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Enhancement of the Portfolio Determination using Multi-Objective Optimization

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Abstract— *Portfolio construction is enabled through the multi objective optimization. The nature of the problem invites the construction through multi objective optimization. Genetic algorithm and the particle swarm optimization is used for the above purpose. The results obtained are compared against the classical Markowitz model. The data from the Nifty from March 2010 to October 2010 has been used. The Stocks from various sectors are used to build the portfolio. The proposed work is promising and the results obtained are outperforming. Comparing on both the algorithms PSO based multi objective optimization serves better than Genetic algorithms based on the results obtained.*

Keywords— Portfolio Optimization; MOPSO; MOGA.

I. INTRODUCTION

Optimization methods have a long history in many financial domains, because optimization models play an increasingly important role in financial decisions [1][42]. The classical approach to portfolio selection reduces the problem of two criteria optimization to a one criterion optimization where the second criterion is converted into a constraint. Reduction of a multi-criteria problem to one criterion problem not always is the best method to solve multi-criteria problems, especially in the case when number of criteria is larger than two.

This paper discusses about the application of multi objective optimization for the construction of the portfolio. The main objectives to be optimized are the risk and the return. Any investor who is investing his wealth considers about the above said constraints. They want to increase their wealth at the same time want to be in the secured status. So typically the problem of construction of portfolio is multi objective in nature.

The multi objective optimization is carried out through two evolutionary approaches. The evolutionary algorithms are adopted to have more teeth in the problem of portfolio management. The evolutionary algorithms are basically highly suitable for the multi objective optimization.

The two algorithms namely genetic algorithm and the particle swarm optimization is used for the multi objective approach. These two algorithms are chosen because of their popularity in solving the multi objective problems. This is discussed in depth in section 2. Section 3 talks about the problem formulation and the section 4 talks about the proposed methodology. Section 5 is about the proposed algorithm. Section 6 deals with the data description where the data used for the experiments are known. Section 7 gives the experiment environment. Section 8 shows the results obtained.

II. RELATED WORKS

This section deals with the related works of the proposed methodology. The multi objective optimization algorithm is used as the back bone of the method. It is tested with the genetic algorithm and the particle swarm optimization to improve its effectiveness. Here we talk about the multi objective optimization theory in detail in 2.1 and evolutionary multi objective optimization in 2.2. The basic working model of the MOGA is discussed in section 2.3, theory of MOPSO is discussed in detail in 2.4.

A. *Multi objective optimization*

A single objective problem could be mathematically defined as the minimization or maximization of a particular function with respect to the variable. It could be stated as follows

$$\min / \max F(x),$$

where $x \in C$,

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C is the set of values of the variable.

The single objective problem concentrates on a single constraint with the various values. But in the real world, problems need to address the optimization of more than one variable. The objective could be also contradicting. In order to solve such kind of problems one tends to move to multi objective optimization. It could be mathematically defined as the minimization or maximization of more than one function with respect to more than one variable. It could be stated as follows

$$\min / \max \{ F_1(x_1), F_2(X_2)\ldots, F_n (X_n)\}$$

Where X_1, X_2.. are the variables to be mapped to the functions f_1, f_2..

There are various approaches to solve the multi objective problem; some of them are discussed below.

a) Weighted sum method

By combining multiple objectives into the one single objective scalar function, the multi objective problem could be solved as a single objective function. This approach is in general known as the weighted-sum method. It is introduced by Zadeh in the literature first [1]. The focus is on the application, and the problems tend to be limited to those with just two objective functions. For instance, as development for a new approach, Koski and Silvennoinen [2] provide an early application and use the weighted sum method to obtain multiple Pareto optimal solutions with a systematic change in the weights, while minimizing the volume and the nodal displacement of a four-bar space truss [3]. Marler and Arora [4] study a three-objective problem, but they use the weighted sum method as a platform for studying various function-transformation methods and their affect on the depiction of the Pareto optimal set. Although the weighted sum method is easy to use, it provides only a linear approximation of the preference function. Thus, the solution may not preserve one's initial preferences no matter how the weights are set, a crucial idea that is often overlooked. The solution depends on multiple factors, one of which is the relative magnitude of the objective functions. However, when setting the weights, only the relative importance of the objectives should be considered, not the relative magnitudes of the function values [3].

b) No preference Methods

Multi-objective optimization methods that do not require any preference information to be explicitly articulated by a decision maker can be classified as no-preference methods [5]. A well-known example is the method of global criterion [6].

