A REVIEW PAPER ON PORTFOLIO OPTIMIZATION USING GENETIC ALGORITHM

Rashi Chandrakar[1], Dr Sanjeev Sharma[2]
Computer Science & Engineering, Rungta College Of Engineering, Bhiali, India

Abstract: Data Mining is the process of analyzing data from a different perspective and shortening it into valuable information It is the process of fetching unknown knowledge from a wide store of raw data. In this paper has been done portfolio optimization using a genetic algorithm. The selection of portfolio optimization is the central problem of financial investment decisions. scientifically talking, portfolio choice refers to the formulation of a purpose function that determines the weights of the portfolio invested in every asset as to maximize return and minimize risk. This paper uses the technique of genetic algorithm (GA) to get an optimal portfolio selection. on the other hand, the GA parameter is of big importance in the procedure of convergence of this algorithm towards the optimal result such as crossover. While a five asset portfolio example is used in this paper to demonstrate the validity and efficiency of genetic algorithm method, GA method can also be used on the other hand for a bigger number of portfolio work. The outcome obtains confirm before research studies about the validity and good organization of genetic algorithm in selecting optimal portfolios.
Index Terms: Data Mining, portfolio, stock selection, genetic algorithm.

I. INTRODUCTION

Portfolio optimization is one of the most challenging problems in the field of finance. Choosing the weights of the portfolio to invest in each asset to meet the risk and return expectations make this problem more crucial. In dealing with this problem, Harry Markowitz 1952 developed a quantitative model, also called mean-variance model. The mean-variance model has been generally measured as either the minimization of an objective function presenting the portfolio variance (risk) for a given point of return or the maximization of an objective function representing the portfolio return for a given level of risk. In this model, however, cardinality and bounding constraints are not considered (Fernandez and Gomez, 2007). To explanation for the restrictions of the mean-variance model of Markowitz, some methods such as Constrained Optimization (CO), Quadratic Programming (QP), Linear Programming (LP) and Second-Order Cone Programming (SOCP) have been developed and used (Davidson, 2011). However, this technique has a various drawback in portfolio optimization as are based on linear assumption and are therefore good for quadratic objective functions (deterministic) with a single objective (Roudier, 2007). But the main question that this paper is trying to answer is what if the objective function is not quadratic and has more than one objective: Maximization of return and minimization of risk simultaneously. just, a various technique based on artificial intelligence such as Genetic algorithm has been applied to overcome this problem. GAs are stochastic, heuristic techniques based on the natural choice principles, and they can deal with nonlinear optimization problems with non-smooth and even non-continuous objective, and continuous and/or integer variables (Lin et al; 2005). However, the choice of GA factors such as the mutation and crossover technique can manipulate the GA performance (Bakhtyar et al, 2012). For the application of GA, three crossover procedures which are: Single point, two points, and arithmetic have been applied, while other procedures such as mutation and selection could be applied also. The procedures of crossover are applied in order to know their impact on the convergence time of GA towards the optimal solution. GAs derives most of their power from a crossover. Crossover, in combination with survival of the fittest structures, allows the best components of differing solutions to combine to form even superior solutions (Mahfoud and Mani, 1996. even as the function of GAs has progress glowing in a different field like health, engineering, electronics, robotic and so, such progress, however, is still not well advanced in the field of finance, especially in portfolio optimization problems. As such, this paper will discard more light on the contribution that GA can make in solving portfolio optimization problems.

II. PORTFOLIO OPTIMIZATION MODELS

Markowitz [1] had proposed a mean-variance model for portfolio optimization in which weighted mean returns of the stocks in the portfolio were considered as a return of the portfolio
and variance of these stocks from mean return was considered
as a risk. Markowitz model can be described using Equation 1, Equation 2, Equation 3 and Equation 4.

$$minimize \sum_{i=1}^{n} \sum_{j=1}^{n} Wz\ Wj\ Oij \qquad (1)$$

$$such\ that \sum_{i=1}^{n} Wi\ Ui >= Up \qquad (2)$$

$$\sum_{i=1}^{n} Wi = 1 \qquad (3)$$

$$0 \leq Wi \leq 1;\ i = 1.....n \qquad (4)$$

where,

n = number of stocks in a dataset,
Ui = the expected return of the asset i,
σij = the covariance between asset i and j,
Wi = proportion of capital invested in asset i,
Up = desired return from portfolio

Equation 1 represents the objective function of the optimization problem which aims to minimize the risk of a portfolio while Equation 2 enforces the portfolio to achieve desired return *Up*. Equation 3 and Equation 4 are constraints on portfolio, assuring that 100% of the investors' capital is invested and no short selling is performed, respectively.

The Markowitz model has been used extensively for portfolio optimization. This model uses historical mean return and co-variance of stocks to optimize a portfolio. Markowitz model selects stocks which have minimum co-variance between them to ensure diversified risk, i.e., to minimize chances of loss. It is easy to understand from statistics that low co-variance stocks do not move together, so if some stocks in portfolio are not performing well, then other stocks (having low co-variance with poorly performing stocks) in portfolio can cover the loss. Adding cardinality constraint to Markowitz model turns the model from a QP problem to a MIQP (Mixed Integer Quadratic Programming) problem, which is a NP-Hard problem. Other constraints like, sector capitalization, minimum transaction lots, etc. make the problem even harder to solve.

MAD (Mean Absolute Deviation) model proposed by Konno and Yamazaki [2] is another popular model which is frequently used to solve portfolio selection problem. It solves the problem through linear programming. It is to be noticed that mean in MAD refers to the mean return of the assets in portfolio. Some of the other models used include Exponential Decay Model [3], Extended Markowitz Model [4], [5], Mean- Variance-Skewness Model [6] and Robust MAD Model [7].

