Portfolio Optimization Using Multi-objective Evolutionary Algorithm

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Abstract: Optimization plays a critical position in lots of regions of technological know-how, management, economics, and engineering. Many techniques in arithmetic and operation research are to be had to resolve such problems. However, those techniques have many shortcomings to offer a fast and correct solution, especially whilst the optimization problem involves many variables and constraints. Funding portfolio optimization is one such crucial but a complicated problem in computational finance which wishes effective and efficient answers. On this hassle, every to be had asset is judiciously selected in this type of way that the entire profit is maximized at the same time as concurrently minimizing the risk, This thesis has proposed and suitably applied three MOEAs for solving the multi-objective optimization problem, The performance of these algorithms has been evaluated and compared between NSGA II, MOEA/D and , MOEA/DD, considering average, variance and, standard deviation, performance of all algorithms, it is observed that, the proposed MOEA/DD provide better pareto solution.

Index Terms—Data Mining, portfolio, stock selection, multi-objective evolutionary algorithm.

I. INTRODUCTION

In the last few year ago, portfolio optimization has emergent as a challenging and interesting multi objective problem, in the field of computational finance. It is still receiving the increasing thought of researchers, fund management companies and individual investors. Selecting of a subset of assets and its corresponding best weights of each selected assets, are key issues in portfolio selection. The composition of each asset is to be selected in such a way Achieving high returns while limiting the risk to minimum.

A Portfolio optimization is the biggest problem in the world, it is a very challenging assignment for an investor, manager, and researcher, in 1952 Harry Markowitz built mean-variance approach, mean- variance has been published portfolio optimization, and portfolio performance, Markowitz do ready a structure, in this structure select the percentage in such a way of every existing asset that the profit of return is maximum and risk minimum simultaneously. the design portfolio of assets that give up minimum risk for a given stage of return from the competent border, Markowitz portfolio assets selection problem for the optimum results which is classified a quadratic programming model, can be solved through exact techniques, interior point techniques etc.

The portfolio threat is the variance of the joint everyday distribution of the linear aggregate of the participation and prediction errors of the shares in a portfolio. Portfolio optimization refers to the choice of assets and their most advantageous weighting, with the intention to maximize the portfolio return while minimizing the total danger concurrently. Subsequently, the portfolio asset selection problem is essentially a multi-goal hassle. In recent years, many researchers have implemented multi-goal evolutionary algorithms (MOEAs) including Non-dominated sorting genetic algorithm (NSGA II), the Multi-objective evolutionary algorithm based on decomposition (MOEA/D) and, Multi-objective evolutionary algorithm based on dominance and decomposition and so on. To solve this problem.

The main blessings of the MOEAs over single objective evolutionary algorithms (SOEAs) to be able to remedy the multi-objective problem is that it offers a set of probably answers in a single run, referred to as a Pareto premiere solution, in a reasonable quantity of time. The Portfolio optimization trouble with many practical constraints that a resolved the use of MOEAs is suggested in [13].

II. MULTI-OBJECTIVE OPTIMIZATION PROBLEM

Optimization refers to finding the first-class possible approach to a trouble given a fixed of limitations or constraints . Multi-Objective optimization problems (MOPs) contain a couple of overall performance standards or objectives which want to be optimized concurrently [7].

A popular multi-Objective optimization hassle (MOP) may be officially defined as follows:

$$\left.\begin{aligned} &\textit{Maximize/Minimize} \quad F(X) = [f1(X), f2(X), \ldots\ldots\ldots, fj(X)] \\ &\textit{Subject to} \quad b_i(X) \geq 0, \quad i = 1,2,\ldots\ldots\ldots, I, \\ &\qquad h_e(X) = 0, \quad e = 1,2,\ldots\ldots\ldots, E, \\ &\qquad X \in \Omega \quad J \geq 2, \end{aligned}\right\} \qquad (1.7.1.1)$$

