify 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, BVPS, value at risk (VaR), mean-variance, compound annual growth rate (CAGR), and PE ratio (Silva *et al.* 2017; Hota *et al.* 2018; Li *et al.* 2019). Beyond stock markets, non-financial measures are considered for asset screening. It should be noted that the criteria should be selected depending upon the nature of investments.

4.2 Literature Review

In the current chapter, the six sectors considered 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 and Chaudhuri 2019).
Most of the clustering techniques in the literature adopted functions with the only single kernel which consequently raises memory complexity and simulation time. To address this complication, a multiple kernel fitness function was introduced as a Fractional Lion Algorithm (FLA), which is an advanced clustering technique (Chander *et al.* 2016; Gope *et al.* 2019). Further, this method is enhanced with the inclusion of multiple kernel functions like Inverse Multiquadratic functions and Gaussian functions, which are considered as the fitness function to increase accuracy. To measure the distance in the considered fitness function, an index by Wu and Li clustering mechanism (Li and Jeff 1997) known as multi kernel WLI (MKWLI) is adopted in the present fractional algorithm. Finally, the algorithm is designed using integration of the Lion Algorithm with a dynamic directive operative searching strategy named Adaptive Dynamic Directive Operative Fractional Lion (ADDOFL) algorithm. In the initial stages, three functions are established using a kernel function. The obtained objective function is selected as a fitness function in the initial process of the

Fractional Lion Algorithm (FLA). FLA which is based on directive operation, increases the time efficiency to choose centroid for clustering of data by around ten percent as compared to other established algorithms such as Particle Swarm clustering (Chander *et al.* 2018).

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 and Udupi 2017). FLA is widely applied in the fields which include 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 the ease of locating optimal centroids, assigning weights, and smooth upgradation of centroids for division of clusters, etc. (Chander *et al.* 2016; Chander *et al.* 2018; Yadav 2018; Mateen *et al.* 2019).

The two considered multi-criteria techniques 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. One of the recent applications of fractional calculus onto the optimization algorithm is FLA. FLA is an advanced technique obtained by generalizing the lion clustering algorithm. This fractional clustering technique helps to classify homogenous data without prior knowledge. The clustering techniques are just the relative abstraction of objects contained in a set. This technique is useful in many fields, such as data mining. The methodology introduced in the current chapter is used for perception based management, which adopts FLA for effective clustering of portfolios depending upon the perception of the user. FLA, which is a population-based optimization technique, uses the method of survival of the fittest (SF). Only a 1-D search is used in the methodology and mutation is utilized to intensify the contingency speed along with modern crossover strategy. Impulsive convergence can be avoided by the inclusion of a crossover strategy. Further, the theory of FLA is solicited post mutation to stabilitate selection of centroid. The stabilization is carried out by the solution produced by iterating itself helps for smooth access to search centroids. The estimations of clusters centroid are time-efficient due to a greater number of considered solutions obtained by crossover, mutation and FLA. Estimation through adaptive centroid data sets in bulk had motivated to develop FLA.

The selection of the portfolio helps to accelerate in achieving sustainable goals, as suggested by Torres-Ruiz & Ravindran (2018) where potential risks in different segments in supply chain management are quantified. The risk management and suppliers' risk were integrated by the proposed framework to enhance traceability. Another threat to sustainable development goals is pollution caused by hazardous substances. An et al. (2015) designed a portfolio to attenuate pollution incurred by dangerous materials by the combination of AHP and VIKOR techniques. A case study in a region of China was considered to implement the developed strategy to take preventive measures for a sustainable environment.

The portfolio selection becomes indispensable in distributed energy, especially to manage resources that are scarce. Hence, a fuzzy 2-type AHP is incorporated in the study to optimize a portfolio to achieve strategic objectives of energy enterprises by considering the uncertain environment under various enterprise scenarios (Wu *et al.* 2019). Besides the use in distributed energy, the energy portfolio gained the utmost importance in the renewable energy sector for any country, predominantly among G20 countries, to achieve sustainable growth. Along with commonly used ANP-DEMATEL technique, Çelikbilek & Tüysüz, (2016) combined multi-criteria optimization and compromise solution technique to access renewable energy sources. Kijewska et al. (2018) had utilized both AHP and DEMATEL methods in the region of Szczecin to form a strategic portfolio for goods distribution in freight transportation.