c) A priori methods

A priori methods require that sufficient preference information is expressed before the solution process [5]. Well-known examples of a priori methods include the utility function method, lexicographic method, and goal programming. The lexicographic method consists of solving a sequence of single-objective optimization problem. Lexicographic method assumes that the objectives can be ranked in the order of importance.

d) A posteriori methods

A posteriori methods aim at producing all the Pareto optimal solutions or a representative subset of the Pareto optimal solutions. Most a posteriori methods fall into either one of the following two classes: mathematical programming -based a posteriori methods, where an algorithm is repeated and each run of the algorithm produces one Pareto optimal solution, and evolutionary algorithms where one run of the algorithm produces a set of Pareto optimal solutions [7].

Well-known examples of mathematical programming -based a posteriori methods are the Normal Boundary Intersection (NBI) [8], Modified Normal Boundary Intersection (NBIm) [9], Normal Constraint (NC) [10-11], Successive Pareto Optimization (SPO)[12] and Directed Search Domain (DSD)[13] methods that solve the multi-objective optimization problem by constructing several scalarizations. The solution to each scalarization yields a Pareto optimal solution, whether locally or globally. The scalarizations of the NBI, NBIm, NC and DSD methods are constructed with the target of obtaining evenly distributed Pareto points that give a good evenly distributed approximation of the real set of Pareto points.

e) Interactive methods

In interactive methods, the solution process is iterative and the decision maker continuously interacts with the method when searching for the most preferred solution [14]. Different interactive methods involve different types of preference information. For example, three types can be identified: methods based on [14]

1) trade-off information,

2) reference points and

3) classification of objective functions.

On the other hand, a fourth type of generating a small sample of solutions is included in[15] and [16].

B. Evolutionary multi objective optimization

Solving optimization problems with multiple (often conflicting) objectives is, generally, a very difficult goal. Evolutionary algorithms (EAs) were initially extended and applied during the mid-eighties in an attempt to stochastically solve problems of this generic class. During the past decade, a variety of multi objective EA (MOEA) techniques have been proposed and applied to many scientific and engineering applications [17].

Evolution is in essence a two-step process of random variation and selection [18]. Evolutionary algorithms seem particularly suitable to solve multi objective optimization problems, because they deal simultaneously with a set of possible solutions (the so-called population). This allows us to find several members of the Pareto optimal set in a single run of the algorithm, instead of having to perform a series of separate runs as in the case of the traditional mathematical programming techniques. Additionally, evolutionary algorithms are less susceptible to the shape or continuity of the Pareto front (e.g., they can easily deal with discontinuous or concave Pareto fronts), whereas these two issues are a real concern for mathematical programming techniques [19].

One of the most striking differences to classical search and optimization algorithms is that EAs use a population of solutions in each iteration, instead of a single solution [20]. Multiple individuals can search for multiple solutions in parallel, eventually taking advantage of any similarities available in the family of possible solutions to the problem. The ability to handle complex problems, involving features such as discontinuities, multimodality, disjoint feasible spaces and noisy functions evaluations, reinforces the potential effectiveness of EAs in multi objective search and optimization, which is perhaps a problem area where evolutionary computation really distinguishes itself from its competitors [21].

C. Multi objective Genetic Algorithm

Being a population based approach, Genetic algorithms (GA) are well suited to solve multi-objective optimization problems. A generic single-objective GA can be easily modified to find a set of multiple non-dominated solutions in a single run. The ability of GA to simultaneously search different regions of a solution space makes it possible to find a diverse set of solutions for difficult problems with non-convex, discontinuous, and multi-modal solutions spaces. The crossover operator of GA may exploit structures of good solutions with respect to different objectives to create new non-dominated solutions in unexplored parts of the Pareto front. In addition, most multi-objective GA do not require the user to prioritize, scale, or weight objectives. Therefore, GA has been the most popular heuristic approach to multi-objective design and optimization problems. Jones et al. [22] reported that 90% of the approaches to multi- objective optimization aimed to approximate the true Pareto front for the underlying problem. A majority of these used a meta-heuristic technique, and 70% of all meta-heuristics approaches were based on evolutionary approaches [23].