Wherein Ω is a decision area and X is a vector of D selection variables: $X = [x1; x2;.....; xD]$; J is the range of targets; I is the variety of inequality constraints; and E is the range of equality constraints. The vector of decision variables X can be either non-stop or discrete. If X is a discrete (and finite) set of solutions, then the hassle described in Eq. (1.7.1.1) is called a multi-objective combinatorial optimization problem. $F(X)$ consists of J objective features $fj : \Omega \quad \Re$, a mapping from choice variables [x1; x2;.....; xD] to objective vectors $[y = a1; a2;..... ..; aJ$], wherein $\Re$ is the objective space [8,9].

There are J objective features considered in Eq. (3.1) and every objective feature may be both minimized or maximized. Within the context of optimization, the duality precept [10] suggests that a maximization problem can be converted into a minimization one by multiplying the objective feature with -1. This principle has made the optimization problems with mixed sort of goals clean to address by way of reworking the objective into one same form of optimization issues.

III. Problem Identification

In the last few years ago, portfolio optimization has emergent as a challenging and interesting multi-objective problem, in the field of computational finance. It is still receiving the increasing thought of researchers, fund management companies, and individual investors. Selecting of a subset of assets and its corresponding best weights of each selected assets, are key issues in portfolio selection. The composition of each asset is to be selected in such a way Achieving high returns while limiting the risk to a minimum. There are some important issues in the portfolio optimization problem which needs to be addressed and resolved.

- The Portfolio optimization problem fulfilling a set of constraints such as budget, floor, ceiling, and cardinality is a difficult problem. These constraints had been holed by the conventional statistical and heuristic techniques using both single and multi-objective optimization. But, those strategies fail to get efficient solutions when the range of constraint will increase. For this reason, it's far required to use appropriate multi-objective evolutionary algorithms to solve the portfolio optimization hassle with an extra number of constraints.
- Because the introduction of the mean-variance portfolio optimization model by Harry Markowitz, sizeable studies interest has been made on version simplifications and the improvement of various threat measures. All these techniques use the mean of the past return as expected return. Hence there is a need to develop efficient ways of approach which would directly predict the future return and would be considered as an expected return.
- There is a need to develop strong portfolio optimization strategies which can efficiently manage the outliers gift within the economic records.
- In lots of conditions, it's far required to invest the fund in future in which the future records aren't available and the existing statistics are uncertain because of the presence of outliers. In such situation, destiny stock must be expected and the expected return and variance are to be estimated. Such complicated hassle desires an ability solution by devising sturdy prediction approach followed by way of efficient optimization.

Solution of the Problem

The portfolio optimization problem is solved by applying multi-objective evolutionary algorithms (MOEAs). One of the main advantages of the MOEA is that, it gives a set of possible solutions in a single run, called as a Pareto optimal solution. 3 multi-objective evolutionary algorithm are using to overcome the problem, first NSGA-II, second MOEA/D and, third MOEA/DD, we are create fitness function with an empty portfolio, where assets are added iteratively, and taking two object risk and, return, we are calculating variance and standard division of output, this 3 MOEAs algorithm are comparing which are return better solution. they are perform 3 operation are following:

1. Selection
2. Crossover
3. Cutation

1. Selection: The new individual's selection is made as follows: Calculate the reproduction probability for each individual

$$Ri = \frac{fi}{\sum_{i=1}^{n} fi}$$

Where: fi is the Fitness of the individual i. (a fitness function is needed to evaluate the quality of each candidate solution with regard to the task to be performed).

n is the size of the population. every time an only chromosome is selected for the new population. This is achieved by generating a casual number r from the interval [0, 1]. If

$r < R1$ then choose the 1st chromosome, otherwise choose the ith chromosome such as $Ri\text{-}1 < r \leq Ri$.

2. crossover:- The crossover operator as follows: Population resulting from choice is split into two components. Each pair fashioned will go through the crossover with a certain chance Pi. Many special types of crossover exist in the literature for example single point crossover, two-point crossover, and mathematics crossover.