III. PORTFOLIO OPTIMIZATION PROBLEM AS A QUADRATIC PROGRAMMING PROBLEM AND HEURISTICS FOR PORTFOLIO OPTIMIZATION

Basic Markowitz model can easily be implemented as a Quadratic Programming problem. Equation 5, Equation 6 and Equation 7 represents Markowitz model as a QP problem.

$$\text{Minimize} \quad \frac{1}{2} W^t H W - M^t W \qquad (5)$$

$$\text{Subject to} \quad E^t W = 1 \qquad (6)$$

$$\text{and} \quad 0 \le W \le 1 \qquad (7)$$

where,
W = weight vector of all stocks,
H = co-variance matrix of mean return of all stocks,
E= vector of ones,
M = mean return vector of all stocks.

The above formulation restricts short selling; however, portfolio optimization problem can be formulated considering short selling as well. Further, if the cardinality constraint is added to the (quadratic programming) model presented above then the problem becomes Mixed Integer Quadratic Programming problem, which is NP-Hard and considerably more difficult to solve than the original problem. Instead of solving NP-Hard optimization problem, researchers have proposed various heuristics approaches to get the near optimal results for portfolio optimization. These heuristic approaches are implemented through various Artificial Intelligence and Soft Computing techniques. Different techniques that are widely used by researchers are mentioned in the next section.

IV. A COMPARATIVE STUDY

This section compares literature in the domain of stock market portfolio optimization across three dimensions: techniques used.

A. Techniques Used

Survey of the existing literature reveals that Genetic Algorithm, Fuzzy Theory and Particle Swarm Optimization are extensively used techniques for portfolio optimization. Other techniques that are used frequently for optimizing the portfolio include; multi-objective evolutionary algorithms (MOEA). NSGA-II (Nondominated Sorting Genetic Algorithm II), SPEA-2 (Strength Pareto Evolutionary Algorithm- 2), PESA-II (Pareto Envelope Based Selection-II) and PAES (Pareto Archived Evolution Strategy) are some of the multiobjective evolutionary algorithms that have been used. Table I summarizes various techniques used for portfolio optimization problem by the researchers around the globe.

Abbreviations used in Table I are enlisted below:

AES = Adaptive Exponential Smoothing,
AHP = Analytical Hierarchy Process,
ARIMA = Autoregressive Integrated Moving Average,
ARM = Association Rule Mining,
ARMS = Autoregressive Markov-Switching Model,
ARX = Autoregressive Exogenous,
EA = Evolutionary Algorithm,
ES = Exponential Smoothing,
FT = Fuzzy Theory,
GA = Genetic Algorithm,
GBM = Geometric Brownian Motion,
GMM = Generalized Method of Moments,
MOEA = Multi-Objective Evolutionary Algorithm,
MPM = Minimal Probability Machine,
NCP = Nadir Compromising Programming,
NSGA-II = Non-dominated Sorting Genetic Algorithm II,
PESA-II = Pareto Envelope Based Selection,
PQP = Parametric Quadratic Programming,
PSO = Particle Swarm Optimization,
RBF = Radial Basis Function,
RS = Rough Set,

SA = Simulated Annealing,
SMO = Sequential Minimal Optimization,
SOM = Self Organising Maps,
SPEA-2 = Strength Pareto Evolutionary Algorithm,
SVM = Support Vector Machine,
SVR = Support Vector Regression,
TS = Tabu Search,
TSD = Time Series Decomposition,
XCS = Extended Classifier System,
Y = Yes.

V. GENETIC ALGORITHM

Genetic algorithm used in portfolio optimization. in this algorithm under many methods; GA manipulates a population with the constant size. This population consists of applicant points called chromosomes. This algorithm leads to an opposition phenomenon between the chromosomes. Each chromosome is the indoctrination of a possible solution for the problem to be solved, it ready for a set of elements called genes, which can take some values. At each iteration (generation) a new population is created with the same size. This generation consists of the better chromosomes "adapted" to their environment as represented by the selective function. regularly, the chromosomes will be inclined in the direction of the optimum of the selective function. The formation of the latest population is ready by applying the genetic operators which are selection, crossover, and mutation.

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 $R_{i-1} < r \leq R_i$.

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

Genetic algorithms are more flexible than most search methods because they require only information concerning the quality of the solution produced by each factor set (objective function values) and not like a lot of optimization technique which calls for derivative information, or yet other, complete knowledge of the problem structure and parameters (Bouktir et al, 2004).

There is some difference between Gas and traditional searching algorithms (Augusto et al, 2006). They could be summarized as follows:
1. they work with a coding of the parameter set and not the parameters themselves;
2. they search from a population of points and not a single point;
3. they use information concerning of (payoff) and not derivatives or other auxiliary knowledge;
4. they use probabilistic transition rules and not deterministic rules.

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 · Combinato

				rial optimization · Constraint programming · Machine learning
Loan Portfolio Optimization using Genetic Algorithm: A case of credit constraints	Journal	2015	Noura Metawal, Mohamed Elhoseny 2,	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-dominated sorting 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 Elhoseny 2	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.

VII. CONCLUSION

Portfolio optimization is one of the most challenging problems in the field of finance. Choosing the weights of the portfolio to invest in each asset to meet the risk and return expectations make this problem more crucial. In dealing with this problem. This paper uses the technique of genetic algorithm (GA) to get an optimal portfolio selection in future we are select the one genetic algorithm method and implement this technique.

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