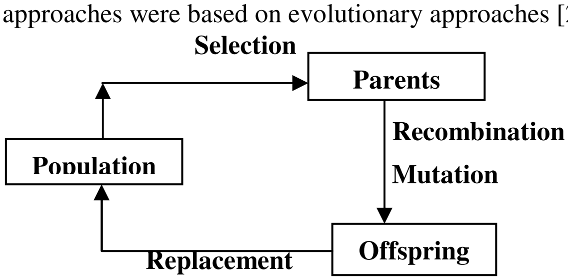

Fig. 1 General Evolutionary Cycle for GA

The first multi-objective GA, called Vector Evaluated Genetic Algorithms (or VEGA), was proposed by Schaffer [24]. Afterward, several major multi-objective evolutionary algorithms were developed such as Multi-objective Genetic Algorithm (MOGA)[25], Niched Pareto Genetic Algorithm [26], Random Weighted Genetic Algorithm (RWGA)[27], Nondominated Sorting Genetic Algorithm (NSGA) [28b], Strength Pareto Evolutionary Algorithm (SPEA) [29], Pareto-Archived Evolution Strategy (PAES) [30], Fast Non-dominated Sorting Genetic Algorithm (NSGA-II) [31], Multi-objective Evolutionary Algorithm (MEA) [32], Rank-Density Based Genetic Algorithm (RDGA) [33].

D. Multi Objective Particle Swarm Optimization

PSO is generally based on the social behavior metaphor of organisms. This is having the assumption that the organisms move synchronously and does not collide. PSO seems particularly suitable for multi objective optimization mainly because of the high speed of convergence that the algorithm presents for single-objective optimization [34]. An interesting aspect of PSO is that it allows individuals to benefit from their past experiences [35].

When solving single-objective optimization problems, the leader that each particle uses to update its position is completely determined once a neighborhood topology is established. However, in the case of multi-objective optimization problems, each particle might have a set of different leaders from which just one can be selected in order to update its position. Such set of leaders is usually stored in a different place from the swarm, that we will call external archive. This is a repository in which the non dominated solutions found so far are stored. The solutions contained in the external archive are used as leaders when the positions of the particles of the swarm have to be updated. Furthermore, the contents of the external archive are also usually reported as the final output of the algorithm [36]. PSO is suited to multi objective because they search for multiple pareto optimal solutions in a single run.

The fact that particles work with stochastic operators and several potential solutions, provides PSO the ability to escape from local optima and to maintain a population with diversity. Moreover, the ability to work with a population of solutions, introduces a global horizon and a wider search variety, making possible a more comprehensive assessment of the search space in each iteration. These characteristics ensure a high ability to find the global optimum in problems that have multiple local optima [37].

The objective is to find not one “global best" solution, but a set of solutions comprising the Pareto Front. To do this, an archive of non-dominated solutions is kept, where all non-dominated solutions found at each iteration are stored. The MOPSO algorithm steps are [38]:

1. Initialize the swarm & archive
2. For each particle in the swarm:
(a) Select leader from the archive
(b) Update velocity
(c) Update position
3. Update the archive of non-dominated solutions
4. Repeat

III. PROBLEM FORMULATION

The portfolio optimization aims to find an optimal set of assets to invest on, as well as the optimal investment for each asset. This optimal selection and weighting of assets is a multi-objective problem where total profit of investment has to be maximized and total risk is to be minimized [39]. Optimization based on even the widely used Markowitz Two Objective Mean-Variance approach becomes computationally challenging for real-life portfolios. Practical portfolio design introduces further complexity as it requires the optimization of multiple return and risk measures subject to a variety of risk and regulatory constraints. Further, some of these measures may be nonlinear and non convex, presenting a daunting challenge to conventional optimization approaches [40]. Mean - variance model cannot satisfy investors' request for different investment preference and risk diversification [41].

In order to obtain the multi objective optimization the problem is to be formulated in such a way that the portfolio is build. These are for building the portfolio to maximize the returns and minimize the risk. This two objectives must be met and an optimal portfolio subject to and meeting both constraints to be built.

IV. PROPOSED METHODOLOGY

The above problem could be encountered in two stages. The first stage concentrates on the diversification of the portfolio thus reducing the risk. The second stage is creation of the efficient portfolio. The proposed methodology could be depicted with the following frame work.

Stage 1: In this stage the stock data to be considered is taken. The data is applied with the PSO algorithm to determine the centroid for the forth coming clustering algorithm. This is the scrutinizing step where the following clustering algorithm will be seeded with the initial centroid. The clustering algorithm here adopted is the K means algorithm, which is a partitioning based clustering algorithm. This PSO adopted clustering algorithm is used to find the Clusters in the initial stock data provided.