3. Mutation:- individuals in the population after crossover will then undertake a method of mutation; this procedure is to randomly change several bits, with a certain probability Pm

VI. LITERATURE REVIEW

Paper	Source of publication	Year	Author	Technique
Portfolio optimization based on funds standardization and genetic algorithm	Journal	2017	YAO-HSIN CHOU, SHU-YU KUO	Portfolio, stock selection, funds standardization, low volatility, Genetic algorithm (GA), modern portfolio theory.
Robust Median Reversion Strategy For Online Portfolio Selection	Journal	2016	Dingjiang Huang, Junlong Zhou,	Portfolio selection, Online learning, Mean Reversion, Robust Median Reversion, L1-median.
Portfolio approaches for constraint optimization problems	Journal	2015	Roberto Amadini.Maurizio Gabbrielli1	Algorithm portfolio · Artificial intelligence · Combinatorial optimization · Constraint programming · Machine learning
Loan Portfolio Optimization using Genetic Algorithm: A case of credit constraints	Journal	2015	Noura Metawal, Mohamed Elhoseny2,	Bank Lending, Genetic Algorithm, Credit Constraints, Bank Profit
Prediction based mean-variance model for constrained portfolio assests selection using multiobjective evolutionary algorithm	journal	2016	Shudhansu kumar mishra, babita majhi	Constrained portfoliooptimization Multiobjectiveoptimization Functional linkartificial neuralnetwork Efficient frontier Non-dominatedsorting Nonparametricstatisticaltest
Surveying Stock Market Portfolio Optimization Techniques	Conference	2015	Mukesh Kumar Pareek	*Stock Market, Stock Market Portfolio Optimization, Risk Models, Stock Market Portfolio Optimization Techniques*
A Robust Statistics Approach to Minimum Variance Portfolio Optimization	journal	2016	Dingjiang Huang, Junlong Zhou, Bin Li	Portfolio selection, Online learning, Mean Reversion, Robust Median Reversion, L1-median
Multi-Objective Portfolio Optimization and Rebalancing Using Genetic Algorithms with Local Search	Journal	2012	Vishal Soam, Leon Palafox	Portfolio optimization
Internal Regret in On-Line Portfolio Selection	Journal	2005	GILLES STOLTZ	individual sequences, internal regret, on-line investment, universal Portfolio, EG strategy
Portfolio optimization using multi-objective genetic algorithm	Journal	2007	Prisadaing skolpadungket	Portfolio optimization, genetic algorithm
Loan Portfolio Optimization using Genetic Algorithm: A case of credit constraints	Journal	2016	Noura Metawal, Mohamed Elhoseny2	Bank Lending, Genetic Algorithm, Credit Constraints Bank Profit

1) Dingjiang Huang, Junlong Zhou, et al. (2016) have found that Robust Median Reversion Strategy for Online Portfolio Selection. In this paper, we plan to use the reversion phenomenon by using robust L1-median estimators and plan a novel online portfolio selection approach named "Robust Median Reversion" (RMR), which build optimal portfolios based on the improved reversion estimator. We observe the presentation of the planned algorithms on various real markets with extensive experiments. Empirical results show that RMR can overcome the drawbacks of existing mean reversion algorithms and get significantly better solutions. Finally, RMR runs in linear time and thus is suitable for large-scale real-time algorithmic trading applications.

(2) Roberto Amadini1 • Maurizio Gabbrielli1l et al. (2015) found that Portfolio approaches for constraint optimization problems. Within the Constraint Satisfaction Problems (CSP) perspective, a technology that has established to be mostly per

formant consists of using a portfolio of dissimilar constraint solvers. other than, relatively little studies and examination have been done in the world of Constraint Optimization Problems (COP). In this work, we award an overview to COP as well as an experiential evaluation of the different state of the art existing CSP portfolio approaches accurately adapted to deal with COP. The results obtained by determining several evaluation metrics confirm the effectiveness of portfolios even in the optimization field and could give rise to some interesting future research.