Although different MCDM techniques had been combined, finally, a representative score for each of the alternatives is evaluated. 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, only the quantitative views obtained by the method of Verbal Decision Analysis are considered, which are restricted to few criteria (Silva *et al.* 2017). Most of the studies have 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.

4.3 Motivation

The discussed limitations motivate to construct a methodology that addresses most of the drawbacks in the previous models. Hence, a framework is proposed based on adaptive centroid estimation in the field of finance and portfolio optimization. The current section discusses the problem definition and the challenges faced by various clustering data techniques along with the detailed stepwise elaboration of FLA.

4.3.1 Problem Definition

Let 'S' be the input data of the attribute, i.e., multi criterial volatility (MCV) in BSE SENSEX set with six numbers of sectors. 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 Figure 4.1, are presented. However, it must be noted that the proposed methodology can be extended for portfolio management in other fields. Then our objective is to cluster these six sectors into two clusters represented by set 'K' using FLA. The centroid identification must be validated with the fitness function for locating optimal centroid for clustering.

4.3.2 Challenges

Locating centroids for optimal clustering is one of the major tasks in any clustering analysis. Hence analyzing any clustering problem can be interpreted as an optimization technique. The problem can be intuited to cluster High risk-tolerant and Low risk-tolerant from the proposed attribute 'MCV,' which is given as data input of sectors 'S' and the set of these centroids is represented by the set 'K.' Here 'S' represents the set of six considered sectors $S = \{S_1, S_2, S_3, S_4, S_5, S_6\}$ as discussed in Chapter 3.

Let 'I' be input data set with 'o' number of objects. Further, let the number of attributes in each data object be 'a.' Then our objective is to cluster these data objects into 'c' number of clusters represented by set 'K' using FLA. The centroid identification must be validated with the fitness function for locating optimal centroid for clustering.

(Yuwono *et al.* 2014) solved the clustering problem with Particle Swarm Clustering (PSC). Updating the location of the centroid is the basis for formulating PSC. Subsequently, each centroid is located by aggregating the squared distance. The following point discusses the major complexities in analyzing PSC's.

1. This clustering analysis is associated with a high risk of local convergence of solution obtained after applying PSC.
2. Due to huge data distribution or high-dimensionality, the updation of a particle may be complicated which is used to initiate clusters centroids.
3. This clustering prefers to locate global optimal centroids rather than initialization.
4. The improvements in centroids quality are not recognized in the termination stage of PSC, hence making the strategy of convergence complex.
5. Even though many Advanced objective functions were introduced in the literature (Yuwono *et al.* 2014), PSC still uses an aggregate of squared distance as its objective function, hence making the effectiveness stagnated.

Hence a strategic methodology is constructed which overcomes these challenges and is discussed in subsequent sections.

4.4 Methodology

The study proposes a sophisticated method which not only routs the limitations 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 Figure 4.1.

In the initial phase of analysis, the nature of each considered criterion is determined, which helps to distinguish the criteria into two classes, namely 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 widely used fuzzy MCDMs in the field of portfolio management. Further, the current study introduces two non-dimensional measures P-index and MCV 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-maker's 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. The decisions are to be categorized depending on various personal views by using advanced clustering algorithms. Hence, FLA is employed for easy finding of cluster centroid and inclusion of memory property, which will be discussed in subsequent sections.