The clustering process aims for least diversity within a group and find most difference among groups is to be reached. The K means algorithm is used for the clustering purpose since the K means clustering algorithm offers a good compactness compared to other clustering techniques such as Self Organizing Maps and Fuzzy K means [l]. But the K means algorithm suffer from the problem of fixing the initial centroid. In order to rectify this limitation, this paper uses the PSO to fix the centroids.

The ability of globalized searching of the PSO algorithm and the fast convergence of the K-means algorithm are combined. The PSO algorithm is used at the initial stage to help discovering the vicinity of the optimal solution by a global search. The result from PSO is used as the initial seed of the K-means algorithm.

Stage 2(a): In this stage the portfolio building is done by the multi objective optimization through the genetic algorithm approach. Here the two objectives, maximization of the returns and the minimization of the risk is being considered. NSGA II is used for the multi objectiveness. The pareto front is build and the crowding distance is sorted and the multi objective criteria is obtained.

Stage 2(b): After the stage 1 , the construction of the portfolio is being done by the multi objective theory using the PSO. The merits of the PSO approach is discussed in section 2 and the reasons to use this approach is concrete. The solutions in multi-objective optimization problems intend to achieve a compromise between different criteria, enabling the existence of several optimal solutions. After the swarm initialization, several loops are performed in order to increase the quality of both the population and the archive. The results of both the approaches are discussed in section 8.

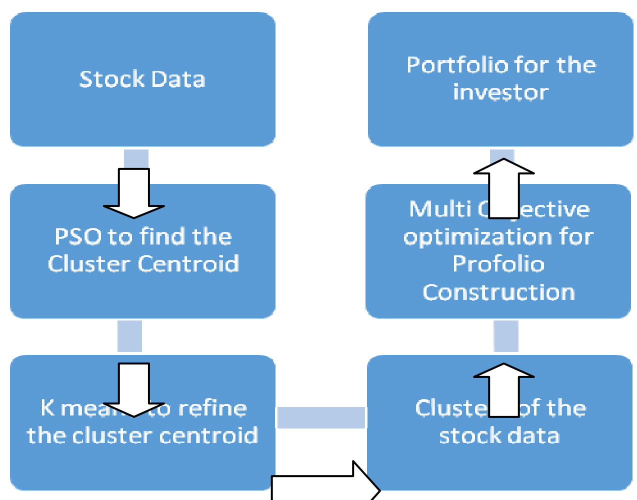

Fig. 2 Frame work of the proposed work

V. PROPOSED ALGORITHM

The proposed algorithm for the efficient portfolio determination is presented as in the pseudo code format.

Stage 1(a) /* PSO to fix the initial seed of the K-means algorithm */

INPUT: Stock data
BEGIN
Each particle randomly chooses k numbers of vectors from the stock data as the cluster centroid vectors.
FOR EACH
Compute pBest and the gBest
Calculate particle velocity
Update particle position
END FOR
Repeat until maximum iterations or a minimum error criterion is not attained.
END
OUTPUT : K Centroids

Stage 1(b) /* PSO Adopted K-means algorithm */
INPUT: Stock data, Initial centroids by PSO
BEGIN
Make initial partition of objects into K clusters by assigning objects to closest K centroids given by PSO
Calculate the centroid(mean)of each of the K clusters.
i)For object i, Calculate its distance to each of the centroids.
ii) Allocate object i to cluster with closest centroid.
iii) If object was reallocated, recalculate centroids based on new clusters.
Repeat Until for object i= 1 to N
Repeat until no reallocations occur
END
OUTPUT: Clusters from Stock data

Stage 2 (a): /* determination of efficient portfolio through MOGA */
INPUT : Clusters from Stock data
BEGIN
FOR each Cluster
//Apply the NSGA II for the twin objectives maximization of returns and minimization of risk
Population Initialization with the budget allocation as the weights associated
For each iteration
Non dominated sort for the classification of population into different fronts
Crowding distance assignment is done
Selection of new individuals for crossover and mutation
Crossover for the offsprings
Mutation for the offsprings
Recombination and selection
Repeat for maximum number of generations
END
Construct the portfolio
OUTPUT: Portfolio with the stocks and the weights associated.

Stage 2 (b): /* determination of efficient portfolio through MOPSO */
INPUT : Clusters from Stock data
BEGIN
FOR each Cluster
//Apply the MOPSO for the twin objectives Maximization of returns and minimization of risk
Initialization of the velocity and position of all particles
For each iteration
Velocity updation
Position updation
Memory updation
Repeat for maximum number of generations
END
Construct the portfolio
OUTPUT: Portfolio with the stocks and the weights associated.