(3) WEI LIt, JI-CHUN GAN2. al(2013) found that portfolio optimization model based on synthesizing effect. This paper to study the investment portfolio problem for the first time. The SEPO model is a crisp programming model and obtained from a class of stochastic programming problems by constructing a class of synthesis effect functions. The SEPO model can further be shown to contain expectation value model by choosing different synthesis effect functions. A synthetically improved genetic algorithm based on real coding and random simulation is used in an illustrative example. It shows that the solutions of the SEPO model are richer than other solution models, and can be aware of different decision making in real life.

(4) Chao Gong, Chunhui Xu, al. (2016) published Portfolio optimization in single-period under cumulative prospect theory using genetic algorithms and bootstrap method. in this paper present an approach to solving the portfolio optimization in single-period under cumulative prospect theory, based upon the coupling of genetic algorithms with bootstrap method. The computational experiments show that the behavior characteristics of CPT investors when they faced the portfolio composed of risky assets by using the method we proposed. Finally, these phenomena are discussed in this paper.

(5) Vishal Soam, Leon Palafox, et. al. (2012) has proposed Multi-Objective Portfolio Optimization and Rebalancing Using Genetic Algorithms with Local Search, in this paper introduced a new "greedy coordinate ascent mutation operator" and we have also included the trading volumes concept. We performed simulations with the past data of NASDAQ100 and DowJones30, concentrating mainly on the 2008 recession period for portfolio optimization, firstly select the assets from a pool of them available in the market and then assign proper weights to them to maximize the return and minimize the risk associated with the Portfolio, and compared results with the indices and the simple Genetic Algorithms approach.

V. PROPOSED METHODOLOGY

4.1 PROCEDURAL STEPS

The whole process involves following set of steps:

STEP 1: INITIALIZATION PARAMETER

Firstly initialize parameter, and create this section empty_individual and, different parameter are create

(1) Position
(2) Cost
(3) Out
(4) Rank
(5) Domination set
(6) Dominated Count
(7) Crowding Distance

Step 2: Randomly Generate Initial Population

A population of candidate solutions for the optimization task to be solved is randomly initialized within the given lower and upper bounds:

$$P^{0} = x^{0}_{i,}j = \varepsilon^{+}j + randj\,[0, 1) * (\delta^{+}j - \varepsilon^{+}j)$$

$$i = 1,....,NPi,\ j = 1,....., D.$$

where randi[0; 1) denotes a uniformly distributed random real value within the range[0,1).

The position of the population is to maintain(the representation of) possible answers, a population is multistep of genotypes, the populace forms the unit of evolution. People are static gadgets no longer changing or adopting, it's miles the population that does, given an illustration, defining a populace may be as easy as specifying what number of people are in it, this is, placing the populace length, in a few sophisticated EAs a population has an additional spatial shape, with a distance measure or a neighbourhood relation. In such cases, the additional shape must be described as nicely to completely specify a population. Instead of variation operators that act on the only or discern people, the choice operators(discern choice and survivor choice) work at populace degree, in popular, they take the whole modern-day populace under consideration and picks are continually made relative to what we've got, as an instance, the nice individual of the given populace is chosen to seed the subsequent technology, or the worst character of the given populace is selected to get replaced by a brand new one. In almost all EA applications the populace size is regular, not changing for the duration of the evolutionary seek.

Step 3: Calculate Fitness:

(1) in this step calculate the fitness function, the evolutionary function is also known as fitness function, we are create fitness_multi or fitness_ga platemo funtion in this under risk and return are calculating .
(2) Fitness Function is an Objective Function which we need to maximize.
(3) define Fitness Function in such a way so that it increases even with searching for minima or maxima.