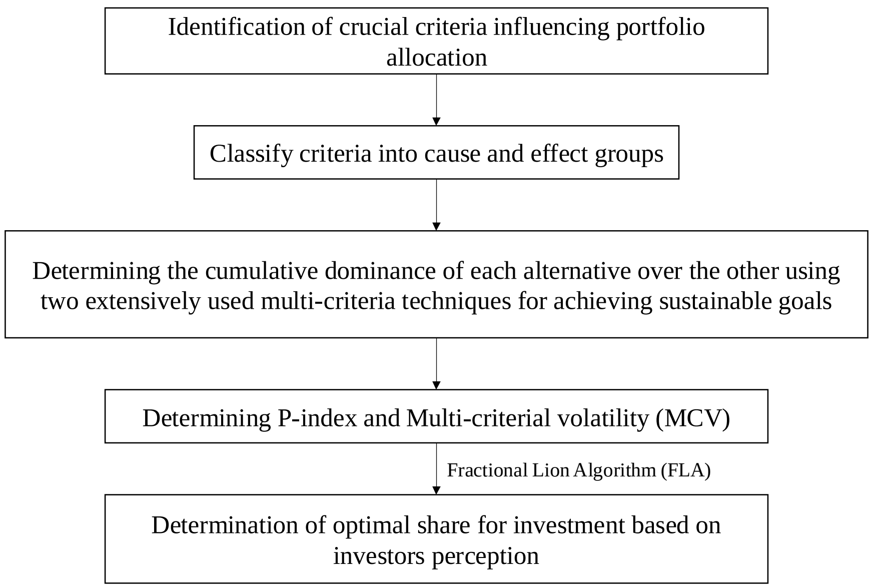

Figure 4.1. Schematic illustration of the proposed framework

4.4.1 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 P-index is defined by taking the mean of cumulative score obtained from two extensively used fuzzy MCDM's for perception based portfolio management. The mathematical representation of P-index of i^{th} alternative in a considered field is shown in (4.1)

$$PI_i = \frac{fmcdm_{1,i} + fmcdm_{2,i}}{2} \tag{4.1}$$

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 fuzzy MCDM’s.

4.4.2 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 (4.2).

$$MCV_i = 200\left|\frac{fmcdm_{1,i} - fmcdm_{2,i}}{fmcdm_{1,i} + fmcdm_{2,i} - \left|fmcdm_{1,i} - fmcdm_{2,i}\right|}\right| \tag{4.2}$$

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. FLA 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. (4.2) 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.

4.5 Fractional Lion Algorithm for Rapid Centroid Estimation

A detailed discussion of the FLA is presented in this section. The flowchart of FLA can be depicted from Figure 4.2 based on the type of data input (attribute or object), the selection of data is processed. 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 (4.4).

$$S_M = [i_1^M, i_2^M, \dots, i_L^M]$$
$$S_F = [i_1^F, i_2^F, \dots, i_L^F] \quad (4.4)$$

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.