VI. DATA DESCRIPTION

The data employed for the proposed approach is the historical data that has been collected between the period of March 2010 to October 2010. The stocks from various sectors are collected to create a diversified portfolio. The various sector indices like financial, Healthcare, Basic materials, Automobiles were collected for the experiment purpose from the National Stock exchange.

VII. EXPERIMENTAL DETAILS

The data collected were used for the clustering process using the PSO adopted K means clustering is applied for the data. This clustering process is used to segregate the stocks based on the unsupervised learning. The efficient portfolio has been built based on the clusters formed in the stage 1 and in the stage 2, multi objective evolutionary algorithms are used for building the portfolio. The stage 2 is using both the multi objective genetic algorithm and multi objective PSO for portfolio construction. Both the results are tabulated in the next section.

VIII. RESULTS AND DISCUSSIONS

Portfolio by Markowitz		**Portfolio by MOPSO**		**Portfolio by MOGA**	
Companies	Weights	Companies	Weights	Companies	Weights
SBI	0.32	Infosys	0.64	Infosys	0.59
Infosys	0.53	Bharti	0.15	SBI	0.2

Reliance	0.08	SBI	0.13	Reliance	0.13
Ranboxy	0.03	Reliance	0.06	Ranboxy	0.06
Tata steel	0.04	Herohonda	0.02	Bharti	0.02

Table 1: Weights of stock taken for the portfolio by both the methods

	Mar-10	Apr-10	May-10	Jun-10	Jul-10	Aug-10	Sep-10	Oct-10
Monthly returns from Nifty	6.6	0.6	-3.6	4.4	1	0.6	11.6	-0.2
Returns from Markowitz	6.261	2.4579	1.0132	3.5932	5.0026	3.072	7.899	2.72
Returns from MOGA based selection	7.139	3.5245	2.3106	3.404	2.863	4.7035	12.8766	2.813
Returns from MOPSO based selection	8.051	3.805	2.7362	3.4841	3.261	4.4735	15.183	3.29

Table 2: Returns from the portfolio created

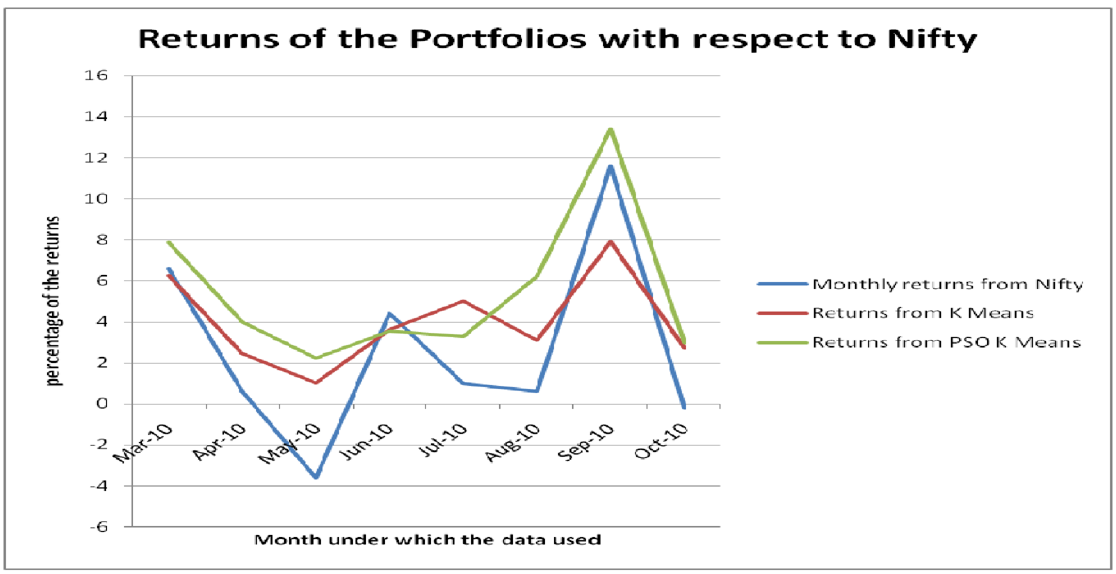

Fig. 3 Comparison based on returns of the portfolios with respect to the Nifty

	Mar-10	Apr-10	May-10	Jun-10	Jul-10	Aug-10	Sep-10	Oct-10
improvement in the MOGA based selection over Markowitz	14.02332	43.39477	128.0497	-5.2655	-42.7698	53.10872	63.01557	3.419118
improvement in the MOPSO based selection over Markowitz	28.58968	54.80695	170.0553	-3.03629	-34.8139	45.62174	92.2142	20.95588