4 Ranking Crowding:
The crowding distance of a particular solution i is the average distance of its two neighbouring solutions. the crowding distance of individual x which is calculated as an average distance of the largest cuboid enclosing x without including any other point. The crowding distance is computed by first sorting the population in an ascending order of objective function values. The boundary solutions of each objective function are set with infinite values in order to ensure that they are always selected. All other intermediate solutions are computed by the absolute normalized difference of two adjacent solutions. The overall crowding distance is obtained by adding the individual distance values of each objective (Deb et al., 2002). The procedure is shown in Algorithm 4.2 where fj(x) denotes the jth objective function value of the individual x in the set X, cdj(x) denotes the crowding distance of jth objective function of individual x and fmax j and fmin j are the maximum and minimum values of the jth objective function.

step 5: Front Create:
in this step create front

step 6: condition:
in this step check condition while termination, when condition is true given follow:
(1) best algorithm
(2) output profit sequence
if condition is false perform following steps:
(1) selection
(2) crossover
(3) mutation
(4) fitness rank
(5) front
(6) select top n solution and distance

Step 7: Termination

VI. EXPECTED RESULT

in this thesis proposed 3 Multi-objective evolutionary algorithm (1) NSGA II (2) MOEA/D (3) MOEA/DD , in three algorithm write code in MATLAB .
The algorithm have been run 10-10 times, and then the maximum, minimum, average, and standard deviation are calculated, and the corresponding result are listed in table 6.1

Algorithm	NSGAII (RISK)	NSGAII (RETURN)	MOEA/D (RISK)	MOEA/D (RETURN)	MOEA/DD (RISK)	MOEA/DD (RETURN)
AVG.	$1.261*10^{-2}$	$1.01*10^{-3}$	$1.275*10^{-2}$	$7.2*10^{-4}$	**$1.197*10^{-2}$**	**$1.89*10^{-3}$**
VAR.	$1.889*10^{-7}$	$1.194*10^{-4}$	$1.245*10^{-7}$	$2.216*10^{-4}$	**$2.1*10^{-9}$**	**$5.3*10^{-9}$**
STD.	$4.346*10^{-4}$	0.01092	$3.5284*10^{-4}$	$4.7074*10^{-4}$	**$4.5825*10^{-5}$**	**$7.2801*10^{-5}$**

Table 6.1: Comparison of performance using different MOEAs

Table 6.1 are show average , variance , and standard deviations of MOEAs algorithm, the best value of each row are highlighted . the standard deviations obtained by proposed MOEAs based MOEA/DD technique, are smallest, that indicate better consistency compared to the other algorithms. it is found that most of the solutions obtained by the MOEA/DD algorithm with the proposed MOEAs model. in this thesis objective is trade-off between risk (variance of return) and return (mean of return) . calculated risk and return all of proposed MOEAs algorithms provide solution but MOEA/DD Result are much better than NSGA II AND, MOEA/D .

VII. CONCLUSION
A Portfolio Optimization using multi-objective evolutionary algorithm has been proposed in the thesis and 3 efficient MOEAs have been successfully applied to the portfolio optimization problem. in the proposed model. The weights of HFLANN structure is updated by applying the MOEA/DD Algorithm which reduces the computational time by substantially reducing the number of iterations to train the network. The multi-objective evolutionary algorithm is proposed and suitable tuned to solve portfolio multi-objective optimization problem. The MOEAs i.e. NSGA II, MOEA/D and, MOEA/DD has been successfully applied to realistic portfolio asset selection problems,
Experimental results reveal that the proposed algorithms are able to adequately handle risk (variance of return) and return (mean of return) simultaneously. From the simulation results it is clear that the investor does not have to invest money on all available

assets rather to invest in fewer assets i.e. approximately 10 percent of available assets, to explore wide risk-return area. The portfolio manager has the option to make a trade-off between risk and return for decide the portfolio according to the requirement. In particular, the MOEA/DD algorithm gives best Pareto solutions maintaining adequate diversity.

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