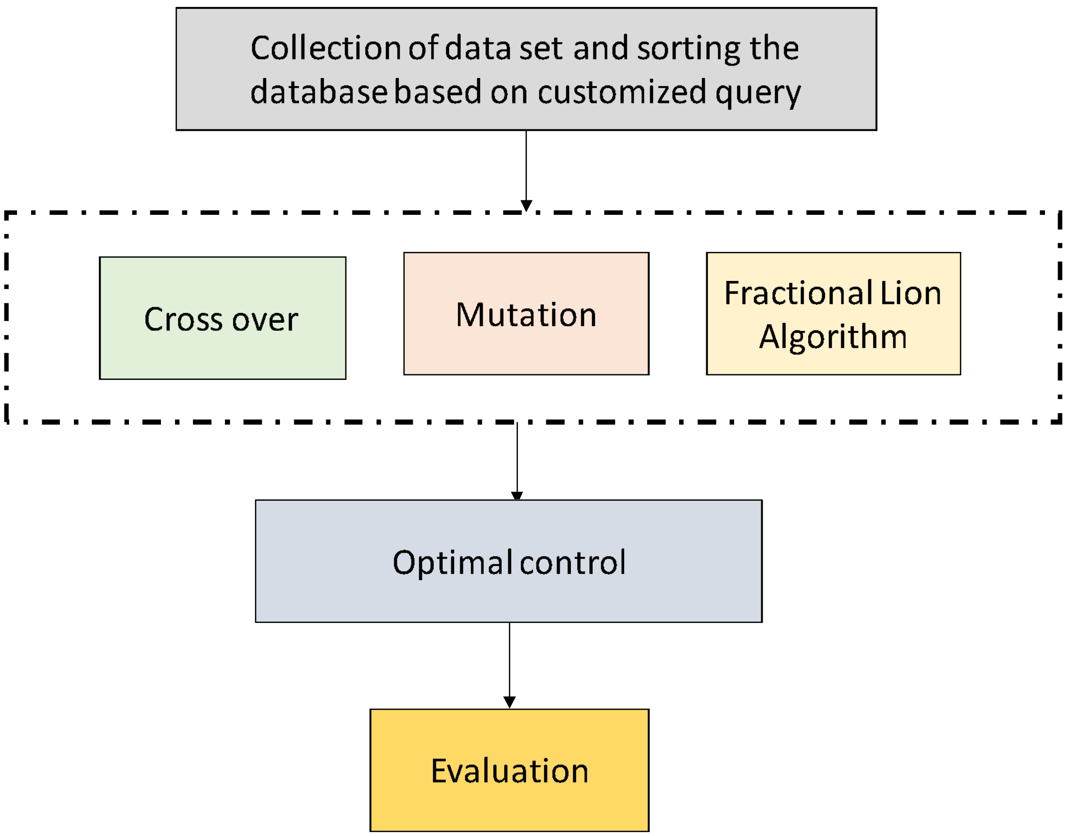

Figure 4.2. Block diagram of proposed FLA algorithm

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 (4.5)

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

$$S_k^{F+} = \min[i_k^{max}, max(i_k^{min}, \nabla_k]] \tag{4.5}$$

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

l and k are solution vectors L which are randomly generated integers in the interval [0,L]. ∇_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

$$S^C(R) = B_R{\circ}S_M + \overline{B_R}{\circ}S_F\ ; R = 1,2,3,4 \tag{4.6}$$

here S^C is the cub generated after cross-over evaluated by (4.6), R denotes the length of cross-over and ° is Hadamord's product.

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 (4.7)

$$f(S_{l+1}^M) = f(S_l^M) \tag{4.7}$$

For negligible change in optimal solution, we obtain (4.8)

$$S_{l+1}^{M} = S_{l}^{M} \tag{4.8}$$

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 (4.9)

$$D^{\alpha}(S_{l+1}^{M}) = S_{l+1}^{M} - \alpha S_{l}^{M} - 0.5\alpha S_{l-1}^{M}$$

$$S_{l+1}^{M} - \alpha S_{l}^{M} - 0.5\alpha S_{l-1}^{M} = 0$$

Then, $S^{lion} = \alpha S_{l}^{M} + 0.5\alpha S_{l-1}^{M}$ (4.9)

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 (4.10)

$$E_2^N = \exp\left(\frac{d_2}{max(d_2, d_1)}\right)\frac{max\left(f(S_1^N), f(S_2^N)\right)}{f(S_2^N)} \tag{4.10}$$

where $d_1$and d_2 are Euclidean distances between S_1^N, S^M and SI_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 II.

4.6 Identification of Multi-criteria Techniques for Equity Based Portfolio

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, 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 Saaty crisp scale 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 Indian stock exchange, namely BSE SENSEX, is considered in the present study due to its high informativeness and market capitalization. The cumulative scores and ranks of fuzzy AHP can be inferred from the previous chapter in Table 3.29. 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 3.35.

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.

4.7 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 4.1.

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).

Table 4.1: P-Index and MCV of the sectors

	Automobiles	Banking	IT	Oil	Pharmaceutical	Power
P-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

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 a higher range, which is evident from Table 4.2. 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.

Table 4.2: 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

4.8 Summary and Conclusions

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 FLA, 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 ROA, EPS, PS ratio, EPS, PS ratio, PCF ratio, DY, ROE, BVPS, PE ratio, and PB ratio was considered to obtain perception-based portfolios. Four cost criteria ROE, BVPS, PE ratio, and PB 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 FLA 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.