Table 3: Improvement of MOGA and MOPSO over Markowitz based portfolio construction

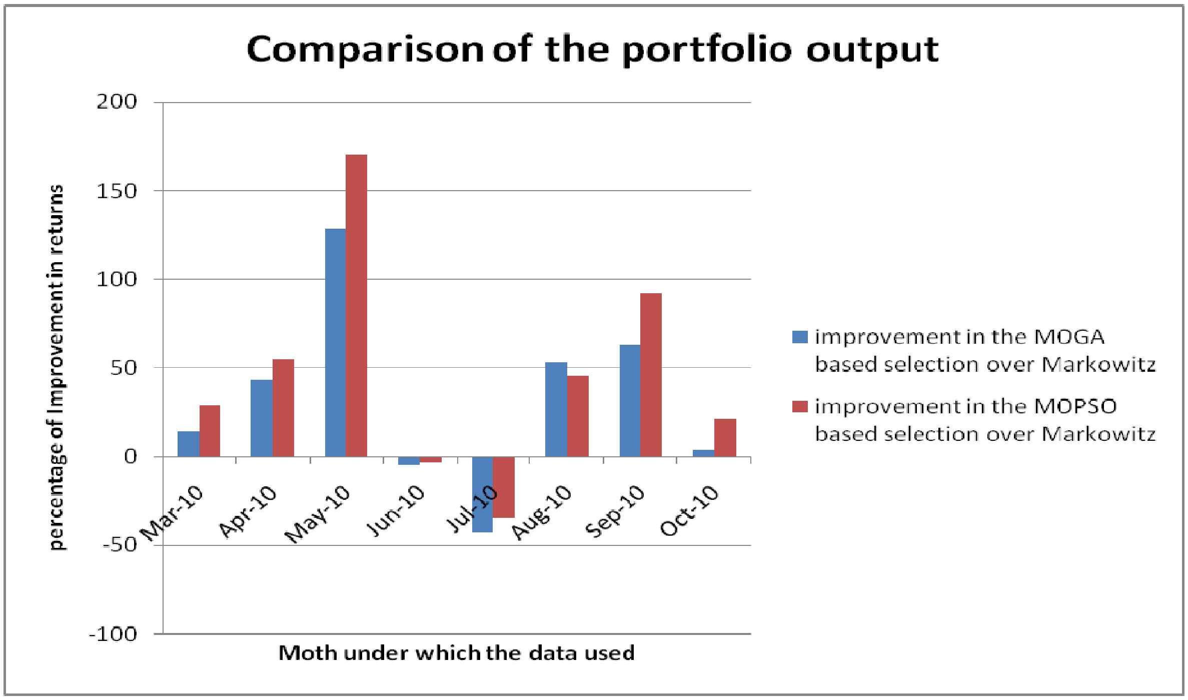

Fig. 4 Comparison of the percentage of returns improvement of MOGA and MOPSO over Markowitz model

	Mar-10	Apr-10	May-10	Jun-10	Jul-10	Aug-10	Sep-10	Oct-10
Difference between MOPSO and MOGA	14.56636	11.41218	42.00553	2.229211	7.955863	-7.48698	29.19863	17.53676

Table 4: Improvement of MOPSO over MOGA

Portfolio construction is enabled through multi objective optimization. The nature of the problem invites the construction through multi objective optimization. Genetic algorithm and the particle swarm optimization is used for the above purpose. The results obtained are compared against the classical Markowitz model. The data from the Nifty from March 2010 to October 2010 has been used. The Stocks from various sectors are used to build the portfolio. The proposed work is promising and the results obtained are outperforming. Comparing on both the algorithms PSO based multi objective optimization serves better than Genetic algorithms based on the results obtained.

IX. CONCLUSION

A novel model for the portfolio creation through the PSO adopted K Means algorithm along with the Multi objective optimization demonstrated. The need for the multi objective optimization is clearly stated and the results also ensure the novel approach adopted. The returns are slightly promoted by the proposed approach. This shows the need of improvement in the stage 2 of the algorithm discussed. The future work concentrates on the improvement of the portfolio creation method, which could be an alternate to the Markowitz model, but the modern portfolio theory cannot be totally denied. The problem could be adopted with the other methods for fine tuning the clustering process through methods like association learning. The semi supervised clustering approach could bring soundness to the existing systems.

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